问题4-思路2

把温度当自变量，找到目标函数为合格率达到要求的数值当作一个解，对得到的多个满足合格率的温度值使用 TOPSIS 评价得到最佳温度

In [1]:

```
import mitosheet
import numpy as np
import pandas as pd
import plotly as py
import cufflinks as cf
import plotly.express as px
import plotly.graph_objects as go
import plotly.figure_factory as ff

cf.set_config_file(
    offline=True,
    world_readable=True,
    theme='white',        # 设置绘图风格
)

import warnings
warnings.filterwarnings("ignore")

import sklearn
import graphviz
from sklearn import tree
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, roc_auc_score

from colorama import Fore
def color(text):
    return Fore.RED + text + Fore.RESET
```

In [2]:

```
file_path = './附件2(Attachment 2)2022-51MCM-Problem B.xlsx'
sheet1 = pd.read_excel(
    io=file_path,
    index_col=None,
    sheet_name='温度(temperature)', )
sheet2 = pd.read_excel(
    io=file_path,
```

```
    index_col=None,
    sheet_name='产品质量(quality of the products)', )
sheet3 = pd.read_excel(
    io=file_path,
    index_col=None,
    sheet_name='原矿参数(mineral parameter)', )
sheet4 = pd.read_excel(
    io=file_path,
    index_col=None,
    sheet_name='过程数据(process parameter)', )
```

准备数据

表1——温度(temperature)

In [3]:
```
# todo 找到有效的温度数据
sheet1_time_string = sheet1.iloc[:, 0].astype('string')

cond1 = sheet1_time_string.apply(lambda x: x[14: 16]) == "50"
data_part1 = sheet1[cond1].iloc[:-2, :]

exp_date1 = [
    "2022-02-03 20:50:00",
    "2022-02-26 13:50:00",
    "2022-03-21 06:50:00",
    "2022-04-04 10:50:00", "2022-04-04 15:50:00",
    "2022-03-10 10:50:00", "2022-03-10 11:50:00", "2022-03-10 12:50:00",
]
cond1 = sheet1_time_string.apply(lambda x: x in exp_date1)
data_part1 = data_part1[cond1.apply(lambda x: not x)]
data_part1.index = [i for i in range(len(data_part1))]
print(data_part1.shape)
# data_part1
# mitosheet.sheet(data_part1, analysis_to_replay="id-conydfcblv")
```

```
(1725, 3)
```

表2——产品质量(quality of the products)

In [4]:
```
# todo 找到有效的产品质量数据
sheet2_time_string = sheet2.iloc[:, 0].astype('string')

exp_date2 = [
```

```python
    "2022-02-20 23:50:00", "2022-02-21 00:50:00", "2022-02-21 01:50:00",

    "2022-02-21 09:50:00", "2022-02-21 10:50:00", "2022-02-21 02:50:00", "2022-02-21 03:50:00", "2022-02-21 04:50:00",
    "2022-02-21 05:50:00", "2022-02-21 06:50:00", "2022-02-21 07:50:00", "2022-02-21 08:50:00",

    "2022-02-26 06:50:00", "2022-02-26 07:50:00", "2022-02-26 08:50:00", "2022-02-26 09:50:00", "2022-02-26 10:50:00",

    "2022-04-08 00:50:00", "2022-04-08 01:50:00",
]

cond2 = sheet2_time_string.apply(lambda x: x in exp_date2)
data_part2_ = sheet2[cond2.apply(lambda x: not x)].iloc[2:, :]
data_part2_.index = [i for i in range(len(data_part2_))]
print(data_part2_.shape)
# data_part2_
# mitosheet.sheet(data_part2_, analysis_to_replay="id-etdktbfykz")
```

(1725, 5)

In [5]:
```python
data_part2_
```

Out[5]:

	时间 (Time)	指标A (index A)	指标B (index B)	指标C (index C)	指标D (index D)
0	2022-01-25 02:50:00	79.08	23.52	12.41	17.86
1	2022-01-25 03:50:00	79.29	22.94	11.72	17.86
2	2022-01-25 04:50:00	79.95	21.42	10.68	17.63
3	2022-01-25 05:50:00	80.20	21.20	10.16	16.92
4	2022-01-25 06:50:00	80.38	20.75	10.16	15.75
...	...	...	...	...	...
1720	2022-04-07 19:50:00	79.82	23.84	11.03	13.52
1721	2022-04-07 20:50:00	78.98	25.36	11.37	12.85
1722	2022-04-07 21:50:00	78.86	25.40	11.37	11.42
1723	2022-04-07 22:50:00	79.10	25.58	11.37	11.55
1724	2022-04-07 23:50:00	79.32	24.82	11.03	11.55

In [6]:
```python
# todo 计算合格数量、合格率
cond10 = 77.78 < data_part2_.iloc[:, 1]
cond11 = data_part2_.iloc[:, 1] < 80.33
cond2 = data_part2_.iloc[:, 2] < 24.15
```

```
cond3 = data_part2_.iloc[:, 3] < 17.15
cond4 = data_part2_.iloc[:, 4] < 15.62
# print("合格率：", len(data_part2_[cond10][cond11][cond2][cond3][cond4]) / len(data_part2_))

# todo 找到产品是否合格
def is_qualified(x):
    return 77.78 < x[1] < 80.33 and x[2] < 24.15 and x[3] < 17.15 and x[4] < 15.62
data_part2 = pd.DataFrame(data_part2_.apply(is_qualified, axis=1))
data_part2.columns = ['是否合格']
# print(len(data_part2))
# print(data_part2.sum() / len(data_part2))

print(data_part2.shape)
print(data_part2.sum(), data_part2.sum() / len(data_part2))
# data_part2
# mitosheet.sheet(data_part2, analysis_to_replay="id-mkgwgrqoel")
```

```
(1725, 1)
是否合格    472
dtype: int64 是否合格    0.273623
dtype: float64
```

表3——原矿参数(mineral parameter)

In [7]:

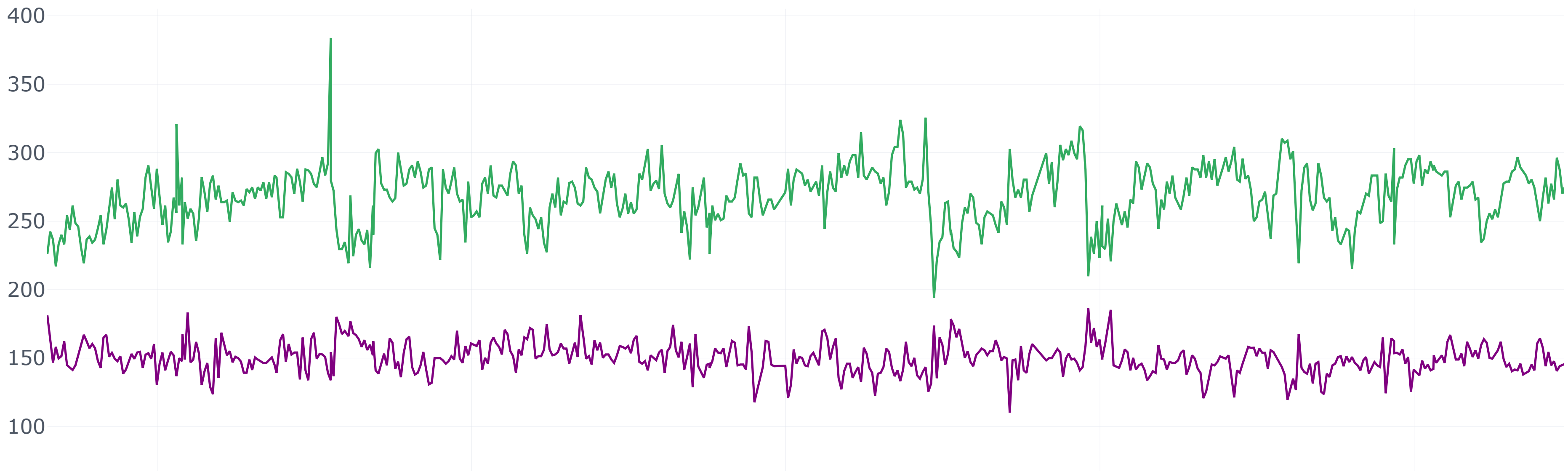
```
# todo 找到原矿参数数据 3
cnt = data_part1.iloc[:, 0].astype('string').apply(lambda x: x[5: 10])
time_cnt = []
for i in pd.DataFrame(cnt).groupby(by='时间 (Time)'):
    time_cnt.append(len(i[1]))
data_part3 = pd.DataFrame(np.repeat(sheet3.iloc[:-4, :].values, time_cnt, axis=0), columns=sheet3.columns)
print(data_part3.shape)
# data_part3
# mitosheet.sheet(data_part3, analysis_to_replay="id-rvruqimmlr")
```

```
(1725, 5)
```

表4——过程数据(process parameter)

In [8]:

```
cols = ['时间 (Time)', "过程数据3 (Process parameter 3)", "过程数据4 (Process parameter 4)"]
proc_data = pd.DataFrame(sheet4)
proc_data.iplot(x='时间 (Time)')
print("相关系数：")
proc_data.iloc[:, 1:].corr()
```



相关系数：

Out[8]:

	过程数据1 (Process parameter 1)	过程数据2 (Process parameter 2)	过程数据3 (Process parameter 3)	过程数据4 (Process parameter 4)
过程数据1 (Process parameter 1)	1.000000	NaN	0.058849	-0.147755
过程数据2 (Process parameter 2)	NaN	NaN	NaN	NaN
过程数据3 (Process parameter 3)	0.058849	NaN	1.000000	-0.497288
过程数据4 (Process parameter 4)	-0.147755	NaN	-0.497288	1.000000

In [9]:

```
def norm(data):
    return (data - data.min()) / (data.max() - data.min())

data_part4 = sheet4.apply(lambda x: (x[3] + x[4]), axis=1)
```

```python
data_part4 = pd.concat([sheet4.iloc[:, 0], data_part4], axis=1).rename(columns={0: "原矿质量"})
print(data_part4.shape)
# data_part4
# mitosheet.sheet(data_part4, analysis_to_replay="id-lntnexsmmk")
```

```
(619, 2)
```

In [10]:

```python
exp_date4 = []
for i in exp_date1 + exp_date2:
    exp_date4.append(i[:-5] + "30")
# print(exp_date4)

sheet4_time_string = data_part4.iloc[:, 0].astype('string')
cond4 = sheet4_time_string.apply(lambda x: x[: -3] not in exp_date4)

data_part4_need = data_part4[cond4]
data_part4_need = data_part4_need.iloc[:-33, :]

for _ in range(5):
    data_part4_need.drop(index=np.random.randint(0, len(data_part4_need)), inplace=True)
data_part4_need.index = [i for i in range(len(data_part4_need))]

data_part4_need = pd.DataFrame(np.repeat(data_part4_need.values, 3, axis=0), columns=data_part4_need.columns)
print(data_part4_need.shape)
# data_part4_need
# mitosheet.sheet(data_part4_need, analysis_to_replay="id-owygulbcev")
```

```
(1725, 2)
```

In [11]:

```python
data_part4_need
```

Out[11]:

	时间 (Time)	原矿质量
0	2022-01-25 02:30:11	407.39
1	2022-01-25 02:30:11	407.39
2	2022-01-25 02:30:11	407.39
3	2022-01-25 05:30:13	406.89
4	2022-01-25 05:30:13	406.89
...	...	...
1720	2022-04-07 20:30:17	485.59
1721	2022-04-07 20:30:17	485.59
1722	2022-04-07 23:30:10	440.34
1723	2022-04-07 23:30:10	440.34
1724	2022-04-07 23:30:10	440.34

In [12]:

```
X = pd.concat([data_part1.iloc[:, 1:], data_part3.iloc[:, 1:], data_part4_need.iloc[:, 1:]], axis=1)
Ys = data_part2
```

In [13]:

```
X
```

Out[13]:

	系统I温度 (Temperature of system I)	系统II温度 (Temperature of system II)	原矿参数1 (Mineral parameter 1)	原矿参数2 (Mineral parameter 2)	原矿参数3 (Mineral parameter 3)	原矿参数4 (Mineral parameter 4)	原矿质量
0	1347.49	950.40	55.26	108.03	43.29	20.92	407.39
1	1274.43	938.20	55.26	108.03	43.29	20.92	407.39
2	1273.86	938.16	55.26	108.03	43.29	20.92	407.39
3	1273.51	937.49	55.26	108.03	43.29	20.92	406.89
4	1272.84	936.67	55.26	108.03	43.29	20.92	406.89
...	...	...	...	...	...	...	...
1720	437.71	540.70	54.4	105.14	49.03	20.82	485.59
1721	494.23	557.21	54.4	105.14	49.03	20.82	485.59
1722	495.47	557.68	54.4	105.14	49.03	20.82	440.34
1723	494.41	572.00	54.4	105.14	49.03	20.82	440.34
1724	495.03	571.61	54.4	105.14	49.03	20.82	440.34

In [14]:

```
Ys
```

Out[14]:

	是否合格
0	False
1	False
2	False
3	False
4	False
...	...
1720	True
1721	False
1722	False
1723	False
1724	False

In [15]:

```
X.to_csv("quention3-X_data.csv")
```

```python
Ys.to_csv("quention3-Y_data.csv")
```

In [16]:
```python
cond = (pd.notna(X).iloc[:, 0] == True)
remain_index = X[cond].index
```

In [17]:
```python
X = X[cond]
Y = Ys[cond].replace(to_replace=[True, False], value=[1, 0])
print(X.shape, Y.shape)
```

```
(1640, 7) (1640, 1)
```

In [18]:
```python
X
```

Out[18]:

	系统I温度 (Temperature of system I)	系统II温度 (Temperature of system II)	原矿参数1 (Mineral parameter 1)	原矿参数2 (Mineral parameter 2)	原矿参数3 (Mineral parameter 3)	原矿参数4 (Mineral parameter 4)	原矿质量
0	1347.49	950.40	55.26	108.03	43.29	20.92	407.39
1	1274.43	938.20	55.26	108.03	43.29	20.92	407.39
2	1273.86	938.16	55.26	108.03	43.29	20.92	407.39
3	1273.51	937.49	55.26	108.03	43.29	20.92	406.89
4	1272.84	936.67	55.26	108.03	43.29	20.92	406.89
...	...	...	...	...	...	...	...
1720	437.71	540.70	54.4	105.14	49.03	20.82	485.59
1721	494.23	557.21	54.4	105.14	49.03	20.82	485.59
1722	495.47	557.68	54.4	105.14	49.03	20.82	440.34
1723	494.41	572.00	54.4	105.14	49.03	20.82	440.34
1724	495.03	571.61	54.4	105.14	49.03	20.82	440.34

In [19]:
```python
Y
```

Out[19]:

	是否合格
0	0
1	0
2	0
3	0
4	0
...	...
1720	1
1721	0
1722	0
1723	0
1724	0

准备数据

In [20]:

```
def norm(data):
    return (data - data.min()) / (data.max() - data.min())

# data_part4 = sheet4.apply(lambda x: (x[3] + x[4]), axis=1)
# data_part4 = pd.concat([sheet4.iloc[:, 0], data_part4], axis=1).rename(columns={0: "原矿质量"})
# print(data_part4.shape)
data_part4 = sheet4[['时间 (Time)', '过程数据3 (Process parameter 3)', '过程数据4 (Process parameter 4)']]
data_part4_need = sheet4[['时间 (Time)', '过程数据3 (Process parameter 3)', '过程数据4 (Process parameter 4)']]
data_part4_need
```

Out[20]:

	时间 (Time)	过程数据3 (Process parameter 3)	过程数据4 (Process parameter 4)
0	2022-01-25 02:30:11	226.16	181.23
1	2022-01-25 05:30:13	242.44	164.45
2	2022-01-25 08:30:33	236.59	146.70
3	2022-01-25 11:30:45	217.01	158.23
4	2022-01-25 14:30:34	233.10	149.76
...	...	...	...
614	2022-04-11 11:30:37	275.99	152.83
615	2022-04-11 14:30:59	288.89	159.78
616	2022-04-11 17:30:31	287.04	156.68
617	2022-04-11 20:30:41	270.51	160.56
618	2022-04-11 23:30:00	247.16	166.01

In [21]:

```
exp_date4 = []
for i in exp_date1 + exp_date2:
    exp_date4.append(i[:-5] + "30")
# print(exp_date4)

sheet4_time_string = data_part4.iloc[:, 0].astype('string')
cond4 = sheet4_time_string.apply(lambda x: x[: -3] not in exp_date4)

data_part4_need = data_part4[cond4]
data_part4_need = data_part4_need.iloc[:-33, :]

for _ in range(5):
    data_part4_need.drop(index=np.random.randint(0, len(data_part4_need)), inplace=True)
data_part4_need.index = [i for i in range(len(data_part4_need))]

data_part4_need = pd.DataFrame(np.repeat(data_part4_need.values, 3, axis=0), columns=data_part4_need.columns)
print(data_part4_need.shape)
data_part4_need
# data_part4_need
# mitosheet.sheet(data_part4_need, analysis_to_replay="id-owygulbcev")
```

```
(1725, 3)
```

Out[21]:

	时间 (Time)	过程数据3 (Process parameter 3)	过程数据4 (Process parameter 4)
0	2022-01-25 02:30:11	226.16	181.23
1	2022-01-25 02:30:11	226.16	181.23
2	2022-01-25 02:30:11	226.16	181.23
3	2022-01-25 05:30:13	242.44	164.45
4	2022-01-25 05:30:13	242.44	164.45
...	...	...	...
1720	2022-04-07 20:30:17	313.31	172.28
1721	2022-04-07 20:30:17	313.31	172.28
1722	2022-04-07 23:30:10	298.21	142.13
1723	2022-04-07 23:30:10	298.21	142.13
1724	2022-04-07 23:30:10	298.21	142.13

In [22]:

```
X = pd.concat([data_part1.iloc[:, 1:], data_part3.iloc[:, 1:], data_part4_need.iloc[:, 1:]], axis=1)
Ys = data_part2_.iloc[:, 1:]
```

In [23]:

```
cond = (pd.notna(X).iloc[:, 0] == True)
remain_index = X[cond].index
```

In [24]:

```
X = X[cond]
Y = Ys[cond].replace(to_replace=[True, False], value=[1, 0])
print(X.shape, Y.shape)
```

```
(1640, 8) (1640, 4)
```

In [25]:

```
X
```

Out[25]:

	系统I温度 (Temperature of system I)	系统II温度 (Temperature of system II)	原矿参数1 (Mineral parameter 1)	原矿参数2 (Mineral parameter 2)	原矿参数3 (Mineral parameter 3)	原矿参数4 (Mineral parameter 4)	过程数据3 (Process parameter 3)	过程数据4 (Process parameter 4)
0	1347.49	950.40	55.26	108.03	43.29	20.92	226.16	181.23
1	1274.43	938.20	55.26	108.03	43.29	20.92	226.16	181.23
2	1273.86	938.16	55.26	108.03	43.29	20.92	226.16	181.23
3	1273.51	937.49	55.26	108.03	43.29	20.92	242.44	164.45
4	1272.84	936.67	55.26	108.03	43.29	20.92	242.44	164.45
...	...	...	...	...	...	...	...	...
1720	437.71	540.70	54.4	105.14	49.03	20.82	313.31	172.28
1721	494.23	557.21	54.4	105.14	49.03	20.82	313.31	172.28
1722	495.47	557.68	54.4	105.14	49.03	20.82	298.21	142.13
1723	494.41	572.00	54.4	105.14	49.03	20.82	298.21	142.13
1724	495.03	571.61	54.4	105.14	49.03	20.82	298.21	142.13

In [26]:

```
Y
```

Out[26]:

	指标A (index A)	指标B (index B)	指标C (index C)	指标D (index D)
0	79.08	23.52	12.41	17.86
1	79.29	22.94	11.72	17.86
2	79.95	21.42	10.68	17.63
3	80.20	21.20	10.16	16.92
4	80.38	20.75	10.16	15.75
...	...	...	...	...
1720	79.82	23.84	11.03	13.52
1721	78.98	25.36	11.37	12.85
1722	78.86	25.40	11.37	11.42
1723	79.10	25.58	11.37	11.55
1724	79.32	24.82	11.03	11.55

In [27]:
```python
from copy import copy

def get_data(X=X, num=10):
    """
    :param X: pd.DataFrame
    """
    x_example = np.squeeze(X.sample(1).astype(float).values)
    data = []
    x1, x2, x3, x4, x5, x6, x7, x8 = [[] for i in range(8)]
    low, high = list(X.min()), list(X.max())
    for i in range(X.shape[1]):
        x_examples = copy(x_example).repeat(num).reshape(-1, num).T
        x_examples[:, i] = np.linspace(low[i], high[i], num)
        data.append(x_examples)
    return data
```

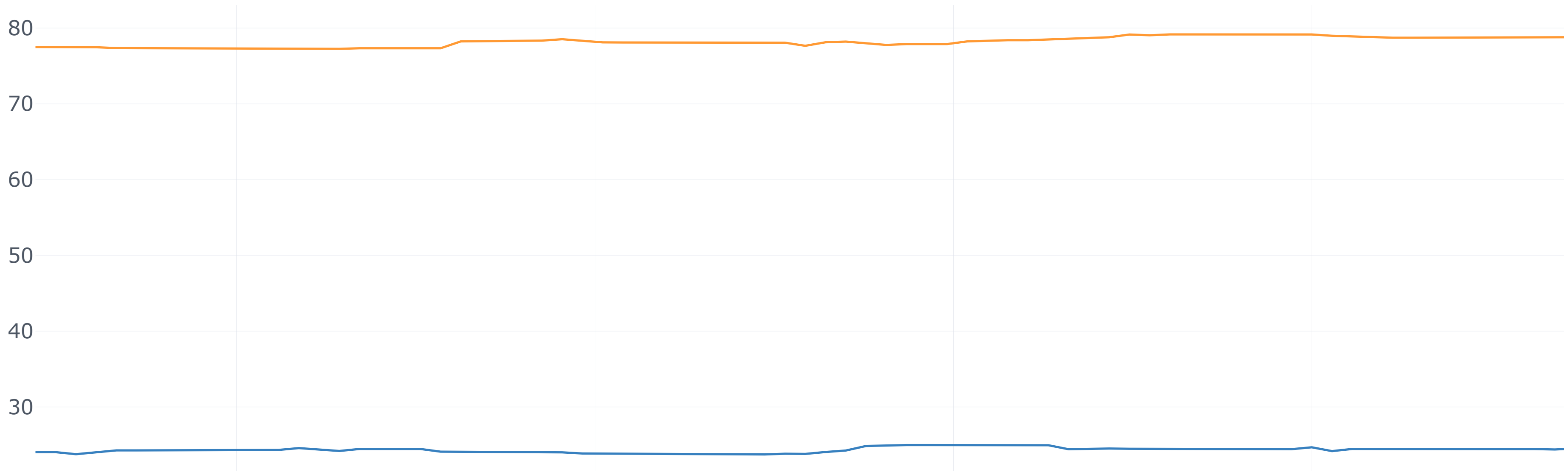
In [28]:
```python
def get_ypred(models, x):
    ys = []
    for model in models:
        ys.append(list(model.predict(x)))
    return ys
```

灵敏性分析

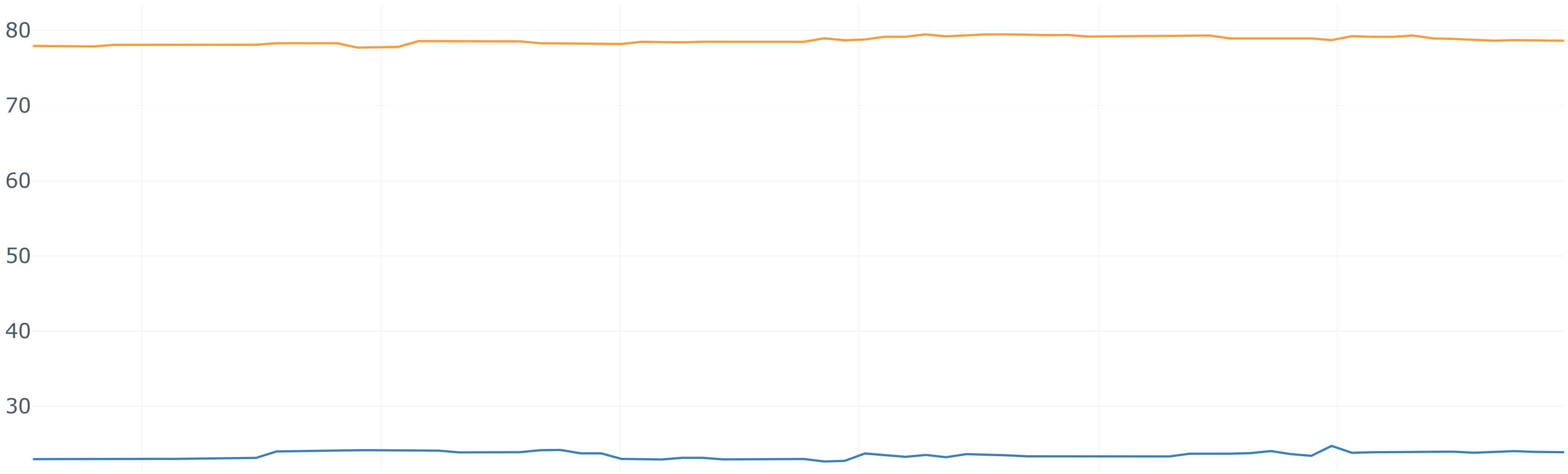
In [29]:
```python
# 温度1、2、原矿参数1、2、3、4、过程参数3、4
from xgboost import XGBRegressor as XGBC

num = 100
x_data_s = get_data(num=num)  # (8, n, 8)

# todo train
model1 = XGBC()
model2 = XGBC()
model3 = XGBC()
model4 = XGBC()
ypreds = []
for i in range(Y.shape[1]):
    xtrain, xtest, ytrain, ytest = train_test_split(
        np.array(X, dtype=float),
        np.array(Y, dtype=float)[:, i],
        test_size=0.3,
        shuffle=True,
    )
    exec(f'model{i+1}.fit(xtrain, ytrain)')
    exec(f'ypred = model{i+1}.predict(xtest)')
```

```python
    ypreds.append(list(ypred))
pd.DataFrame(ypreds).T
# print(model1, model2, model3, model4)

# todo Sensitivity analysis
y_preds_s = []  # (8, n, 4)
for i in range(len(x_data_s)):
    x_data = x_data_s[i]  # (n, m) = (8, n, m)[i]
    ypreds = get_ypred([model1, model2, model3, model4], x_data)
    y_preds_s.append(ypreds)  # (8, n, 4)

# args = ['温度1', '温度2', '原矿参数1', '原矿参数2', '原矿参数3', '原矿参数4', '过程参数3', '过程参数4']
args = ["系统I温度", "系统II温度", "原矿参数1", "原矿参数2", "原矿参数3", "原矿参数4", "过程数据3", "过程数据4"]
yargs = ['指标A', '指标B', '指标C', '指标D']
for i in range(len(args)):
    arg = args[i]
    traces = []
    y_preds = pd.DataFrame(y_preds_s[i], index=yargs).T  # (n, 4) = (8, n, 4)[i]
    x_preds = pd.DataFrame(np.linspace(X.min()[i], X.max()[i], num), columns=['x'])
    y_preds = pd.concat([x_preds, y_preds], axis=1)
    y_preds.iplot(
        x='x', y=yargs,
        title="XGBoost模型——" + arg + "的灵敏性分析",
    )
    y_preds.figure(
        x='x', y=yargs,
        title="XGBoost模型——" + arg + "的灵敏性分析",
    ).write_image('./img/问题4-' + "XGBoost模型——" + arg + "的灵敏性分析.svg")
```

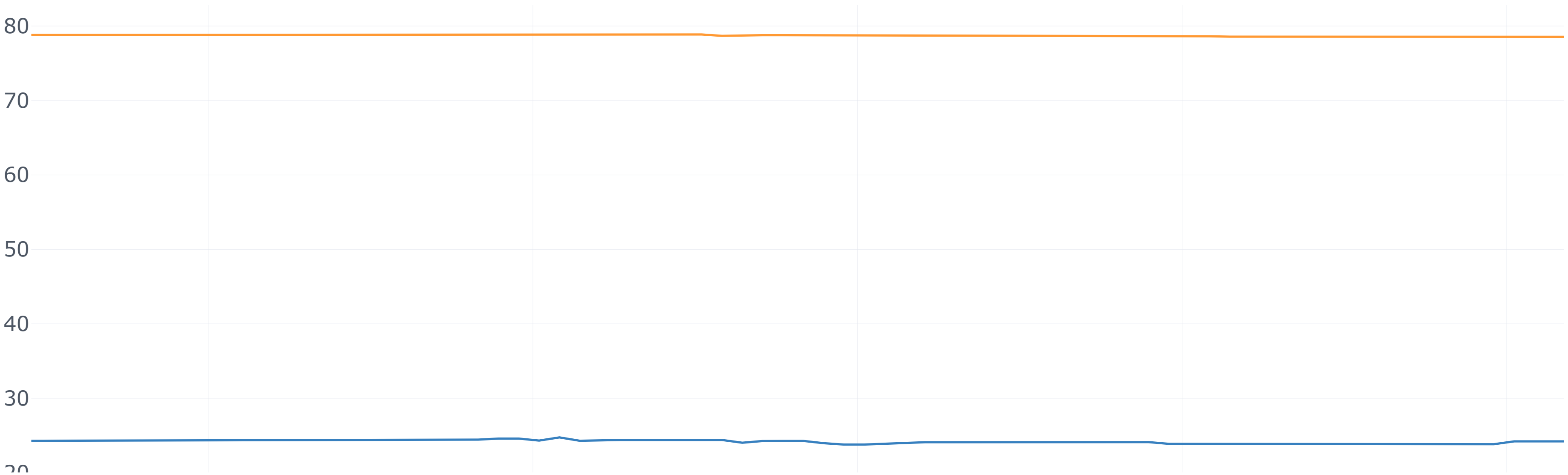
XGBoost模型——系统I温度的灵敏性分析



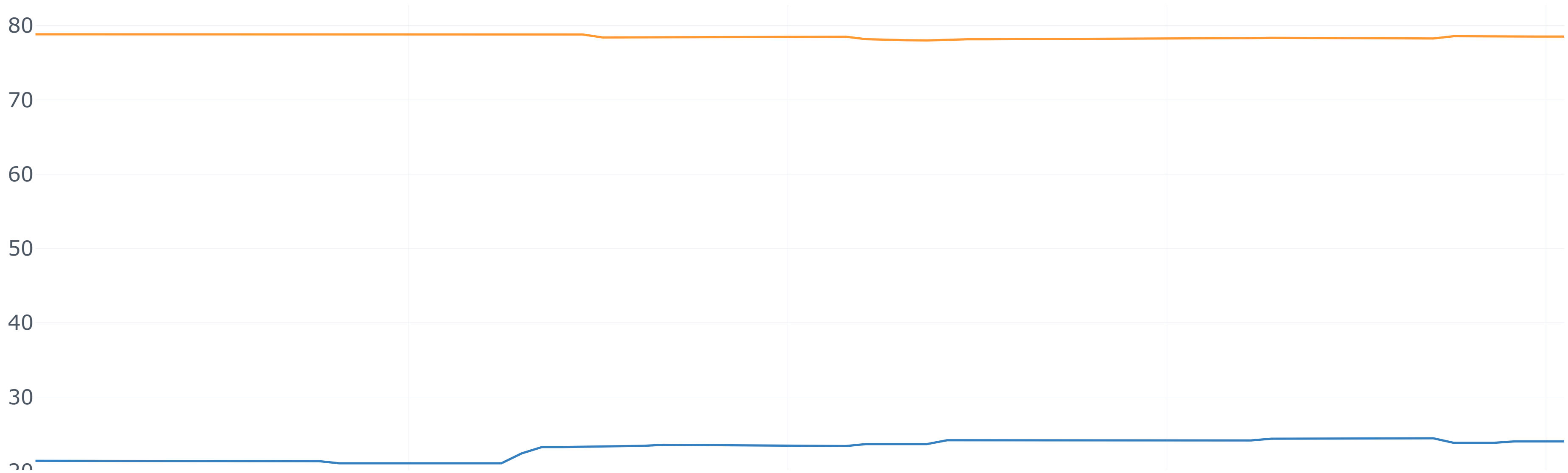
XGBoost模型——系统II温度的灵敏性分析



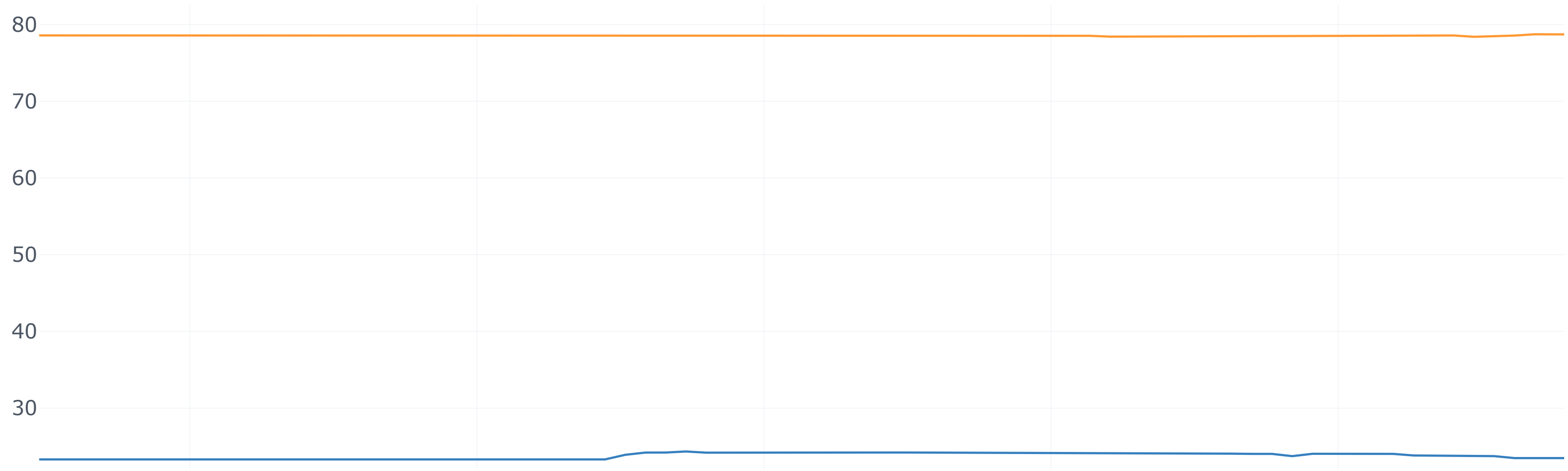
XGBoost模型——原矿参数1的灵敏性分析



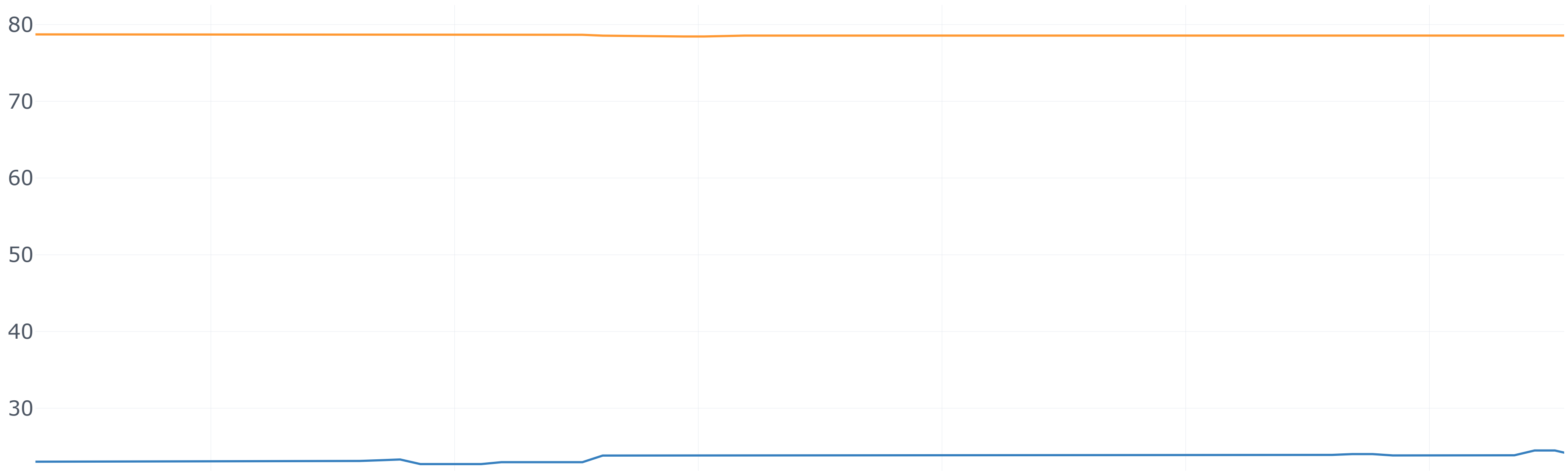
XGBoost模型——原矿参数2的灵敏性分析

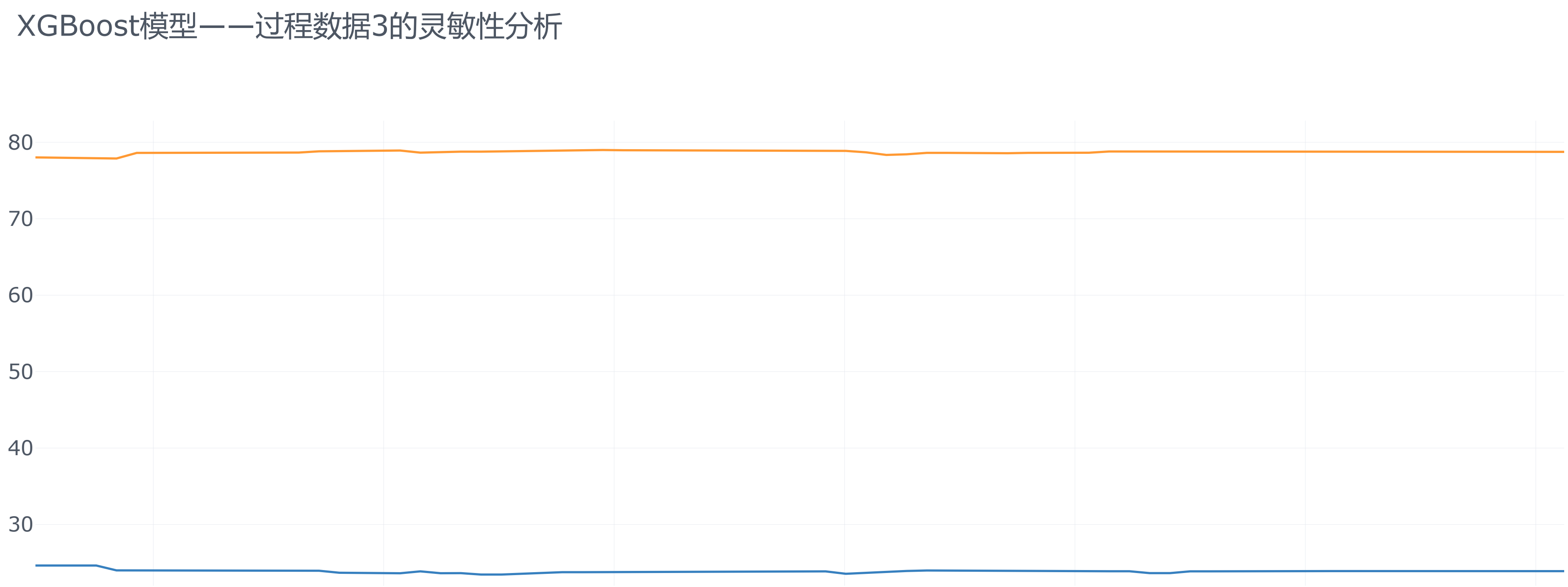


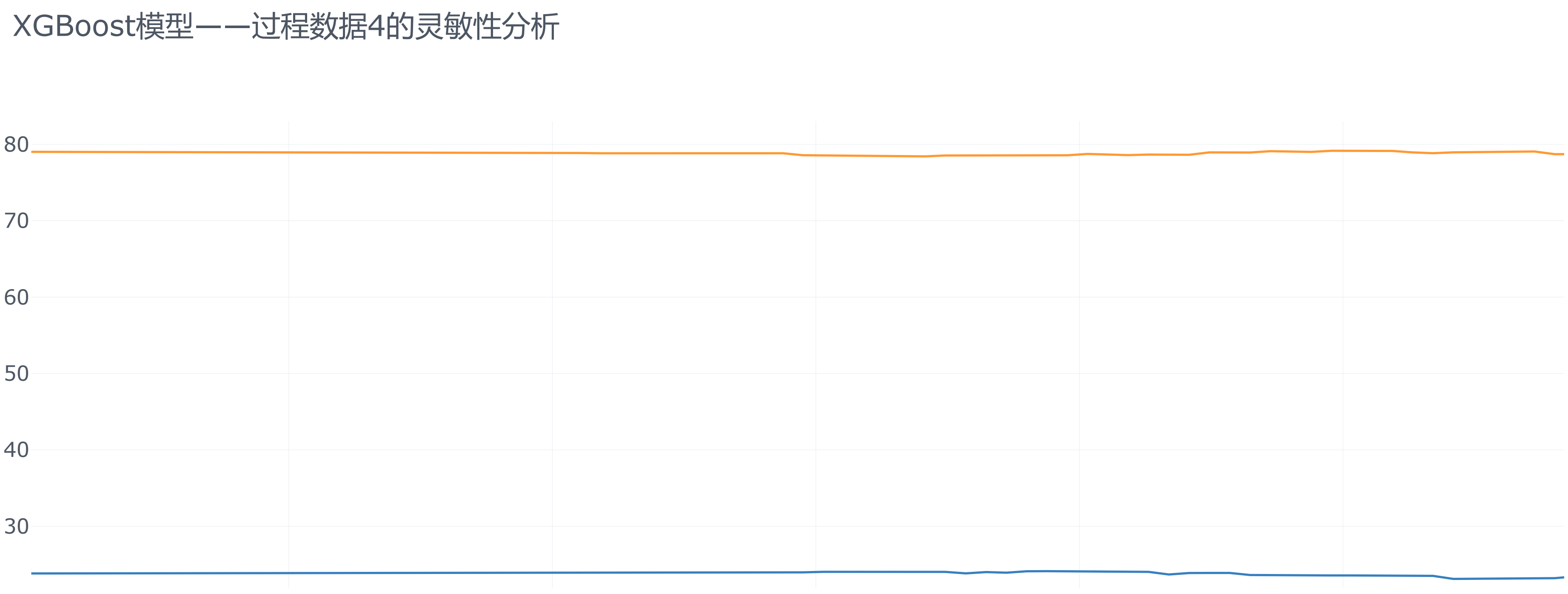
XGBoost模型——原矿参数3的灵敏性分析



XGBoost模型——原矿参数4的灵敏性分析




XGBoost模型——过程数据3的灵敏性分析
80
70
60
50
40
30



预测系统温度

可以运行多次，取自认为最好的结果

In [30]:
```
x
```

Out[30]:

	系统I温度 (Temperature of system I)	系统II温度 (Temperature of system II)	原矿参数1 (Mineral parameter 1)	原矿参数2 (Mineral parameter 2)	原矿参数3 (Mineral parameter 3)	原矿参数4 (Mineral parameter 4)	过程数据3 (Process parameter 3)	过程数据4 (Process parameter 4)
0	1347.49	950.40	55.26	108.03	43.29	20.92	226.16	181.23
1	1274.43	938.20	55.26	108.03	43.29	20.92	226.16	181.23
2	1273.86	938.16	55.26	108.03	43.29	20.92	226.16	181.23
3	1273.51	937.49	55.26	108.03	43.29	20.92	242.44	164.45
4	1272.84	936.67	55.26	108.03	43.29	20.92	242.44	164.45
...	...	...	...	...	...	...	...	...
1720	437.71	540.70	54.4	105.14	49.03	20.82	313.31	172.28
1721	494.23	557.21	54.4	105.14	49.03	20.82	313.31	172.28
1722	495.47	557.68	54.4	105.14	49.03	20.82	298.21	142.13
1723	494.41	572.00	54.4	105.14	49.03	20.82	298.21	142.13
1724	495.03	571.61	54.4	105.14	49.03	20.82	298.21	142.13

In [31]:

```
Y
```

Out[31]:

	指标A (index A)	指标B (index B)	指标C (index C)	指标D (index D)
0	79.08	23.52	12.41	17.86
1	79.29	22.94	11.72	17.86
2	79.95	21.42	10.68	17.63
3	80.20	21.20	10.16	16.92
4	80.38	20.75	10.16	15.75
...	...	...	...	...
1720	79.82	23.84	11.03	13.52
1721	78.98	25.36	11.37	12.85
1722	78.86	25.40	11.37	11.42
1723	79.10	25.58	11.37	11.55
1724	79.32	24.82	11.03	11.55

In [32]:
```
index_num = Y.shape[1]
index_name = ["指标A", "指标B", "指标C", "指标D"]
index_colors = ["red", "lightpink", "darkorange", "khaki", "green", "lightgreen", "blue", "lightblue"]

data_to_predict = np.array(
    [[1404.89,859.77,52.75,96.87,46.61,22.91, ],
    [1151.75,859.77,52.75,96.87,46.61,22.91, ],],
)
```

In [33]:
```
# 4-10
mineral_param410 = np.array([56.27, 111.38, 47.52, 20.26])
process_param410 = np.array(sheet4[-8:])[:, 3:]
data_to_predict410 = np.concatenate([mineral_param410.repeat(8).reshape(-1, 8).T, process_param410], axis=1)
pd.DataFrame(data_to_predict410, columns=['原矿参数1', '原矿参数2', '原矿参数3', '原矿参数4', '过程数据1', '过程数据2'])
# 4-11
mineral_param411 = np.array([56.71, 111.46, 46.67, 18.48])
process_param411 = np.array(sheet4[-16:-8])[:, 3:]
data_to_predict411 = np.concatenate([mineral_param411.repeat(8).reshape(-1, 8).T, process_param411], axis=1)
pd.DataFrame(data_to_predict411, columns=['原矿参数1', '原矿参数2', '原矿参数3', '原矿参数4', '过程数据1', '过程数据2'])
```

Out[33]:

	原矿参数1	原矿参数2	原矿参数3	原矿参数4	过程数据1	过程数据2
0	56.71	111.46	46.67	18.48	290.75	160.56
1	56.71	111.46	46.67	18.48	301.96	155.91
2	56.71	111.46	46.67	18.48	288.89	140.62
3	56.71	111.46	46.67	18.48	283.34	148.99
4	56.71	111.46	46.67	18.48	266.88	165.23
5	56.71	111.46	46.67	18.48	265.06	159.01
6	56.71	111.46	46.67	18.48	261.45	155.91
7	56.71	111.46	46.67	18.48	268.69	159.01

调优获得系统设定温度

In [34]:
```
xtrain
```

```
Out[34]: array([[ 719.44,  684.02,   56.19, ...,   19.33,  275.99,  148.99],
                [ 862.01,  799.5 ,   56.43, ...,   19.88,  252.85,  167.57],
                [1376.17,  881.89,   62.29, ...,   16.36,  275.99,  135.63],
                ...,
                [1403.97, 1039.93,   54.41, ...,   19.31,  247.16,  148.38],
                [ 593.45,  623.25,   53.74, ...,   21.16,  289.26,  139.25],
                [1149.46,  805.52,   55.12, ...,   20.26,  283.34,  146.55]])
```

```
In [35]: ytrain
```

```
Out[35]: array([12.4 , 14.37, 18.62, ..., 12.94, 21.26, 13.83])
```

```
In [36]: model1 = XGBC()
         model2 = XGBC()
         model3 = XGBC()
         model4 = XGBC()

         xtrain, xtest, ytrain, ytest = train_test_split(
             np.array(X, dtype=float),
             np.array(Y, dtype=float),
             test_size=0.3,
             shuffle=True,
         )

         for i in range(Y.shape[1]):
             exec(f'model{i+1}.fit(xtrain, ytrain[:, {i}])')
```

```
In [37]: from numba import jit

         def get_preds(models, x):
             ypreds = []
             for model in models:
                 ypred = list(model.predict(x))
                 ypreds.append(ypred)
             return ypreds
         def check_pass(y, th):
             boolean = list(map(lambda x: 77.78 < x[0] < 80.33 and x[1] < 24.15 and x[2] < 17.15 and x[3] < 15.62, y))
             rate = sum(boolean) / len(boolean)
             flag = True if rate >= th else False
             return [flag, rate, boolean]

         @jit
         def run_tuning(models, data_to_predict, th, X=X):
             degree_ans_list = []
             index_ans_list = []
```

```python
    step=10

    low, high = list(X.min())[:2], list(X.max())[:2]
    degree1_low, degree2_low = low
    degree1_high, degree2_high = high
    degree1 = list(np.arange(degree1_low, degree1_high, step=step))
    degree2 = list(np.arange(degree2_low, degree2_high, step=step))

    degree = []
    for i in degree1:
        for j in degree2:
            degree.append([i, j])
    degree = np.array(degree)
    l = len(degree)
    print(l)

    for j in range(l):
        x = degree[j].repeat(8).reshape(-1, 8).T
        x = np.concatenate([x, data_to_predict], axis=1)
        ypreds = np.array(get_preds(models, x)).T
        check = check_pass(ypreds, th)
        if check[0]:
            print('.', end='')
#             print('one more ans!')
#             print(j, ":")
#             print("合格", check[2])
#             print("合格率", check[1])
#             print()
            index_ans_list.append(list(ypreds))
            degree_ans_list.append(list(degree[j]))
        if j % (l // 10) == 0:
            print(j, '/', l)
    return degree_ans_list, index_ans_list
```

In [38]:

```python
degree_ans410, index410 = run_tuning([model1, model2, model3, model4], data_to_predict410, 0.8)
pd.DataFrame(degree_ans410)
```

```
9520
0 / 9520
........................952 / 9520
1904 / 9520
.................................2856 / 9520
............................................................................3808 / 9520
............4760 / 9520
..5712 / 9520
.6664 / 9520
.7616 / 9520
8568 / 9520
...............................................................................................................................
```

Out[38]:

	0	1
0	287.76	744.47
1	287.76	754.47
2	297.76	744.47
3	297.76	754.47
4	297.76	954.47
...	...	...
271	1397.76	884.47
272	1397.76	894.47
273	1397.76	904.47
274	1397.76	914.47
275	1397.76	924.47

In [39]:

```python
degree_ans411, index411 = run_tuning([model1, model2, model3, model4], data_to_predict411, 0.99)
pd.DataFrame(degree_ans411)
```

```
9520
0 / 9520
952 / 9520
1904 / 9520
2856 / 9520
3808 / 9520
4760 / 9520
5712 / 9520
6664 / 9520
7616 / 9520
8568 / 9520
...............................
```

Out[39]:

	0	1
0	1397.76	464.47
1	1397.76	604.47
2	1397.76	614.47
3	1397.76	624.47
4	1397.76	634.47
...	...	...
26	1397.76	854.47
27	1397.76	864.47
28	1397.76	874.47
29	1397.76	884.47
30	1397.76	904.47

使用 TOPSIS 评出最优温度

In [40]:

```python
from hmz.math_model.evaluate import TOPSIS

def get_max_score_of_degree(X=np.array(index410), degree=degree_ans410):
    fin_scores = []
    for i in range(8):
        topsis410 = TOPSIS(pd.DataFrame(X[:, i, :]))
        fin_score = topsis410.score()
        fin_scores.append(list(np.squeeze(fin_score.values)))

    finscores410 = np.array(fin_scores).sum(0) / 8
```

```
    maxscoresarg410 = np.argsort(finscores410)[-1]

    return degree[maxscoresarg410]
```

In [41]:
```
# 4-10
ans_410 = get_max_score_of_degree(np.array(index410), degree_ans410)
# 4-11
ans_411 = get_max_score_of_degree(np.array(index411), degree_ans411)
# 以下是 hmz 这个(自己写的)库的内部输出，暂时无法关闭，直接忽略即可（后期完善）
```

原始数据:

```
             0          1          2          3
0    79.764633  24.048122  10.924195  12.420654
1    79.738739  24.074551  10.801689  12.330379
2    80.097137  23.670055  10.979162  12.430060
3    80.071259  23.696484  10.856656  12.339784
4    78.260117  23.674995  10.928226  12.427949
..         ...        ...        ...        ...
271  79.706123  22.745268  10.015746  12.681078
272  79.207275  24.111877  10.268134  12.406067
273  79.357895  23.362579  10.069987  11.202466
274  79.273247  23.998615   9.844916  12.590789
275  79.273247  23.967379   9.780243  12.157454

[276 rows x 4 columns]
```

去量纲（求和归一化）后的数据:

```
            0         1         2         3
0    0.003644  0.003640  0.003691  0.003611
1    0.003643  0.003644  0.003650  0.003584
2    0.003659  0.003583  0.003709  0.003613
3    0.003658  0.003587  0.003668  0.003587
4    0.003575  0.003583  0.003692  0.003613
..        ...       ...       ...       ...
271  0.003641  0.003443  0.003384  0.003686
272  0.003618  0.003649  0.003469  0.003606
273  0.003625  0.003536  0.003402  0.003257
274  0.003621  0.003632  0.003326  0.003660
275  0.003621  0.003628  0.003304  0.003534

[276 rows x 4 columns]
```

数据信息熵权重:

```
                       0         1         2         3
entropy weight  0.008933  0.019355  0.626799  0.344913
```

指标权重:

```
                       0         1         2         3
entropy weight  0.008933  0.019355  0.626799  0.344913
```

未归一化得分:

```
     final score
0        0.63752
1        0.58710
2        0.65494
3        0.60538
```

```
4        0.63959
..           ...
271      0.39127
272      0.42393
273      0.21122
274      0.33990
275      0.25708

[276 rows x 1 columns]

归一化后最终得分:
     final score
0        0.00402
1        0.00370
2        0.00413
3        0.00382
4        0.00403
..           ...
271      0.00247
272      0.00267
273      0.00133
274      0.00214
275      0.00162

[276 rows x 1 columns]

原始数据:
             0          1          2          3
0    79.600266  24.490633  10.898557  12.116571
1    79.574371  24.517061  10.881515  12.026297
2    79.932770  24.112566  10.953524  12.125978
3    79.906891  24.138994  10.936481  12.035701
4    78.188751  24.088915  10.990034  12.045560
..         ...        ...        ...        ...
271  79.551483  22.650713  10.020551  12.208196
272  79.115501  24.017323  10.256428  11.681862
273  79.266121  23.302156  10.041856  10.478261
274  79.181473  23.938192   9.816785  11.614734
275  79.181473  23.906956   9.752111  11.181397

[276 rows x 4 columns]

去量纲（求和归一化）后的数据:
            0         1         2         3
0    0.003641  0.003706  0.003693  0.003470
1    0.003639  0.003710  0.003687  0.003444
```

```
2    0.003656  0.003649  0.003712  0.003473
3    0.003655  0.003653  0.003706  0.003447
4    0.003576  0.003645  0.003724  0.003450
..        ...       ...       ...       ...
271  0.003638  0.003427  0.003396  0.003497
272  0.003618  0.003634  0.003475  0.003346
273  0.003625  0.003526  0.003403  0.003001
274  0.003621  0.003622  0.003327  0.003327
275  0.003621  0.003617  0.003305  0.003202

[276 rows x 4 columns]

数据信息熵权重:
                       0         1        2         3
entropy weight  0.003594  0.010783  0.23734  0.748282

指标权重:
                       0         1        2         3
entropy weight  0.003594  0.010783  0.23734  0.748282

未归一化得分:
     final score
0        0.42399
1        0.40155
2        0.42705
3        0.40464
4        0.40783
..           ...
271      0.43617
272      0.30765
273      0.03426
274      0.28637
275      0.17745

[276 rows x 1 columns]

归一化后最终得分:
     final score
0        0.00278
1        0.00264
2        0.00280
3        0.00266
4        0.00268
..           ...
271      0.00286
272      0.00202
```

```
273      0.00023
274      0.00188
275      0.00117

[276 rows x 1 columns]

原始数据:
             0          1          2          3
0    79.740768  23.913185  11.225509  13.524830
1    79.714890  23.939613  11.103003  13.434555
2    80.073288  23.535118  11.243889  13.534236
3    80.047394  23.561546  11.121383  13.443959
4    78.233246  23.545671  11.207811  13.604304
..         ...        ...        ...        ...
271  79.654060  22.587654   9.934772  14.695075
272  79.116150  23.954264  10.187160  13.727303
273  79.266769  23.204966   9.989013  12.523702
274  79.182121  23.841002   9.763942  13.912024
275  79.182121  23.809765   9.699268  13.478691

[276 rows x 4 columns]

去量纲 (求和归一化) 后的数据:
            0         1         2         3
0    0.003646  0.003617  0.003774  0.003390
1    0.003645  0.003621  0.003733  0.003367
2    0.003662  0.003560  0.003780  0.003392
3    0.003660  0.003564  0.003739  0.003370
4    0.003577  0.003562  0.003768  0.003410
..        ...       ...       ...       ...
271  0.003642  0.003417  0.003340  0.003683
272  0.003618  0.003624  0.003425  0.003441
273  0.003625  0.003510  0.003358  0.003139
274  0.003621  0.003606  0.003283  0.003487
275  0.003621  0.003602  0.003261  0.003378

[276 rows x 4 columns]

数据信息熵权重:
                       0         1         2         3
entropy weight  0.002584  0.010084  0.228769  0.758563

指标权重:
                       0         1         2         3
entropy weight  0.002584  0.010084  0.228769  0.758563
```

未归一化得分:
```
     final score
0        0.31380
1        0.29273
2        0.31608
3        0.29501
4        0.33027
..           ...
271      0.55358
272      0.34449
273      0.07980
274      0.38180
275      0.28634

[276 rows x 1 columns]
```

归一化后最终得分:
```
     final score
0        0.00223
1        0.00208
2        0.00225
3        0.00210
4        0.00235
..           ...
271      0.00394
272      0.00245
273      0.00057
274      0.00272
275      0.00204

[276 rows x 1 columns]
```

原始数据:
```
             0          1          2          3
0    79.606781  23.618134  11.215198  12.258276
1    79.580887  23.644562  11.198155  12.430330
2    79.731613  23.240067  11.233578  12.401795
3    79.705719  23.266495  11.216536  12.573850
4    77.916214  23.617666  11.284947  12.922679
..         ...        ...        ...        ...
271  79.501251  22.483269   9.760892  13.166908
272  79.139244  23.849878   9.996769  12.611273
273  79.215889  23.134712   9.782197  11.407672
274  79.063530  23.770748   9.557126  12.544144
275  79.063530  23.739511   9.492453  12.110809
```

```
[276 rows x 4 columns]

去量纲（求和归一化）后的数据：
            0         1         2         3
0    0.003656  0.003589  0.003784  0.003308
1    0.003655  0.003593  0.003778  0.003355
2    0.003662  0.003531  0.003790  0.003347
3    0.003661  0.003535  0.003784  0.003394
4    0.003579  0.003589  0.003807  0.003488
..        ...       ...       ...       ...
271  0.003651  0.003416  0.003293  0.003554
272  0.003635  0.003624  0.003373  0.003404
273  0.003638  0.003515  0.003300  0.003079
274  0.003631  0.003612  0.003224  0.003386
275  0.003631  0.003607  0.003203  0.003269

[276 rows x 4 columns]

数据信息熵权重：
                       0         1         2         3
entropy weight  0.003402  0.022324  0.341235  0.633039

指标权重：
                       0         1         2         3
entropy weight  0.003402  0.022324  0.341235  0.633039

未归一化得分：
     final score
0        0.29916
1        0.32953
2        0.32638
3        0.35865
4        0.43489
..           ...
271      0.42199
272      0.30312
273      0.04756
274      0.27393
275      0.17076

[276 rows x 1 columns]

归一化后最终得分：
     final score
0        0.00210
1        0.00231
```

```
2        0.00229
3        0.00251
4        0.00305
..           ...
271      0.00296
272      0.00212
273      0.00033
274      0.00192
275      0.00120

[276 rows x 1 columns]

原始数据:
             0          1          2          3
0    79.467545  23.922579  10.629008  12.349236
1    79.466187  23.949007  10.738872  12.521290
2    80.215500  23.544512  10.672751  12.609084
3    80.214142  23.570940  10.782615  12.781138
4    78.483383  24.591230  10.601325  12.926341
..         ...        ...        ...        ...
271  79.882248  22.919056   9.674474  12.869946
272  79.520241  24.038708   9.926862  12.712962
273  79.596886  23.393278   9.716475  11.632993
274  79.488197  23.927557   9.431499  12.474279
275  79.488197  23.896320   9.366826  12.040943

[276 rows x 4 columns]

去量纲 (求和归一化) 后的数据:
            0         1         2         3
0    0.003614  0.003637  0.003670  0.003495
1    0.003614  0.003641  0.003708  0.003543
2    0.003648  0.003579  0.003685  0.003568
3    0.003648  0.003584  0.003723  0.003617
4    0.003569  0.003739  0.003661  0.003658
..        ...       ...       ...       ...
271  0.003633  0.003484  0.003341  0.003642
272  0.003616  0.003655  0.003428  0.003598
273  0.003620  0.003556  0.003355  0.003292
274  0.003615  0.003638  0.003257  0.003530
275  0.003615  0.003633  0.003234  0.003408

[276 rows x 4 columns]

数据信息熵权重:
                       0         1         2         3
```

```
entropy weight  0.009891  0.024854  0.452447  0.512808

指标权重:
                       0         1         2         3
entropy weight  0.009891  0.024854  0.452447  0.512807

未归一化得分:
     final score
0        0.49478
1        0.55639
2        0.57097
3        0.63442
4        0.64968
..           ...
271      0.48653
272      0.48287
273      0.15226
274      0.35844
275      0.23083

[276 rows x 1 columns]

归一化后最终得分:
     final score
0        0.00303
1        0.00341
2        0.00350
3        0.00389
4        0.00398
..           ...
271      0.00298
272      0.00296
273      0.00093
274      0.00220
275      0.00141

[276 rows x 1 columns]

原始数据:
             0          1          2          3
0    79.152390  23.962713  10.792052  11.870848
1    79.126495  23.989141  10.901916  12.042902
2    79.894821  23.584646  10.835795  12.130696
3    79.868942  23.611074  10.945659  12.302751
4    77.915634  24.023657  10.832456  12.405244
..         ...        ...        ...        ...
```

```
271  79.634178  22.988487   9.914741  11.913091
272  79.272171  24.080072  10.167129  11.891924
273  79.348816  23.434643   9.956742  10.811954
274  79.240128  24.004358   9.671766  11.653240
275  79.240128  23.973122   9.607093  11.219906

[276 rows x 4 columns]

去量纲 (求和归一化) 后的数据:
            0         1         2         3
0    0.003623  0.003643  0.003707  0.003434
1    0.003621  0.003647  0.003745  0.003483
2    0.003657  0.003586  0.003722  0.003509
3    0.003655  0.003590  0.003760  0.003558
4    0.003566  0.003652  0.003721  0.003588
..        ...       ...       ...       ...
271  0.003645  0.003495  0.003406  0.003446
272  0.003628  0.003661  0.003493  0.003440
273  0.003632  0.003563  0.003420  0.003127
274  0.003627  0.003649  0.003322  0.003371
275  0.003627  0.003645  0.003300  0.003245

[276 rows x 4 columns]

数据信息熵权重:
                       0         1         2         3
entropy weight  0.004221  0.008194  0.241341  0.746245

指标权重:
                       0         1         2         3
entropy weight  0.004221  0.008194  0.241341  0.746245

未归一化得分:
     final score
0        0.33205
1        0.38287
2        0.40637
3        0.45754
4        0.48512
..           ...
271      0.32732
272      0.32495
273      0.03964
274      0.24855
275      0.12078
```

```
[276 rows x 1 columns]

归一化后最终得分:
     final score
0        0.00234
1        0.00269
2        0.00286
3        0.00322
4        0.00341
..           ...
271      0.00230
272      0.00229
273      0.00028
274      0.00175
275      0.00085

[276 rows x 1 columns]

原始数据:
             0          1          2          3
0    79.766800  23.505770  10.758327  12.246002
1    79.740921  23.532198  10.741285  12.155725
2    80.092941  23.127703  10.813294  12.389522
3    80.067047  23.154131  10.796252  12.299245
4    78.518219  23.394386  10.781718  12.351813
..         ...        ...        ...        ...
271  79.951462  22.446222   9.813476  12.953490
272  79.515480  23.812832  10.049353  12.291340
273  79.528938  23.097666   9.834781  11.087739
274  79.444283  23.733702   9.609710  12.224212
275  79.444283  23.702465   9.545036  11.790875

[276 rows x 4 columns]

去量纲 (求和归一化) 后的数据:
            0         1         2         3
0    0.003638  0.003568  0.003650  0.003496
1    0.003636  0.003572  0.003644  0.003470
2    0.003652  0.003510  0.003669  0.003537
3    0.003651  0.003514  0.003663  0.003511
4    0.003581  0.003551  0.003658  0.003526
..        ...       ...       ...       ...
271  0.003646  0.003407  0.003329  0.003698
272  0.003626  0.003614  0.003409  0.003509
273  0.003627  0.003506  0.003337  0.003165
274  0.003623  0.003602  0.003260  0.003490
```

```
275  0.003623  0.003598  0.003238  0.003366

[276 rows x 4 columns]

数据信息熵权重:
                       0         1         2        3
entropy weight  0.006855  0.032661  0.424194  0.53629

指标权重:
                       0         1         2        3
entropy weight  0.006855  0.032661  0.424194  0.53629

未归一化得分:
     final score
0        0.49450
1        0.46930
2        0.53825
3        0.51262
4        0.52476
..           ...
271      0.55364
272      0.42187
273      0.09449
274      0.36380
275      0.24268

[276 rows x 1 columns]

归一化后最终得分:
     final score
0        0.00302
1        0.00286
2        0.00329
3        0.00313
4        0.00320
..           ...
271      0.00338
272      0.00258
273      0.00058
274      0.00222
275      0.00148

[276 rows x 1 columns]

原始数据:
             0          1          2          3
```

```
0    80.131454  23.536272  10.793567  12.626909
1    80.105576  23.562700  10.671061  12.786196
2    80.463974  23.158203  10.848534  12.636315
3    80.438080  23.184631  10.726027  12.795602
4    79.228745  23.020424  10.528901  12.879308
..         ...        ...        ...        ...
271  79.805542  21.876425  10.021272  13.181669
272  79.273712  23.070349  10.265304  13.318564
273  79.408134  22.457951  10.176111  12.541399
274  79.487961  23.053745   9.948914  13.070413
275  79.532158  22.857344   9.772976  12.868498

[276 rows x 4 columns]

去量纲（求和归一化）后的数据:
            0         1         2         3
0    0.003654  0.003631  0.003627  0.003407
1    0.003653  0.003636  0.003586  0.003450
2    0.003670  0.003573  0.003646  0.003410
3    0.003668  0.003577  0.003605  0.003453
4    0.003613  0.003552  0.003539  0.003476
..        ...       ...       ...       ...
271  0.003639  0.003375  0.003368  0.003557
272  0.003615  0.003560  0.003450  0.003594
273  0.003621  0.003465  0.003420  0.003384
274  0.003625  0.003557  0.003344  0.003527
275  0.003627  0.003527  0.003284  0.003473

[276 rows x 4 columns]

数据信息熵权重:
                       0         1         2         3
entropy weight  0.004338  0.045683  0.254575  0.695405

指标权重:
                       0         1         2         3
entropy weight  0.004338  0.045683  0.254575  0.695405

未归一化得分:
     final score
0        0.40211
1        0.44345
2        0.40567
3        0.44695
4        0.46589
..           ...
```

```
271      0.53761
272      0.58179
273      0.36386
274      0.50673
275      0.44802

[276 rows x 1 columns]

归一化后最终得分:
     final score
0        0.00237
1        0.00261
2        0.00239
3        0.00263
4        0.00274
..           ...
271      0.00317
272      0.00343
273      0.00214
274      0.00299
275      0.00264

[276 rows x 1 columns]

原始数据:
            0          1          2          3
0   79.829887  23.005432  10.628290  12.378992
1   79.717094  23.316051  10.221199  12.596301
2   80.276855  23.106533   9.718573  12.566521
3   79.717728  23.127262  10.040483  13.009837
4   79.767410  23.098364  10.040483  12.179219
5   79.537994  23.214788  10.110101  12.239650
6   79.537994  23.214788  10.150516  12.239650
7   79.499802  23.379076  10.192090  12.286936
8   79.538872  23.124134  10.269629  12.267331
9   79.503799  23.189041  10.134656  12.533977
10  80.105553  22.968794  10.279283  12.527067
11  79.263229  23.492081  10.308683  12.428029
12  79.263229  23.174654  10.142380  12.583354
13  79.220306  23.349674  10.308239  12.508672
14  79.381683  23.415661  10.192671  12.702552
15  79.308861  23.147036  10.205710  12.702552
16  79.541870  23.244547  10.161258  12.872066
17  79.518311  23.029554  10.213611  12.672649
18  79.537651  22.907923  10.159216  12.672649
19  79.587311  22.949686  10.159216  12.852307
```

20	79.563240	22.739334	10.096224	12.920726
21	79.563240	22.780781	10.043509	12.974807
22	79.563240	22.654457	10.152330	12.974807
23	79.546707	22.621225	9.933713	12.974807
24	79.496216	22.922806	10.013960	12.622882
25	79.472511	22.676493	10.013960	12.622882
26	79.754745	22.701401	9.961439	12.647752
27	80.131577	22.724527	10.018920	13.002899
28	80.118332	22.658957	9.893783	12.145371
29	80.099403	22.709785	10.294139	12.260662
30	79.814041	23.184008	10.336141	11.023709

去量纲 (求和归一化) 后的数据:

	0	1	2	3
0	0.032336	0.032228	0.033806	0.031823
1	0.032290	0.032663	0.032511	0.032382
2	0.032517	0.032370	0.030912	0.032305
3	0.032290	0.032399	0.031936	0.033445
4	0.032310	0.032358	0.031936	0.031310
5	0.032218	0.032522	0.032157	0.031465
6	0.032218	0.032522	0.032286	0.031465
7	0.032202	0.032752	0.032418	0.031587
8	0.032218	0.032395	0.032665	0.031536
9	0.032204	0.032485	0.032235	0.032222
10	0.032447	0.032177	0.032696	0.032204
11	0.032106	0.032910	0.032789	0.031949
12	0.032106	0.032465	0.032260	0.032349
13	0.032089	0.032710	0.032788	0.032157
14	0.032154	0.032803	0.032420	0.032655
15	0.032125	0.032427	0.032461	0.032655
16	0.032219	0.032563	0.032320	0.033091
17	0.032210	0.032262	0.032487	0.032578
18	0.032217	0.032092	0.032314	0.032578
19	0.032238	0.032150	0.032314	0.033040
20	0.032228	0.031855	0.032113	0.033216
21	0.032228	0.031914	0.031946	0.033355
22	0.032228	0.031737	0.032292	0.033355
23	0.032221	0.031690	0.031596	0.033355
24	0.032201	0.032112	0.031852	0.032450
25	0.032191	0.031767	0.031852	0.032450
26	0.032305	0.031802	0.031685	0.032514
27	0.032458	0.031835	0.031867	0.033427
28	0.032453	0.031743	0.031469	0.031223
29	0.032445	0.031814	0.032743	0.031519
30	0.032329	0.032478	0.032876	0.028339

数据信息熵权重:
```
                       0         1         2         3
entropy weight  0.008357  0.089755  0.190963  0.710925
```

指标权重:
```
                       0         1         2         3
entropy weight  0.008357  0.089755  0.190963  0.710925
```

未归一化得分:
```
    final score
0       0.68494
1       0.78679
2       0.75225
3       0.92357
4       0.57805
5       0.60948
6       0.61023
7       0.63478
8       0.62568
9       0.75366
10      0.75286
11      0.70673
12      0.77750
13      0.74618
14      0.83673
15      0.83597
16      0.90742
17      0.82135
18      0.81815
19      0.89581
20      0.90753
21      0.91370
22      0.92008
23      0.89890
24      0.78956
25      0.78706
26      0.79615
27      0.91233
28      0.55700
29      0.62096
30      0.08328
```

归一化后最终得分:
```
    final score
0       0.02947
1       0.03385
```

```
2       0.03236
3       0.03973
4       0.02487
5       0.02622
6       0.02625
7       0.02731
8       0.02692
9       0.03242
10      0.03239
11      0.03040
12      0.03345
13      0.03210
14      0.03600
15      0.03596
16      0.03904
17      0.03534
18      0.03520
19      0.03854
20      0.03904
21      0.03931
22      0.03958
23      0.03867
24      0.03397
25      0.03386
26      0.03425
27      0.03925
28      0.02396
29      0.02671
30      0.00358
```

原始数据:

```
            0          1          2          3
0   79.554565  21.556030  10.490689  13.648721
1   79.336067  21.897203  10.083598  13.110179
2   79.895828  21.687683   9.580972  13.080399
3   79.349823  21.963305   9.902882  13.553323
4   79.551147  21.892693   9.902882  12.722704
5   79.321732  22.045456   9.972500  12.783135
6   79.321732  22.045456  10.012915  12.783135
7   79.283539  22.209743  10.054489  12.830421
8   79.322609  22.068089  10.132028  12.810817
9   79.287537  22.132996  10.170598  13.077462
10  79.889290  21.912746  10.315225  13.089062
11  79.100883  22.506905  10.344625  12.990024
12  79.100883  22.319195  10.178322  13.145349
13  79.057961  22.369602  10.344181  13.070665
```

14	79.169556	22.435591	10.228613	13.109693
15	79.066597	22.503206	10.241652	13.109693
16	79.001007	22.600718	10.197200	13.279206
17	78.977448	22.385725	10.249553	13.079790
18	79.131325	22.264093	10.195158	13.079790
19	79.180984	22.305857	10.195158	13.163020
20	79.205711	22.095505	10.132166	13.231439
21	79.205711	22.095505	10.079452	13.285520
22	79.205711	21.969179	10.188272	13.285520
23	79.235641	21.935949	9.969655	13.285520
24	79.219841	22.206446	10.049902	13.230452
25	79.196136	21.960131	10.049902	13.064794
26	79.424606	22.029604	9.997381	13.324735
27	79.825600	22.267355	10.081585	13.703675
28	79.773682	22.296730	9.956448	11.372197
29	79.724312	22.301895	10.344945	11.389767
30	79.762352	22.773792	10.450836	10.049046

去量纲（求和归一化）后的数据：

	0	1	2	3
0	0.032343	0.031375	0.033400	0.034059
1	0.032255	0.031872	0.032104	0.032715
2	0.032482	0.031567	0.030504	0.032641
3	0.032260	0.031968	0.031528	0.033821
4	0.032342	0.031866	0.031528	0.031748
5	0.032249	0.032088	0.031750	0.031899
6	0.032249	0.032088	0.031879	0.031899
7	0.032233	0.032327	0.032011	0.032017
8	0.032249	0.032121	0.032258	0.031968
9	0.032235	0.032215	0.032381	0.032633
10	0.032480	0.031895	0.032841	0.032662
11	0.032159	0.032760	0.032935	0.032415
12	0.032159	0.032486	0.032405	0.032803
13	0.032142	0.032560	0.032933	0.032616
14	0.032187	0.032656	0.032565	0.032714
15	0.032145	0.032754	0.032607	0.032714
16	0.032118	0.032896	0.032465	0.033137
17	0.032109	0.032583	0.032632	0.032639
18	0.032171	0.032406	0.032459	0.032639
19	0.032192	0.032467	0.032459	0.032847
20	0.032202	0.032161	0.032258	0.033018
21	0.032202	0.032161	0.032091	0.033153
22	0.032202	0.031977	0.032437	0.033153
23	0.032214	0.031928	0.031741	0.033153
24	0.032207	0.032322	0.031997	0.033015
25	0.032198	0.031964	0.031997	0.032602

```
26  0.032291  0.032065  0.031829  0.033250
27  0.032454  0.032411  0.032097  0.034196
28  0.032433  0.032454  0.031699  0.028378
29  0.032412  0.032461  0.032936  0.028422
30  0.032428  0.033148  0.033273  0.025076

数据信息熵权重:
                       0         1         2         3
entropy weight  0.003097  0.037381  0.085379  0.874143

指标权重:
                       0         1         2         3
entropy weight  0.003097  0.037381  0.085379  0.874143

未归一化得分:
    final score
0       0.97940
1       0.83705
2       0.82764
3       0.95513
4       0.73112
5       0.74775
6       0.74779
7       0.76080
8       0.75548
9       0.82837
10      0.83156
11      0.80474
12      0.84698
13      0.82675
14      0.83734
15      0.83737
16      0.88363
17      0.82918
18      0.82908
19      0.85183
20      0.87028
21      0.88489
22      0.88501
23      0.88447
24      0.86992
25      0.82466
26      0.89525
27      0.98772
28      0.36214
29      0.36727
```

```
30      0.02655

归一化后最终得分:
    final score
0       0.04013
1       0.03430
2       0.03391
3       0.03913
4       0.02996
5       0.03064
6       0.03064
7       0.03117
8       0.03095
9       0.03394
10      0.03407
11      0.03297
12      0.03470
13      0.03387
14      0.03431
15      0.03431
16      0.03620
17      0.03397
18      0.03397
19      0.03490
20      0.03566
21      0.03626
22      0.03626
23      0.03624
24      0.03564
25      0.03379
26      0.03668
27      0.04047
28      0.01484
29      0.01505
30      0.00109

原始数据:
            0          1          2          3
0   79.137421  23.586304  11.249568  15.196502
1   79.108170  23.560209  10.820970  14.375246
2   79.631004  23.350691  10.318343  14.345466
3   79.045258  23.442585  10.688270  14.932489
4   79.035492  23.413687  10.688270  14.075293
5   78.865524  23.436062  10.754486  14.348900
6   78.992493  23.436062  10.794901  14.348900
7   78.954300  23.694399  10.802315  14.396186
```

8	78.993370	23.439457	10.867324	14.376581
9	78.958298	23.439566	10.969735	14.416362
10	79.715698	22.961010	11.114362	14.427961
11	78.584534	23.790228	11.063099	14.252664
12	78.584534	23.514765	10.896795	14.407989
13	78.508682	23.689785	10.964857	14.105323
14	78.670059	23.755772	10.947086	14.262424
15	78.597237	23.509233	10.899153	14.262424
16	78.830246	23.520863	10.921148	14.431937
17	78.813301	23.305870	10.973501	14.182735
18	78.803230	23.184238	10.919106	14.182735
19	78.852890	23.226002	10.990088	14.362393
20	78.877617	23.115450	10.963353	14.430253
21	78.877617	23.156897	10.910639	14.484334
22	78.877617	23.061516	11.019460	14.484334
23	78.810760	23.028284	10.800842	14.484334
24	78.803978	23.298922	10.745881	14.375519
25	78.831841	23.049393	10.745881	14.375519
26	79.060310	23.149281	10.693360	14.404039
27	79.550095	23.291389	10.686138	14.634890
28	79.469208	23.245367	10.436413	13.041426
29	79.434845	23.296196	10.827145	11.951121
30	79.215752	23.797321	11.013682	10.621563

去量纲（求和归一化）后的数据:

	0	1	2	3
0	0.032321	0.032544	0.033432	0.034618
1	0.032309	0.032508	0.032159	0.032747
2	0.032522	0.032219	0.030665	0.032679
3	0.032283	0.032346	0.031764	0.034016
4	0.032279	0.032306	0.031764	0.032064
5	0.032210	0.032337	0.031961	0.032687
6	0.032262	0.032337	0.032081	0.032687
7	0.032246	0.032693	0.032103	0.032795
8	0.032262	0.032342	0.032296	0.032750
9	0.032248	0.032342	0.032601	0.032841
10	0.032557	0.031681	0.033031	0.032867
11	0.032095	0.032826	0.032878	0.032468
12	0.032095	0.032445	0.032384	0.032822
13	0.032064	0.032687	0.032586	0.032132
14	0.032130	0.032778	0.032534	0.032490
15	0.032100	0.032438	0.032391	0.032490
16	0.032195	0.032454	0.032456	0.032876
17	0.032189	0.032157	0.032612	0.032309
18	0.032184	0.031989	0.032450	0.032309
19	0.032205	0.032047	0.032661	0.032718

```
20  0.032215  0.031895  0.032582  0.032872
21  0.032215  0.031952  0.032425  0.032996
22  0.032215  0.031820  0.032749  0.032996
23  0.032187  0.031774  0.032099  0.032996
24  0.032185  0.032148  0.031936  0.032748
25  0.032196  0.031803  0.031936  0.032748
26  0.032289  0.031941  0.031779  0.032813
27  0.032489  0.032137  0.031758  0.033339
28  0.032456  0.032074  0.031016  0.029709
29  0.032442  0.032144  0.032177  0.027225
30  0.032353  0.032835  0.032731  0.024196

数据信息熵权重:
                      0         1         2         3
entropy weight  0.00348  0.023066  0.068602  0.904852

指标权重:
                      0         1         2         3
entropy weight  0.00348  0.023066  0.068602  0.904852

未归一化得分:
    final score
0       0.99873
1       0.82038
2       0.81345
3       0.94156
4       0.75479
5       0.81458
6       0.81460
7       0.82494
8       0.82069
9       0.82943
10      0.83196
11      0.79370
12      0.82757
13      0.76147
14      0.79579
15      0.79577
16      0.83281
17      0.77838
18      0.77835
19      0.81763
20      0.83243
21      0.84422
22      0.84426
23      0.84414
```

```
24       0.82038
25       0.82035
26       0.82655
27       0.87691
28       0.52883
29       0.29070
30       0.01229
```

归一化后最终得分:

```
    final score
0        0.04164
1        0.03420
2        0.03391
3        0.03925
4        0.03147
5        0.03396
6        0.03396
7        0.03439
8        0.03421
9        0.03458
10       0.03468
11       0.03309
12       0.03450
13       0.03174
14       0.03318
15       0.03317
16       0.03472
17       0.03245
18       0.03245
19       0.03409
20       0.03470
21       0.03519
22       0.03520
23       0.03519
24       0.03420
25       0.03420
26       0.03446
27       0.03656
28       0.02205
29       0.01212
30       0.00051
```

原始数据:

```
            0          1          2          3
0   79.270454  24.074968  10.566037  14.584608
1   79.421974  23.886597  10.094568  14.044095
```

2	79.944809	23.634201	9.591942	14.014315
3	79.303543	23.775175	9.961868	14.475039
4	79.353226	23.768717	9.961868	13.860060
5	79.123810	23.887783	10.031487	13.920491
6	79.123810	23.887783	10.071901	13.920491
7	79.085617	24.052071	10.113476	13.967777
8	79.124687	23.917387	10.297141	13.948173
9	79.089615	23.797237	10.335711	14.279982
10	79.691368	23.514111	10.480338	14.291581
11	78.961128	24.058109	10.509739	14.116283
12	78.961128	23.855890	10.343435	14.271608
13	78.918205	24.030910	10.509295	14.015072
14	79.016708	23.899731	10.393726	14.172173
15	78.918060	23.357395	10.406766	14.172173
16	79.177803	23.454906	10.270412	14.341686
17	79.098923	23.239914	10.322765	14.142270
18	79.088852	23.118282	10.268371	14.142270
19	79.166191	23.160046	10.268371	14.321928
20	79.190918	23.420570	10.205379	14.390347
21	79.190918	23.462017	10.152664	14.444427
22	79.190918	23.366636	10.261485	14.444427
23	79.124062	23.333405	10.042868	14.444427
24	79.117279	23.604042	10.215015	14.335612
25	79.093575	23.354513	10.215015	14.335612
26	79.322044	23.423985	10.162495	14.319608
27	79.698875	23.542967	10.263668	14.698548
28	79.685631	23.493753	10.138531	12.894372
29	79.694595	23.544582	10.398499	11.804068
30	79.381340	24.064264	10.565552	10.350878

去量纲 (求和归一化) 后的数据:

	0	1	2	3
0	0.032269	0.032845	0.033287	0.033647
1	0.032331	0.032588	0.031802	0.032400
2	0.032544	0.032244	0.030218	0.032331
3	0.032283	0.032436	0.031384	0.033394
4	0.032303	0.032427	0.031384	0.031975
5	0.032210	0.032590	0.031603	0.032114
6	0.032210	0.032590	0.031730	0.032114
7	0.032194	0.032814	0.031861	0.032224
8	0.032210	0.032630	0.032440	0.032178
9	0.032196	0.032466	0.032562	0.032944
10	0.032441	0.032080	0.033017	0.032971
11	0.032143	0.032822	0.033110	0.032566
12	0.032143	0.032546	0.032586	0.032925
13	0.032126	0.032785	0.033108	0.032333

```
14  0.032166  0.032606  0.032744  0.032695
15  0.032126  0.031866  0.032785  0.032695
16  0.032232  0.031999  0.032356  0.033086
17  0.032199  0.031706  0.032521  0.032626
18  0.032195  0.031540  0.032349  0.032626
19  0.032227  0.031597  0.032349  0.033041
20  0.032237  0.031952  0.032151  0.033198
21  0.032237  0.032009  0.031985  0.033323
22  0.032237  0.031879  0.032328  0.033323
23  0.032210  0.031834  0.031639  0.033323
24  0.032207  0.032203  0.032181  0.033072
25  0.032197  0.031862  0.032181  0.033072
26  0.032290  0.031957  0.032016  0.033035
27  0.032444  0.032119  0.032335  0.033909
28  0.032438  0.032052  0.031940  0.029747
29  0.032442  0.032122  0.032759  0.027232
30  0.032314  0.032831  0.033286  0.023879

数据信息熵权重:
                       0        1         2        3
entropy weight  0.002298  0.03235  0.088503  0.87685

指标权重:
                       0        1         2        3
entropy weight  0.002298  0.03235  0.088503  0.87685

未归一化得分:
    final score
0       0.97380
1       0.84914
2       0.84123
3       0.94676
4       0.80673
5       0.82070
6       0.82075
7       0.83166
8       0.82734
9       0.90358
10      0.90629
11      0.86611
12      0.90168
13      0.84284
14      0.87889
15      0.87877
16      0.91751
17      0.87179
```

```
18       0.87168
19       0.91282
20       0.92846
21       0.94060
22       0.94087
23       0.94007
24       0.91608
25       0.91596
26       0.91223
27       0.99172
28       0.58500
29       0.33460
30       0.02343
```

归一化后最终得分:

```
    final score
0        0.03760
1        0.03279
2        0.03248
3        0.03656
4        0.03115
5        0.03169
6        0.03169
7        0.03211
8        0.03194
9        0.03489
10       0.03499
11       0.03344
12       0.03482
13       0.03254
14       0.03394
15       0.03393
16       0.03543
17       0.03366
18       0.03366
19       0.03525
20       0.03585
21       0.03632
22       0.03633
23       0.03630
24       0.03537
25       0.03537
26       0.03522
27       0.03829
28       0.02259
29       0.01292
```

30 0.00090

原始数据:

	0	1	2	3
0	79.755402	22.704536	10.467842	12.218777
1	79.514107	22.932007	10.145816	12.733525
2	80.073868	22.679611	9.631437	12.703745
3	79.459221	22.929638	9.968149	13.065671
4	79.602386	22.923180	9.968149	12.331566
5	79.372971	23.042246	10.004985	12.391996
6	79.372971	23.042246	10.045400	12.391996
7	79.334778	23.153605	10.086974	12.439282
8	79.373848	23.018921	10.379776	12.419678
9	79.338776	22.972540	10.241261	12.686323
10	79.555679	22.840509	10.385888	12.679414
11	79.116806	23.309511	10.415289	12.713449
12	79.116806	22.992085	10.248985	12.868773
13	79.073883	23.042158	10.414845	12.794090
14	79.172386	22.800741	10.299276	13.189000
15	79.073738	22.383352	10.312316	13.189000
16	79.333481	22.480864	9.880606	13.157485
17	79.247986	22.477329	10.126229	12.958069
18	79.237915	22.355698	10.071835	12.958069
19	79.315254	22.464787	10.071835	13.137727
20	79.291183	22.725311	10.008842	13.061252
21	79.291183	22.766758	9.956128	12.926972
22	79.291183	22.640434	10.064949	13.157473
23	79.274651	22.640434	9.846332	13.157473
24	79.224159	22.968161	10.064422	12.716629
25	79.200455	22.721848	10.064422	12.716629
26	79.461357	22.837597	10.011901	12.700345
27	79.838188	22.837597	10.161432	13.055492
28	79.864014	22.782589	10.040726	12.527368
29	79.845085	22.833418	10.390121	12.653388
30	79.436348	23.446955	10.487106	10.675463

去量纲（求和归一化）后的数据:

	0	1	2	3
0	0.032402	0.032080	0.033309	0.030983
1	0.032304	0.032401	0.032284	0.032288
2	0.032531	0.032045	0.030648	0.032212
3	0.032281	0.032398	0.031719	0.033130
4	0.032340	0.032389	0.031719	0.031269
5	0.032246	0.032557	0.031836	0.031422
6	0.032246	0.032557	0.031965	0.031422
7	0.032231	0.032715	0.032097	0.031542

```
8   0.032247  0.032524  0.033029  0.031492
9   0.032232  0.032459  0.032588  0.032168
10  0.032321  0.032272  0.033048  0.032151
11  0.032142  0.032935  0.033142  0.032237
12  0.032142  0.032486  0.032613  0.032631
13  0.032125  0.032557  0.033141  0.032441
14  0.032165  0.032216  0.032773  0.033443
15  0.032125  0.031626  0.032814  0.033443
16  0.032230  0.031764  0.031441  0.033363
17  0.032196  0.031759  0.032222  0.032857
18  0.032191  0.031587  0.032049  0.032857
19  0.032223  0.031741  0.032049  0.033313
20  0.032213  0.032109  0.031849  0.033119
21  0.032213  0.032168  0.031681  0.032778
22  0.032213  0.031989  0.032027  0.033363
23  0.032206  0.031989  0.031331  0.033363
24  0.032186  0.032453  0.032025  0.032245
25  0.032176  0.032104  0.032025  0.032245
26  0.032282  0.032268  0.031858  0.032204
27  0.032435  0.032268  0.032334  0.033104
28  0.032446  0.032190  0.031950  0.031765
29  0.032438  0.032262  0.033062  0.032085
30  0.032272  0.033129  0.033370  0.027069

数据信息熵权重:
                       0        1        2         3
entropy weight  0.004722  0.06203  0.20498  0.728268

指标权重:
                       0        1        2         3
entropy weight  0.004722  0.06203  0.20498  0.728268

未归一化得分:
    final score
0       0.61626
1       0.81529
2       0.78802
3       0.92420
4       0.65582
5       0.68015
6       0.68073
7       0.69998
8       0.69517
9       0.79863
10      0.79712
11      0.81162
```

```
12       0.86978
13       0.84296
14       0.97053
15       0.96064
16       0.92817
17       0.89598
18       0.89260
19       0.94168
20       0.92432
21       0.88004
22       0.94634
23       0.92697
24       0.80711
25       0.80637
26       0.79929
27       0.93344
28       0.73305
29       0.78691
30       0.09314

归一化后最终得分：
    final score
0        0.02475
1        0.03274
2        0.03164
3        0.03711
4        0.02634
5        0.02731
6        0.02734
7        0.02811
8        0.02792
9        0.03207
10       0.03201
11       0.03259
12       0.03493
13       0.03385
14       0.03897
15       0.03858
16       0.03727
17       0.03598
18       0.03584
19       0.03782
20       0.03712
21       0.03534
22       0.03800
23       0.03722
```

```
24      0.03241
25      0.03238
26      0.03210
27      0.03748
28      0.02944
29      0.03160
30      0.00374

原始数据:
            0          1          2          3
0   79.826454  22.702297  11.094396  12.317365
1   79.585159  22.929770  10.684255  12.832113
2   80.144920  22.677374  10.169876  12.802333
3   79.543396  22.747183  10.506588  13.164259
4   79.686562  22.740725  10.506588  12.430154
5   79.457146  22.859791  10.576206  12.490584
6   79.457146  22.859791  10.616621  12.490584
7   79.418953  22.971149  10.658195  12.537870
8   79.458023  22.836466  10.950997  12.518266
9   79.484818  22.716316  10.812483  12.784911
10  79.639854  22.584286  10.957109  12.778002
11  79.200981  23.270235  10.986510  12.812037
12  79.200981  23.014696  10.820207  12.967361
13  79.158058  23.002882  10.986066  12.892679
14  79.256561  22.761465  10.870498  13.287588
15  79.157913  22.389420  10.883537  13.287588
16  79.417656  22.486931  10.451827  13.256073
17  79.332161  22.483397  10.697451  13.056657
18  79.322090  22.361765  10.643056  13.056657
19  79.399429  22.470854  10.643056  13.236315
20  79.355911  22.731379  10.460920  13.159840
21  79.355911  22.727482  10.408206  13.025560
22  79.355911  22.601158  10.517027  13.256061
23  79.339386  22.601158  10.298409  13.256061
24  79.288887  22.928885  10.476222  12.861996
25  79.332146  22.682571  10.476222  12.861996
26  79.560616  22.752043  10.423701  12.845712
27  79.937447  22.975723  10.519928  13.375242
28  79.963272  22.940264  10.399221  12.425081
29  79.944344  22.991093  10.748617  12.767580
30  79.658981  23.608404  10.777570  10.941514

去量纲（求和归一化）后的数据:
           0         1         2         3
0   0.032394  0.032138  0.033617  0.030966
1   0.032296  0.032460  0.032374  0.032260
```

```
2   0.032523  0.032102  0.030816  0.032185
3   0.032279  0.032201  0.031836  0.033095
4   0.032337  0.032192  0.031836  0.031249
5   0.032244  0.032361  0.032047  0.031401
6   0.032244  0.032361  0.032169  0.031401
7   0.032229  0.032518  0.032295  0.031520
8   0.032244  0.032328  0.033183  0.031471
9   0.032255  0.032158  0.032763  0.032141
10  0.032318  0.031971  0.033201  0.032124
11  0.032140  0.032942  0.033290  0.032209
12  0.032140  0.032580  0.032786  0.032600
13  0.032123  0.032563  0.033289  0.032412
14  0.032163  0.032221  0.032939  0.033405
15  0.032123  0.031695  0.032978  0.033405
16  0.032228  0.031833  0.031670  0.033325
17  0.032193  0.031828  0.032414  0.032824
18  0.032189  0.031656  0.032250  0.032824
19  0.032221  0.031810  0.032250  0.033276
20  0.032203  0.032179  0.031698  0.033084
21  0.032203  0.032173  0.031538  0.032746
22  0.032203  0.031995  0.031868  0.033325
23  0.032196  0.031995  0.031205  0.033325
24  0.032176  0.032458  0.031744  0.032335
25  0.032193  0.032110  0.031744  0.032335
26  0.032286  0.032208  0.031585  0.032294
27  0.032439  0.032525  0.031876  0.033625
28  0.032449  0.032475  0.031511  0.031236
29  0.032442  0.032547  0.032569  0.032097
30  0.032326  0.033420  0.032657  0.027507

数据信息熵权重:
                       0         1         2         3
entropy weight  0.005296  0.064872  0.236099  0.693733

指标权重:
                       0         1         2         3
entropy weight  0.005296  0.064872  0.236099  0.693733

未归一化得分:
    final score
0       0.57086
1       0.77093
2       0.73838
3       0.88063
4       0.60639
5       0.63231
```

```
6        0.63316
7        0.65323
8        0.64998
9        0.75457
10       0.75365
11       0.77003
12       0.82846
13       0.80182
14       0.94369
15       0.93614
16       0.89552
17       0.85440
18       0.85064
19       0.90807
20       0.87555
21       0.82957
22       0.90318
23       0.88169
24       0.77507
25       0.77407
26       0.76607
27       0.92267
28       0.60241
29       0.74722
30       0.08881

归一化后最终得分:
    final score
0        0.02419
1        0.03267
2        0.03129
3        0.03732
4        0.02570
5        0.02679
6        0.02683
7        0.02768
8        0.02754
9        0.03197
10       0.03194
11       0.03263
12       0.03511
13       0.03398
14       0.03999
15       0.03967
16       0.03795
17       0.03620
```

```
18      0.03605
19      0.03848
20      0.03710
21      0.03515
22      0.03827
23      0.03736
24      0.03284
25      0.03280
26      0.03246
27      0.03910
28      0.02553
29      0.03166
30      0.00376
```

原始数据:

	0	1	2	3
0	79.780380	22.883705	10.492202	14.541156
1	79.516083	23.111177	10.082061	14.991610
2	80.075844	22.858782	9.567682	14.961829
3	79.474319	22.928591	9.904394	15.353363
4	79.617485	22.922132	9.904394	14.619258
5	79.388069	23.041199	9.974012	14.679688
6	79.388069	23.041199	10.014427	14.679688
7	79.349876	23.152557	10.056002	14.726974
8	79.388947	23.017874	10.348804	14.707370
9	79.415741	22.897724	10.383832	14.974015
10	79.570778	22.765694	10.528459	14.985615
11	79.015457	23.451643	10.557859	15.019650
12	79.015457	23.196104	10.391556	15.174974
13	78.972534	23.184290	10.557415	15.100291
14	79.071037	22.942873	10.441847	15.509471
15	78.972389	22.580626	10.454886	15.509471
16	79.232132	22.678137	10.023176	15.477956
17	79.146637	22.870731	10.268800	15.278540
18	79.136566	22.749100	10.214405	15.278540
19	79.213905	22.858189	10.214405	15.361770
20	79.170387	22.936022	10.151413	15.285295
21	79.170387	22.932125	10.098699	15.151015
22	79.170387	22.805801	10.207520	15.381516
23	79.153862	22.805801	9.988902	15.381516
24	79.103363	22.970446	10.166715	14.920248
25	79.087288	22.724133	10.166715	14.754590
26	79.315758	22.793604	10.155952	14.971167
27	79.766273	23.017284	10.322860	15.350107
28	79.792099	22.981825	10.202153	12.680475
29	79.773170	23.032654	10.551549	12.746693

```
30  79.424942  23.649965  10.589279  11.301964

去量纲（求和归一化）后的数据:
           0         1         2         3
0   0.032435  0.032150  0.033100  0.031690
1   0.032328  0.032469  0.031806  0.032672
2   0.032556  0.032115  0.030184  0.032607
3   0.032311  0.032213  0.031246  0.033460
4   0.032369  0.032204  0.031246  0.031860
5   0.032276  0.032371  0.031466  0.031992
6   0.032276  0.032371  0.031593  0.031992
7   0.032260  0.032528  0.031724  0.032095
8   0.032276  0.032338  0.032648  0.032052
9   0.032287  0.032170  0.032758  0.032633
10  0.032350  0.031984  0.033215  0.032659
11  0.032124  0.032948  0.033307  0.032733
12  0.032124  0.032589  0.032783  0.033071
13  0.032107  0.032572  0.033306  0.032909
14  0.032147  0.032233  0.032941  0.033800
15  0.032107  0.031724  0.032983  0.033800
16  0.032213  0.031861  0.031621  0.033732
17  0.032178  0.032132  0.032395  0.033297
18  0.032174  0.031961  0.032224  0.033297
19  0.032205  0.032114  0.032224  0.033478
20  0.032187  0.032223  0.032025  0.033312
21  0.032187  0.032218  0.031859  0.033019
22  0.032187  0.032040  0.032202  0.033521
23  0.032181  0.032040  0.031512  0.033521
24  0.032160  0.032272  0.032073  0.032516
25  0.032154  0.031926  0.032073  0.032155
26  0.032247  0.032023  0.032039  0.032627
27  0.032430  0.032338  0.032566  0.033453
28  0.032440  0.032288  0.032185  0.027635
29  0.032432  0.032359  0.033287  0.027779
30  0.032291  0.033226  0.033407  0.024631

数据信息熵权重:
                       0         1         2         3
entropy weight  0.002584  0.018357  0.116468  0.862591

指标权重:
                       0         1         2         3
entropy weight  0.002584  0.018357  0.116468  0.862591

未归一化得分:
    final score
```

```
0       0.76995
1       0.87597
2       0.86627
3       0.95699
4       0.78752
5       0.80200
6       0.80210
7       0.81340
8       0.80929
9       0.87259
10      0.87548
11      0.88364
12      0.92026
13      0.90277
14      0.99406
15      0.99309
16      0.97999
17      0.94409
18      0.94372
19      0.96276
20      0.94489
21      0.91343
22      0.96703
23      0.96396
24      0.85939
25      0.82016
26      0.87137
27      0.96109
28      0.32802
29      0.34432
30      0.03216

归一化后最终得分:
    final score
0       0.02989
1       0.03400
2       0.03363
3       0.03715
4       0.03057
5       0.03113
6       0.03114
7       0.03157
8       0.03141
9       0.03387
10      0.03398
11      0.03430
```

12	0.03572
13	0.03504
14	0.03859
15	0.03855
16	0.03804
17	0.03665
18	0.03663
19	0.03737
20	0.03668
21	0.03546
22	0.03754
23	0.03742
24	0.03336
25	0.03184
26	0.03382
27	0.03731
28	0.01273
29	0.01337
30	0.00125

原始数据:

	0	1	2	3
0	79.758018	22.894794	11.111638	12.084625
1	79.634705	23.122267	10.701497	12.599374
2	80.194466	22.869871	10.187119	12.569593
3	79.592941	22.939680	10.523830	12.931520
4	79.736107	22.933222	10.523830	12.197413
5	79.506691	23.052288	10.593449	12.257845
6	79.506691	23.052288	10.633863	12.257845
7	79.468498	23.163647	10.675438	12.305131
8	79.507568	23.028963	10.968240	12.285526
9	79.472496	22.908813	10.829725	12.552172
10	79.689400	22.776783	10.974352	12.545262
11	79.250526	23.462732	11.003753	12.579297
12	79.250526	23.145306	10.837449	12.734622
13	79.207603	23.195379	11.003308	12.659940
14	79.306107	22.953962	10.887740	13.054849
15	79.207458	22.536573	10.900780	13.054849
16	79.467201	22.634085	10.469069	13.023334
17	79.381706	22.494667	10.714693	12.823917
18	79.371635	22.373035	10.660298	12.823917
19	79.448975	22.482124	10.660298	13.003575
20	79.405457	22.742649	10.478163	12.927100
21	79.405457	22.784096	10.425448	12.792820
22	79.405457	22.657772	10.534269	13.023321
23	79.388924	22.657772	10.315652	13.023321

24	79.338432	22.985498	10.493464	12.629256
25	79.314728	22.739185	10.493464	12.629256
26	79.543198	22.808657	10.440944	12.612972
27	79.920029	23.032337	10.537170	13.142503
28	79.945854	22.996878	10.416464	12.192342
29	79.926926	23.047707	10.765860	12.572759
30	79.641563	23.699150	10.787165	10.707007

去量纲（求和归一化）后的数据：

	0	1	2	3
0	0.032354	0.032238	0.033616	0.030939
1	0.032304	0.032559	0.032375	0.032257
2	0.032531	0.032203	0.030819	0.032180
3	0.032287	0.032302	0.031837	0.033107
4	0.032345	0.032292	0.031837	0.031228
5	0.032252	0.032460	0.032048	0.031382
6	0.032252	0.032460	0.032170	0.031382
7	0.032236	0.032617	0.032296	0.031503
8	0.032252	0.032427	0.033182	0.031453
9	0.032238	0.032258	0.032763	0.032136
10	0.032326	0.032072	0.033200	0.032118
11	0.032148	0.033038	0.033289	0.032205
12	0.032148	0.032591	0.032786	0.032603
13	0.032130	0.032662	0.033288	0.032412
14	0.032170	0.032322	0.032938	0.033423
15	0.032130	0.031734	0.032978	0.033423
16	0.032236	0.031871	0.031672	0.033342
17	0.032201	0.031675	0.032415	0.032832
18	0.032197	0.031504	0.032250	0.032832
19	0.032228	0.031657	0.032250	0.033292
20	0.032211	0.032024	0.031699	0.033096
21	0.032211	0.032082	0.031540	0.032752
22	0.032211	0.031905	0.031869	0.033342
23	0.032204	0.031905	0.031208	0.033342
24	0.032183	0.032366	0.031746	0.032333
25	0.032174	0.032019	0.031746	0.032333
26	0.032266	0.032117	0.031587	0.032292
27	0.032419	0.032432	0.031878	0.033647
28	0.032430	0.032382	0.031513	0.031215
29	0.032422	0.032454	0.032570	0.032189
30	0.032306	0.033371	0.032634	0.027412

数据信息熵权重：

	0	1	2	3
entropy weight	0.004249	0.075632	0.226471	0.693648

指标权重:

	0	1	2	3
entropy weight	0.004249	0.075632	0.226471	0.693648

未归一化得分:

	final score
0	0.57075
1	0.77158
2	0.74025
3	0.88238
4	0.60710
5	0.63300
6	0.63379
7	0.65387
8	0.65013
9	0.75477
10	0.75352
11	0.77034
12	0.82863
13	0.80204
14	0.94392
15	0.93320
16	0.89644
17	0.85226
18	0.84827
19	0.90481
20	0.87540
21	0.83016
22	0.90259
23	0.88277
24	0.77568
25	0.77424
26	0.76654
27	0.92381
28	0.60307
29	0.76232
30	0.09082

归一化后最终得分:

	final score
0	0.02417
1	0.03267
2	0.03134
3	0.03736
4	0.02570
5	0.02680

```
6       0.02683
7       0.02768
8       0.02753
9       0.03196
10      0.03190
11      0.03262
12      0.03508
13      0.03396
14      0.03997
15      0.03951
16      0.03796
17      0.03608
18      0.03592
19      0.03831
20      0.03706
21      0.03515
22      0.03822
23      0.03738
24      0.03284
25      0.03278
26      0.03246
27      0.03911
28      0.02553
29      0.03228
30      0.00385
```

In [42]:
```
ans_410  # 4-10号两个系统温度数据
```

Out[42]:
```
[1367.76, 844.47]
```

In [43]:
```
ans_411  # 4-11号两个系统温度数据
```

Out[43]:
```
[1397.76, 864.47]
```

In [ ]:
```

```