Homework 1

> 编辑日期：2023/05/11

1 Data Source

- 本数据来源于 Kaggle， 包含了 570 种 cancer cell 的 30 个 feature信息 所有的数据被标记为两类:
    - Benign Cancer (B)
    - Malignant Cancer (M)
- CSV 中各字段类型如下:
    - Col 0 为该记录的 id (String)
    - Col 1 为该记录的 class(B/M)
    - Col 2~31 为记录的 30 个其余 feature 信息 (Float)

```
import csv

data_file = 'Cancer_Data.csv'

try:
      f = open(data_file, encoding='utf-8')
except:
  print(f'Fail to open file "{data_file}"')

reader = csv.reader(f)
header = next(reader)
n_cols = len(header)

print(f"本数据集共有 {n_cols} 个字段: ")
for idx, key in enumerate(header):
      print("   ", '{0:<2}'.format(idx), key)
```

```
本数据集共有 32 个字段:
   0  id
   1  diagnosis
   2  radius_mean
   3  texture_mean
   4  perimeter_mean
   5  area_mean
   6  smoothness_mean
   7  compactness_mean
   8  concavity_mean
   9  concave points_mean
   10 symmetry_mean
   11 fractal_dimension_mean
```

```
12 radius_se
13 texture_se
14 perimeter_se
15 area_se
16 smoothness_se
17 compactness_se
18 concavity_se
19 concave points_se
20 symmetry_se
21 fractal_dimension_se
22 radius_worst
23 texture_worst
24 perimeter_worst
25 area_worst
26 smoothness_worst
27 compactness_worst
28 concavity_worst
29 concave points_worst
30 symmetry_worst
31 fractal_dimension_worst
```

2 Data Processing

2.1 转化数据格式

- 由于 `id` 字段对于构建分类器没有帮助，此处我们不予保留
- 由于本数据集中 `diagnose` 字段仅有 `M / B` 两种取值，为方便计算，此处分别将两种取值替换为 `0 / 1`

```python
#  初始化
total = 0                     # 数据总量
original_data = []            # 存储原始数据，Col_N 存储在数组 original_data[N] 中
count_null = [0] * (n_cols-1) # 统计空数据信息

for i in range(1, n_cols):
    original_data.append([])

for row in reader:
    total += 1
    flag = True
    for idx in range(1, n_cols):
        if not row[idx]:
            count_null[idx] += 1
            flag = False
    if flag:
        for i in range(1, n_cols):
            if(i==1):
                if (row[1][0] == 'M'):
                    original_data[0].append(0)
                else:
```

```
                original_data[0].append(1)
            else:
                original_data[i-1].append(float(row[i]))

f.close()
```

2.2 Handle Missing Value

数据缺失信息的统计实现在上一个代码块，此处仅展示统计结果。

不幸的是，本数据集的内容非常完整，不需要进行补全

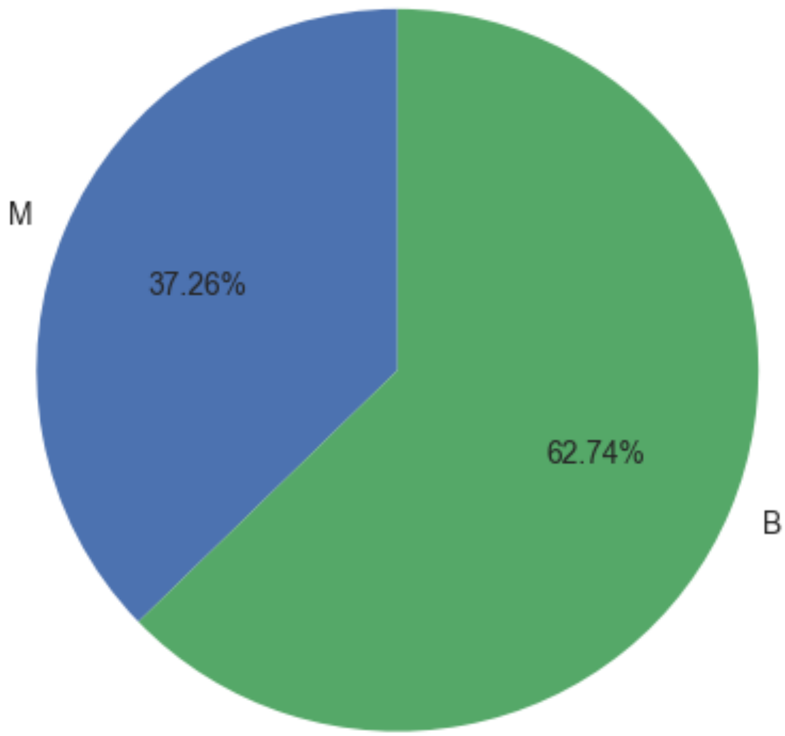
```
print(f"本数据集共有 {len(original_data[0])} / {total} 条完整数据，空缺详情如下")
for idx in range(0, n_cols-1):
    print("   ", '{0:<4}'.format(idx), '{0:<25}'.format(header[idx+1]), count_null[idx])
```

```
本数据集共有 569 / 569 条完整数据，空缺详情如下
    0    diagnosis                 0
    1    radius_mean               0
    2    texture_mean              0
    3    perimeter_mean            0
    4    area_mean                 0
    5    smoothness_mean           0
    6    compactness_mean          0
    7    concavity_mean            0
    8    concave points_mean       0
    9    symmetry_mean             0
    10   fractal_dimension_mean    0
    11   radius_se                 0
    12   texture_se                0
    13   perimeter_se              0
    14   area_se                   0
    15   smoothness_se             0
    16   compactness_se            0
    17   concavity_se              0
    18   concave points_se         0
    19   symmetry_se               0
    20   fractal_dimension_se      0
    21   radius_worst              0
    22   texture_worst             0
    23   perimeter_worst           0
    24   area_worst                0
    25   smoothness_worst          0
    26   compactness_worst         0
    27   concavity_worst           0
    28   concave points_worst      0
    29   symmetry_worst            0
    30   fractal_dimension_worst   0
```

`diagnose` 字段中各类型数据占比情况如下：

```
import matplotlib.pyplot as plt
plt.style.use('seaborn')
plt.pie([original_data[0].count(0), original_data[0].count(1)], labels=["M", "B"],
autopct='%1.2f%%', startangle=90)
plt.show()
```

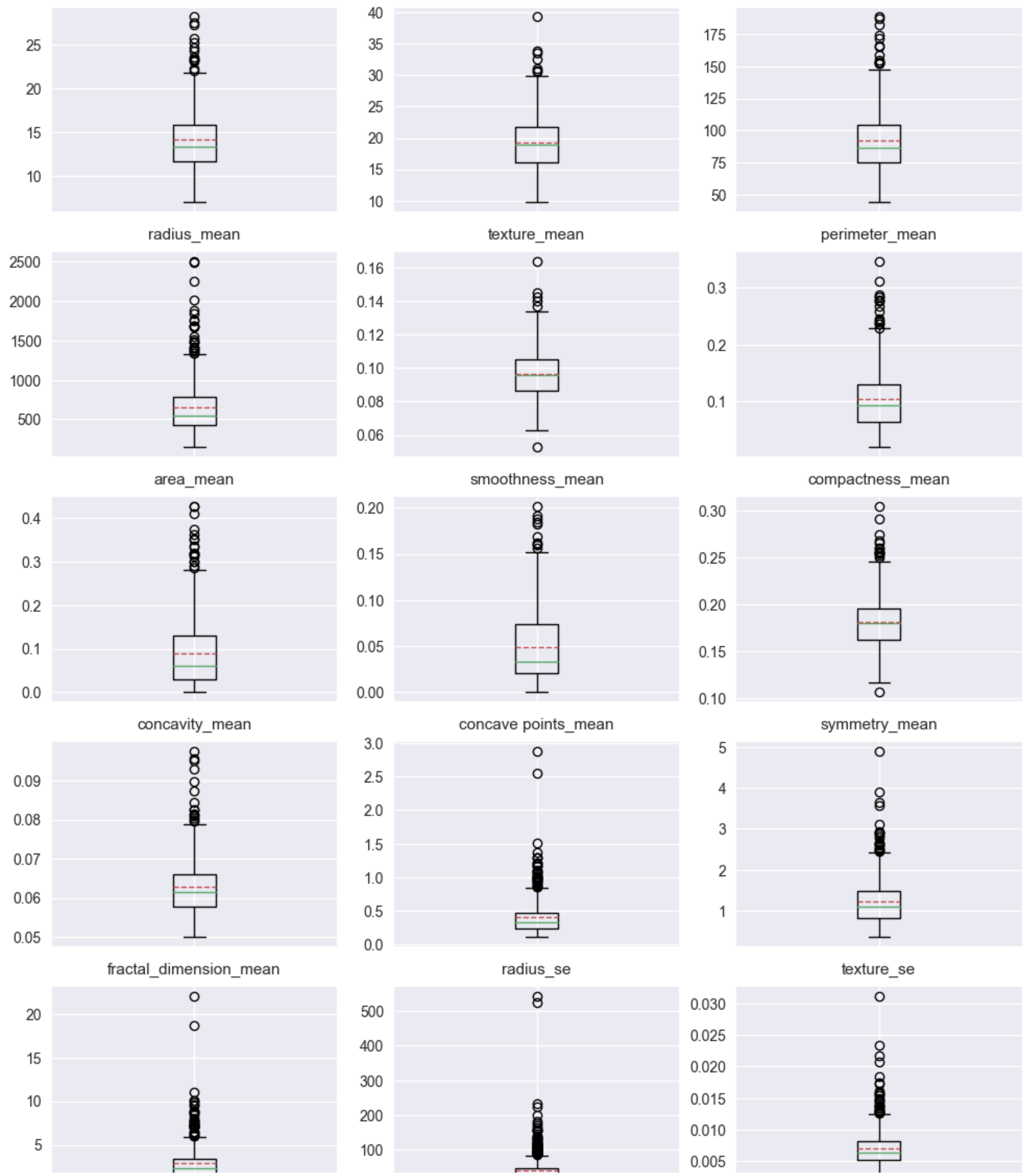
```
/var/folders/bv/mc555hkn509dv41d0yq119jr0000gn/T/ipykernel_43189/676113794.py:2:
MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are deprecated since
3.6, as they no longer correspond to the styles shipped by seaborn. However, they will remain
available as 'seaborn-v0_8-<style>'. Alternatively, directly use the seaborn API instead.
  plt.style.use('seaborn')
```

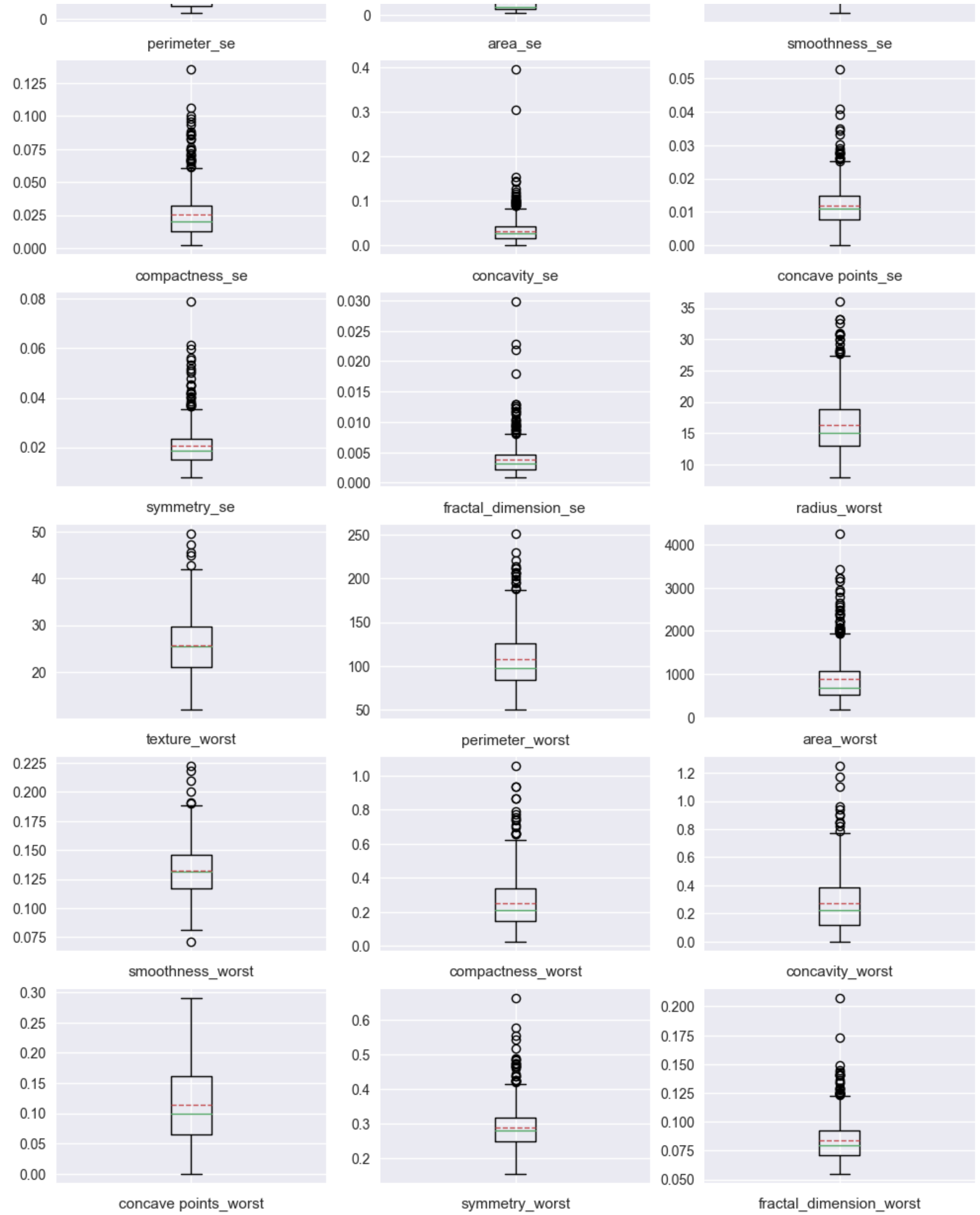


2.3 Remove Outliers

为原始数据绘制箱线图，检查 outliers 的分布状态

```python
# 原始数据箱线图
plt.figure(figsize=(12,30))
for i in range(0, 30):
    ax = plt.subplot(10, 3, i+1)
    ax.set_xlabel(header[i+2])
    ax.set_xticks(range(0,1))
    ax.boxplot(original_data[i+1],
               showmeans=True,
               meanline=True)
```





显然，除 `concave points_worst` 外，各 Feature 均在不同程度上存在 outlier。

下面标记存在 outlier 的记录，并进行移除。

```
import math
```

```python
q1_pos, q3_pos = math.floor(total*0.25), math.ceil(total*0.75)

lowers, uppers = [], []
for i in range(0,30):
    q1 = sorted(original_data[i+1])[q1_pos]
    q3 = sorted(original_data[i+1])[q3_pos]
    iqr = q3 - q1
    lowers.append(q1-1.5*iqr)
    uppers.append(q3+1.5*iqr)


outlier_rm = []
for i in range(0,31):
    outlier_rm.append([])

removed = []
for i in range(0, total):
    flag = True
    for j in range(0, 30):
        val = original_data[j+1][i]
        lower = lowers[j]
        upper = uppers[j]
        if val < lower or val > upper:
            flag = False
            break
    if flag:
        for j in range(0, 31):
            outlier_rm[j].append(original_data[j][i])
    else:
        removed.append(i)

print(f"{len(removed)} ({'{:.2f}'.format(len(removed)/total*100)}%) lines has been removed, detail is as follows:")
print(removed)
```

```
169 (29.70%) lines has been removed, detail is as follows:
[0, 1, 2, 3, 4, 5, 8, 9, 12, 14, 15, 18, 22, 23, 24, 25, 26, 27, 30, 31, 33, 34, 35, 38, 41,
42, 53, 56, 60, 62, 63, 68, 70, 71, 72, 76, 77, 78, 82, 83, 95, 105, 108, 110, 111, 112, 116,
118, 119, 121, 122, 136, 138, 145, 146, 147, 150, 151, 152, 156, 161, 162, 164, 168, 173, 176,
180, 181, 185, 190, 192, 196, 199, 202, 203, 210, 212, 213, 214, 218, 219, 229, 232, 236, 239,
242, 245, 250, 252, 254, 256, 257, 258, 259, 262, 265, 272, 273, 275, 288, 290, 300, 302, 314,
318, 323, 329, 332, 335, 337, 339, 343, 345, 351, 352, 366, 368, 369, 370, 372, 376, 379, 388,
389, 391, 393, 400, 416, 417, 424, 430, 433, 443, 449, 450, 455, 460, 461, 465, 468, 469, 471,
473, 485, 489, 492, 498, 503, 504, 505, 507, 520, 521, 528, 533, 535, 537, 539, 553, 556, 557,
559, 561, 562, 563, 564, 565, 567, 568]
```

3 Data Reduction

3.1 Feature Selection

使用 Variace Threshold Filtering 进行数据降维

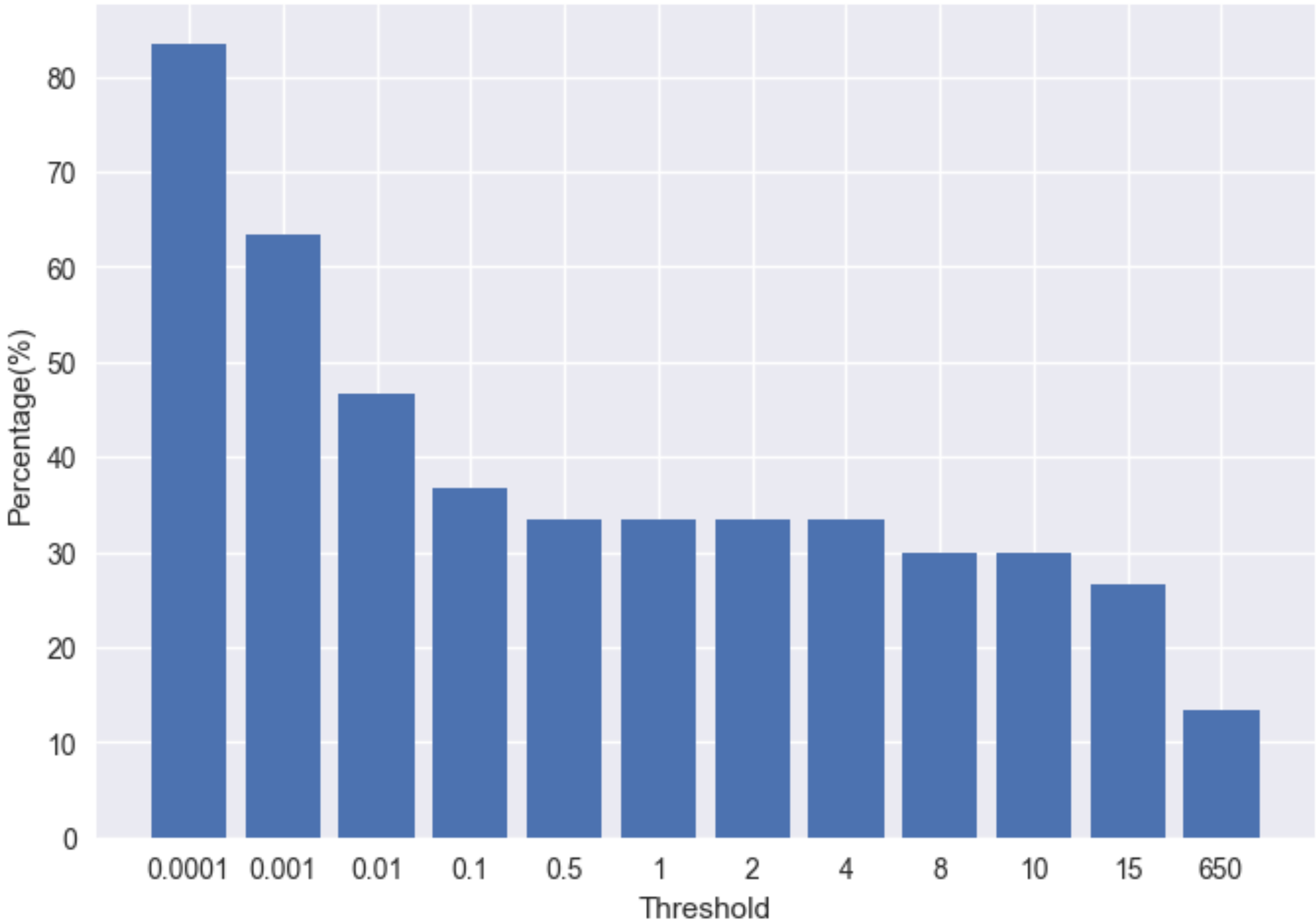
```
# 仅对后 30 个 Feature 进行筛选
vairances = []
for i in range(1, len(original_data)):
    avg = sum(original_data[i])/total
    tot = 0
    for j in range(0, total):
        tot += (original_data[i][j] - avg)*(original_data[i][j] - avg)
    vairances.append(tot/total)
```

```
# 输出不同阈值取值对筛选结果的影响
thresholds = [0.0001, 0.001, 0.01, 0.1, 0.5, 1, 2, 4, 8, 10, 15, 650]
percentages = []

print('{0:^11}'.format("Threshold"), '{0:^10}'.format('N-Feature'),
'{0:^12}'.format("Percentage"), "  " , "Feature List")
print("------------------------------------------------------------------------------------------
-----------")

for i in range(0, len(thresholds)):
    threshold = thresholds[i]
    selected = []
    for j in range(0, len(vairances)):
        if vairances[j] > threshold:
            selected.append(j+1)
    percentages.append(len(selected)/30*100)
    print('{0:^11}'.format(threshold), '{0:^10}'.format(len(selected)),
'{0:^12}'.format('{0:.2f}'.format(percentages[i]) + "%"), "  " , selected)
```

```
 Threshold  N-Feature   Percentage     Feature List
------------------------------------------------------------------------------------------
----
  0.0001       25         83.33%       [1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 14, 16, 17, 21,
22, 23, 24, 25, 26, 27, 28, 29, 30]
   0.001       19         63.33%       [1, 2, 3, 4, 6, 7, 8, 11, 12, 13, 14, 21, 22, 23, 24,
26, 27, 28, 29]
   0.01        14         46.67%       [1, 2, 3, 4, 11, 12, 13, 14, 21, 22, 23, 24, 26, 27]
    0.1        11         36.67%       [1, 2, 3, 4, 12, 13, 14, 21, 22, 23, 24]
    0.5        10         33.33%       [1, 2, 3, 4, 13, 14, 21, 22, 23, 24]
     1         10         33.33%       [1, 2, 3, 4, 13, 14, 21, 22, 23, 24]
     2         10         33.33%       [1, 2, 3, 4, 13, 14, 21, 22, 23, 24]
     4         10         33.33%       [1, 2, 3, 4, 13, 14, 21, 22, 23, 24]
     8         9          30.00%       [1, 2, 3, 4, 14, 21, 22, 23, 24]
    10         9          30.00%       [1, 2, 3, 4, 14, 21, 22, 23, 24]
    15         8          26.67%       [2, 3, 4, 14, 21, 22, 23, 24]
    650        4          13.33%       [4, 14, 23, 24]
```

Threshold 取值与 Featrue 筛选数量的关系如下图所示：

```
ax = plt.subplot()
ax.bar(range(len(thresholds)), percentages)
ax.set_xlabel('Threshold')
ax.set_xticks(range(0, len(thresholds)))
ax.set_xticklabels([str(i) for i in thresholds])
ax.set_ylabel('Percentage(%)')
plt.show()
```



以上是对于原始数据的筛选结果，下面尝试对去除 outlier 的数据进行筛选：

```
# 计算方差
vairances = []
total = len(outlier_rm[0])
for i in range(1, 31):
    avg = sum(outlier_rm[i])/total
    tot = 0
    for j in range(0, total):
        tot += (outlier_rm[i][j] - avg)*(outlier_rm[i][j] - avg)
    vairances.append(tot/total)

# 不同阈值取值对筛选结果的影响
percentages = []
```

```
print('{0:^11}'.format("Threshold"), '{0:^10}'.format('N-Feature'),
'{0:^12}'.format("Percentage"), "  " , "Feature List")
print("------------------------------------------------------------------------------------------------------------")

for i in range(0, len(thresholds)):
    threshold = thresholds[i]
    selected = []
    for j in range(0, len(vairances)):
        if vairances[j] > threshold:
            selected.append(j+1)
    percentages.append(len(selected)/30*100)
    print('{0:^11}'.format(threshold), '{0:^10}'.format(len(selected)),
'{0:^12}'.format('{0:.2f}'.format(percentages[i]) + "%"), "  " , selected)
```

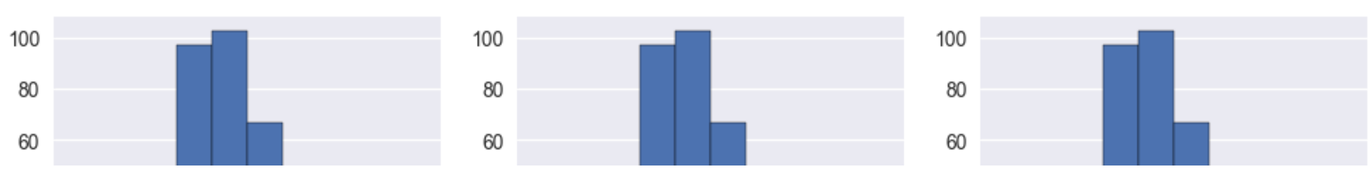
```
 Threshold  N-Feature   Percentage     Feature List
------------------------------------------------------------------------------------------------
----
  0.0001        25         83.33%       [1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 14, 16, 17, 21,
22, 23, 24, 25, 26, 27, 28, 29, 30]
   0.001        18         60.00%       [1, 2, 3, 4, 6, 7, 11, 12, 13, 14, 21, 22, 23, 24, 26,
27, 28, 29]
   0.01         14         46.67%       [1, 2, 3, 4, 11, 12, 13, 14, 21, 22, 23, 24, 26, 27]
    0.1         11         36.67%       [1, 2, 3, 4, 12, 13, 14, 21, 22, 23, 24]
    0.5         10         33.33%       [1, 2, 3, 4, 13, 14, 21, 22, 23, 24]
     1          9          30.00%       [1, 2, 3, 4, 14, 21, 22, 23, 24]
     2          9          30.00%       [1, 2, 3, 4, 14, 21, 22, 23, 24]
     4          9          30.00%       [1, 2, 3, 4, 14, 21, 22, 23, 24]
     8          8          26.67%       [2, 3, 4, 14, 21, 22, 23, 24]
    10          8          26.67%       [2, 3, 4, 14, 21, 22, 23, 24]
    15          7          23.33%       [2, 3, 4, 14, 22, 23, 24]
    650         2          6.67%        [4, 24]
```

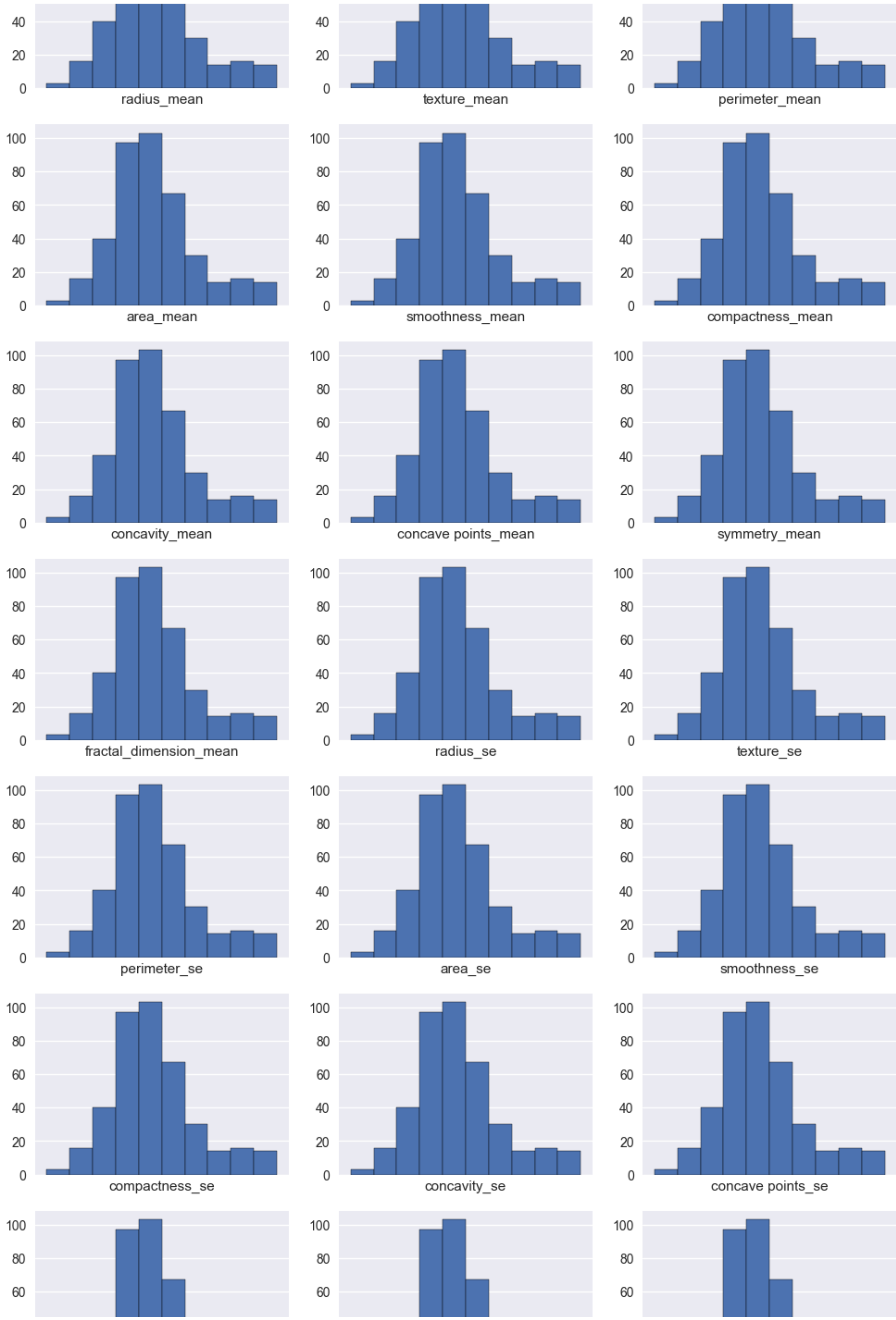
对比前表可知，在相同的 Threshold 下，对去除 outlier 的数据集进行筛选将保留 **更多的 Feature** 。

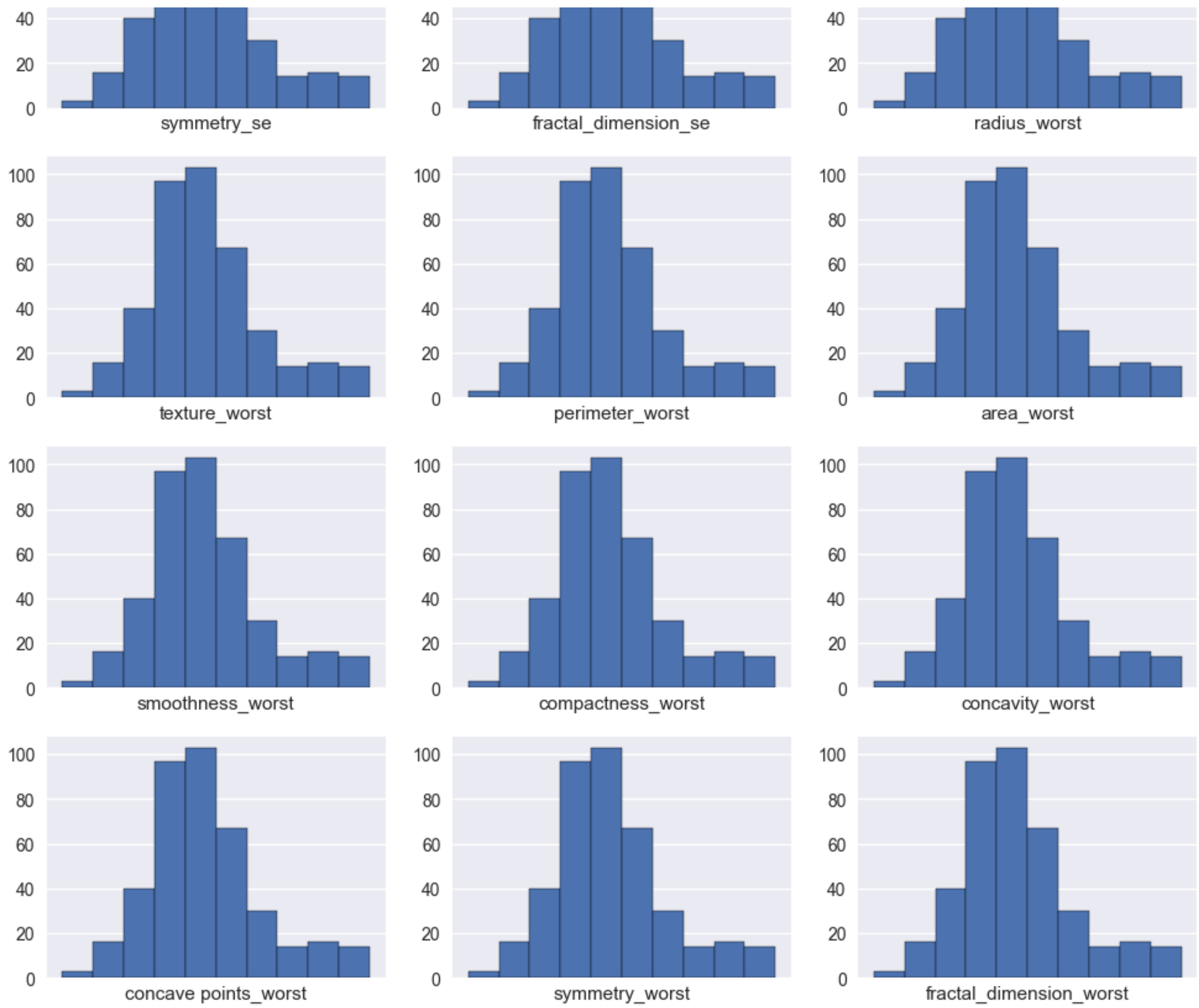
3.2 Histogram Analysis

通过绘制去除 outlier 数据的 equl-width 直方图，观察数据分布情况。

```
# 去除 outlier 数据的直方图
plt.figure(figsize=(12,30))
for i in range(0, 30):
    ax = plt.subplot(10, 3, i+1)
    ax.set_xlabel(header[i+2])
    ax.set_xticks(range(0,1))
    ax.hist(outlier_rm[1], edgecolor="black")
```

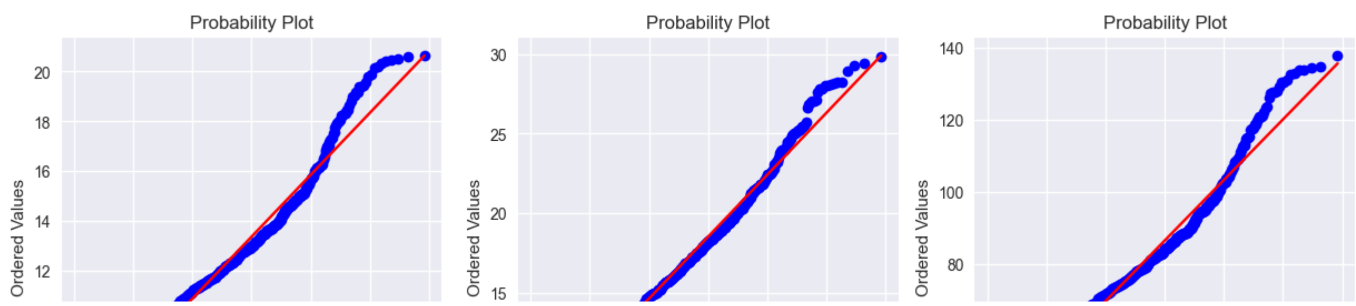


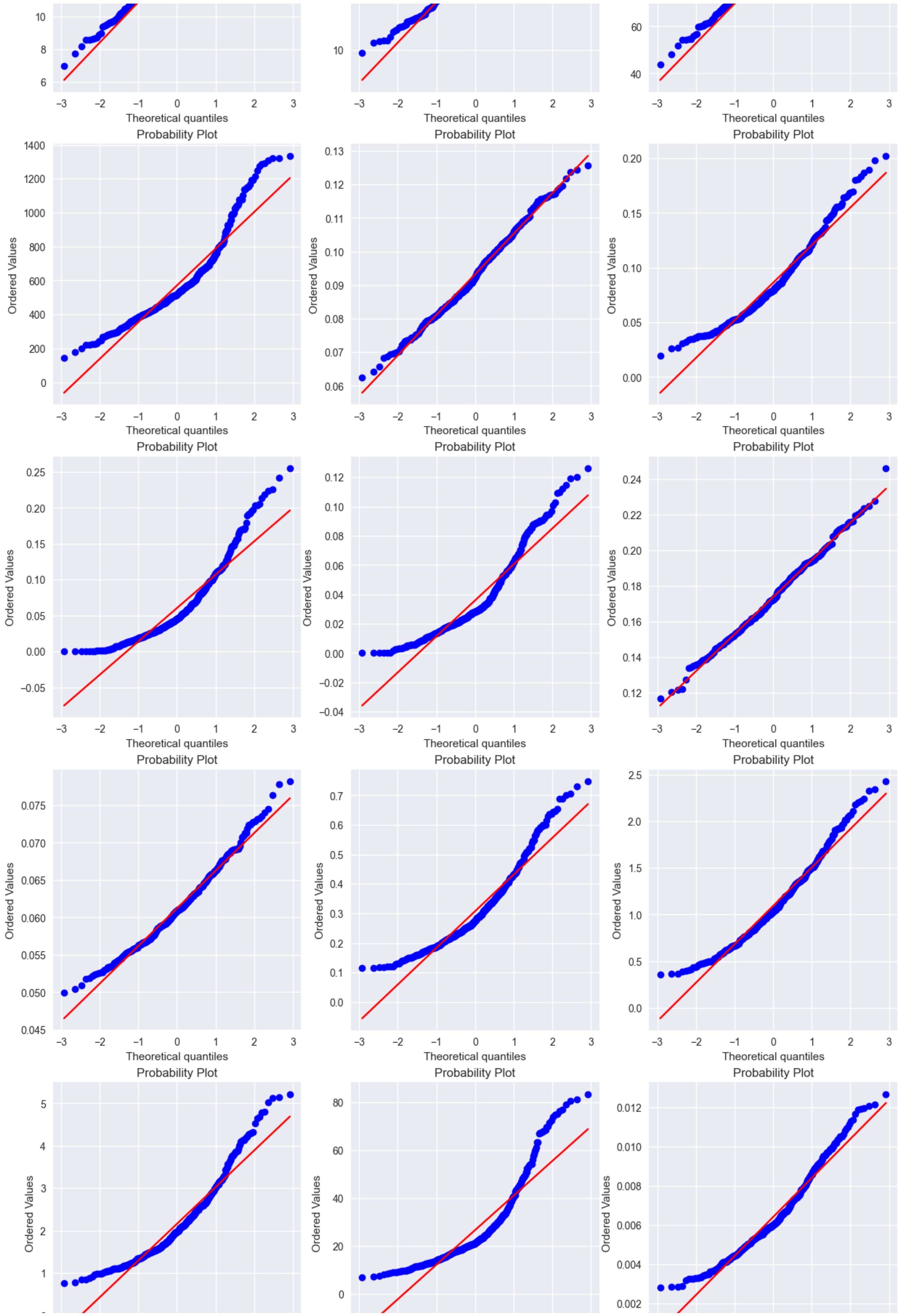

radius_mean
texture_mean
perimeter_mean
area_mean
smoothness_mean
compactness_mean
concavity_mean
concave points_mean
symmetry_mean
fractal_dimension_mean
radius_se
texture_se
perimeter_se
area_se
smoothness_se
compactness_se
concavity_se
concave points_se



从上图可知，去除 outlier 后的各 Feature 数据基本符合正态分布，下面通过 Q-Q 图进行验证：

```
# 绘制各 Feature 的 Q-Q 图
from scipy import stats
plt.figure(figsize=(15,55))

for i in range(0,30):
    ax = plt.subplot(10, 3, i+1)
    # 没办法设小标题（我裂开）
    stats.probplot(outlier_rm[i+1], dist="norm", plot=ax)

plt.show()
```




Theoretical quantiles
Theoretical quantiles
Theoretical quantiles
Probability Plot
Probability Plot
Probability Plot
Ordered Values
Ordered Values
Ordered Values
Theoretical quantiles
Theoretical quantiles
Theoretical quantiles
Probability Plot
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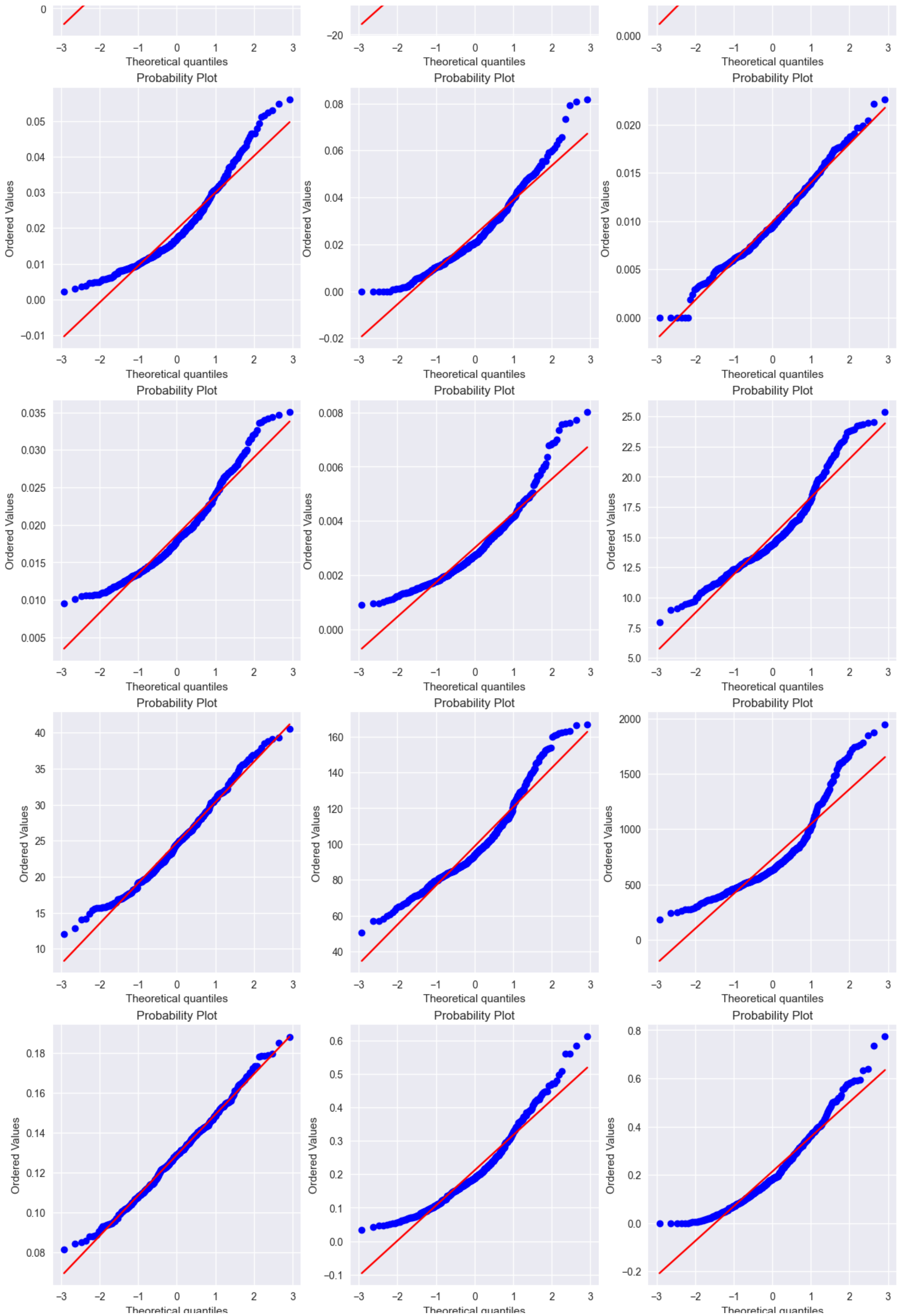
Probability Plot
Probability Plot
Probability Plot
Ordered Values
Ordered Values
Ordered Values



Theoretical quantiles
Theoretical quantiles
Theoretical quantiles
Probability Plot
Probability Plot
Probability Plot
Ordered Values
Ordered Values
Ordered Values
Theoretical quantiles
Theoretical quantiles
Theoretical quantiles
Probability Plot
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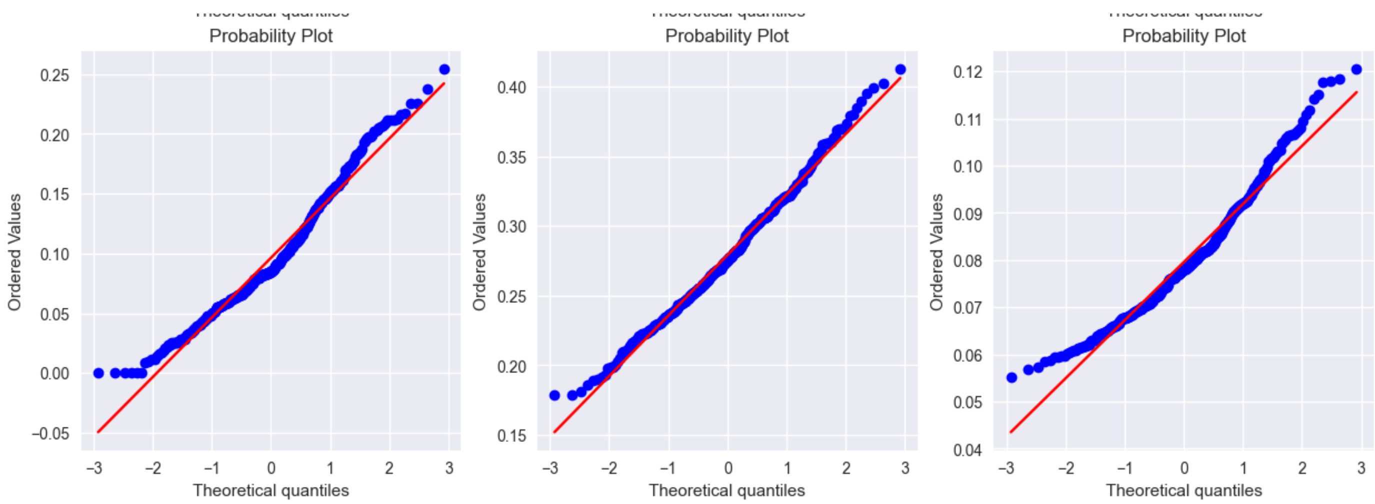
Ordered Values
Ordered Values
Ordered Values



4 Data Transformation

由于不同的 `diagnose` 组别间的数据可能满足不同的正态分布，下面通过 MinMax 方式对数据进行标准化：

$$x_{norm} = \frac{x - x_{min}}{x_{max} - xmin}$$

```python
# 统计每个属性的 min / max 值
mins = [0]
maxs = [1]

print("各属性取值的 min / max 信息如下：")
print('{0:^24}'.format("Attribute Name"), '{0:^10}'.format("min"), '{0:^10}'.format("max"))
print("----------------------------------------------")

for i in range(1, len(outlier_rm)):
    minn = min(outlier_rm[i])
    maxx = max(outlier_rm[i])
    mins.append(minn)
    maxs.append(maxx)
    print('{0:^24}'.format(header[i]), '{0:^10}'.format(minn), '{0:^10}'.format(maxx))
```

```
各属性取值的 min / max 信息如下：
     Attribute Name          min        max
----------------------------------------------
       diagnosis            6.981      20.64
      radius_mean            9.71      29.81
      texture_mean          43.79      137.8
     perimeter_mean         143.5      1335.0
       area_mean           0.06251     0.1257
    smoothness_mean        0.01938     0.2022
    compactness_mean         0.0       0.2545
     concavity_mean          0.0       0.1259
```

```
   concave points_mean      0.1167     0.2459
      symmetry_mean        0.04996    0.07818
  fractal_dimension_mean    0.1144     0.7474
        radius_se           0.3602     2.426
        texture_se          0.757      5.216
       perimeter_se         6.802       83.5
         area_se           0.002826   0.01266
      smoothness_se        0.002252   0.05592
      compactness_se         0.0      0.08158
       concavity_se          0.0      0.02258
    concave points_se      0.009539   0.03504
       symmetry_se        0.0008948   0.008015
   fractal_dimension_se     7.93       25.37
       radius_worst         12.02      40.54
      texture_worst         50.41      166.8
     perimeter_worst        185.2      1946.0
        area_worst         0.08125     0.1878
     smoothness_worst      0.03432     0.611
    compactness_worst        0.0       0.7727
     concavity_worst         0.0       0.2543
   concave points_worst     0.1783     0.4128
      symmetry_worst       0.05521     0.1205
```

```
# 对数据进行标准化
normalized_data = []
for i in range(0, 31):
    normalized_data.append([])

for i in range(0, total):
    normalized_data[0].append(outlier_rm[0][i])
    for j in range(1, 31):
        normalized_data[j].append((outlier_rm[j][i] - mins[j])/(maxs[j] - mins[j]))
```

下面重新计算输出经过 MinMax 标准化后，各 Feature 字段的最大最小值以验证操作的正确性。

```
print("完成标准化后，各属性取值的 min / max 信息如下：")
print('{0:^24}'.format("Attribute Name"), '{0:^10}'.format("min"), '{0:^10}'.format("max"))
print("---------------------------------------------")

for i in range(1, len(normalized_data)):
    minn = min(normalized_data[i])
    maxx = max(normalized_data[i])
    print('{0:^24}'.format(header[i]), '{0:^10}'.format(minn), '{0:^10}'.format(maxx))
```

```
完成标准化后，各属性取值的 min / max 信息如下：
     Attribute Name          min        max
---------------------------------------------
       diagnosis             0.0        1.0
      radius_mean            0.0        1.0
      texture_mean           0.0        1.0
```

```
          perimeter_mean        0.0        1.0
              area_mean         0.0        1.0
         smoothness_mean        0.0        1.0
        compactness_mean        0.0        1.0
          concavity_mean        0.0        1.0
     concave points_mean        0.0        1.0
           symmetry_mean        0.0        1.0
  fractal_dimension_mean        0.0        1.0
               radius_se        0.0        1.0
              texture_se        0.0        1.0
            perimeter_se        0.0        1.0
                 area_se        0.0        1.0
           smoothness_se        0.0        1.0
          compactness_se        0.0        1.0
            concavity_se        0.0        1.0
       concave points_se        0.0        1.0
             symmetry_se        0.0        1.0
    fractal_dimension_se        0.0        1.0
            radius_worst        0.0        1.0
           texture_worst        0.0        1.0
         perimeter_worst        0.0        1.0
              area_worst        0.0        1.0
        smoothness_worst        0.0        1.0
       compactness_worst        0.0        1.0
         concavity_worst        0.0        1.0
    concave points_worst        0.0        1.0
          symmetry_worst        0.0        1.0
```

从上表可知，经过 MinMax 标准化后，所有 Feature 的取值均处于区间 `[0,1]` 内。