rice_viz

November 17, 2025

1 Rice

1.1 Questions

- What is the best feature to differentiate between `jasmine` and `baldo` rice?
- Are `length` and `roundness` the key features to differentiate them?

[1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

data = pd.read_csv("./dataset/Rice-Gonen andJasmine.csv")

data = data.drop(columns=["id"]).dropna()
data.head(10)
```

[1]:
```
   Area  MajorAxisLength  MinorAxisLength  Eccentricity  ConvexArea  \
0  4537        92.229316        64.012769      0.719916        4677
1  2872        74.691881        51.400454      0.725553        3015
2  3048        76.293164        52.043491      0.731211        3132
3  3073        77.033628        51.928487      0.738639        3157
4  3693        85.124785        56.374021      0.749282        3802
5  2990        77.417073        50.954344      0.752861        3080
6  3556        84.323564        55.413061      0.753762        3636
7  3788        86.952411        56.444769      0.760664        3866
8  2629        74.133114        48.074144      0.761228        2790
9  5719       106.721142        68.977700      0.763053        5819

   EquivDiameter    Extent  Perimeter  Roundness  AspectRation    Class
0      76.004525  0.657536    273.085   0.764510      1.440796  jasmine
1      60.471018  0.713009    208.317   0.831658      1.453137  jasmine
2      62.296341  0.759153    210.012   0.868434      1.465950  jasmine
3      62.551300  0.783529    210.657   0.870203      1.483456  jasmine
4      68.571668  0.769375    230.332   0.874743      1.510000  jasmine
5      61.700780  0.584898    216.930   0.798439      1.519342  jasmine
6      67.287739  0.750211    227.007   0.867148      1.521727  jasmine
7      69.448048  0.800676    235.476   0.858473      1.540487  jasmine
```

```
8      57.856260  0.640595    207.325    0.768594      1.542058  jasmine
9      85.332625  0.754983    281.839    0.904748      1.547183  jasmine
```

1.2 Explaination

1.2.1 Axis Length and Aspect Ratio

aspect_ratio = major_axis / minor_axis

1.2.2 Eccentricity

0…perfect Circle

1…perfect Line

1.2.3 Roundness

roundness = 4 * PI * area / perimeter^2

1.2.4 Extent

extend = area / bounding_box_area

1.2.5 (Convex) Area

[2]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18185 entries, 0 to 18184
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Area             18185 non-null  int64
 1   MajorAxisLength  18185 non-null  float64
 2   MinorAxisLength  18185 non-null  float64
 3   Eccentricity     18185 non-null  float64
 4   ConvexArea       18185 non-null  int64
 5   EquivDiameter    18185 non-null  float64
 6   Extent           18185 non-null  float64
 7   Perimeter        18185 non-null  float64
 8   Roundness        18185 non-null  float64
 9   AspectRation     18185 non-null  float64
 10  Class            18185 non-null  object
dtypes: float64(8), int64(2), object(1)
memory usage: 1.5+ MB
```

[3]:
```
data.describe()
```

[3]:
```
               Area  MajorAxisLength  MinorAxisLength  Eccentricity  \
count  18185.000000     18185.000000     18185.000000  18185.000000
```

```
mean     7036.492989        151.680754        59.807851       0.915406
std      1467.197150         12.376402        10.061653       0.030575
min      2522.000000         74.133114        34.409894       0.676647
25%      5962.000000        145.675910        51.393151       0.891617
50%      6660.000000        153.883750        55.724288       0.923259
75%      8423.000000        160.056214        70.156593       0.941372
max     10210.000000        183.211434        82.550762       0.966774

         ConvexArea  EquivDiameter        Extent     Perimeter     Roundness  \
count  18185.000000   18185.000000  18185.000000  18185.000000  18185.000000
mean    7225.817872      94.132952      0.616653    351.606949      0.707998
std     1502.006571       9.906250      0.104389     29.500620      0.067310
min     2579.000000      56.666658      0.383239    197.015000      0.174590
25%     6125.000000      87.126656      0.538530    333.990000      0.650962
50%     6843.000000      92.085696      0.601194    353.088000      0.701941
75%     8645.000000     103.559146      0.695664    373.003000      0.769280
max    11008.000000     114.016559      0.886573    508.511000      0.904748

        AspectRation
count  18185.000000
mean       2.599081
std        0.434836
min        1.358128
25%        2.208527
50%        2.602966
75%        2.964101
max        3.911845
```

[4]:
```
data["Class"].value_counts()
```

[4]:
```
Class
jasmine    9985
Gonen      8200
Name: count, dtype: int64
```

1.3 What can we see?

1.3.1 Problems

- no units of measurements
- a lot of features
- maybe strong correlations?

[5]:
```
rice_palette = sns.xkcd_palette(["hot pink", "azure"])
rice_palette
```

[5]:
```
[(1.0, 0.00784313725490196, 0.5529411764705883),
 (0.023529411764705882, 0.6039215686274509, 0.9529411764705882)]
```

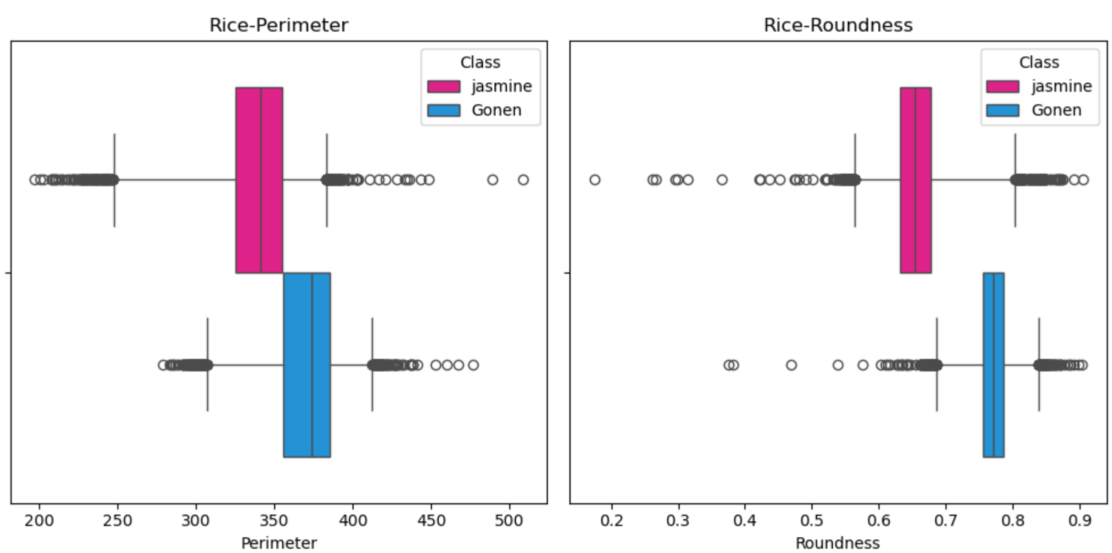
1.4 BoxPlots first look

[6]:
```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 5))
axes = axes.flatten()

sns.boxplot(
    data=data,
    hue="Class",
    palette=rice_palette,
    x='Perimeter',
    whis=[1,99],
    ax=axes[0],
)
axes[0].set_title('Rice-Perimeter')

sns.boxplot(
    data=data,
    hue="Class",
    palette=rice_palette,
    x='Roundness',
    whis=[1,99],
    ax=axes[1],
)
axes[1].set_title('Rice-Roundness')

plt.tight_layout()
plt.show()
```



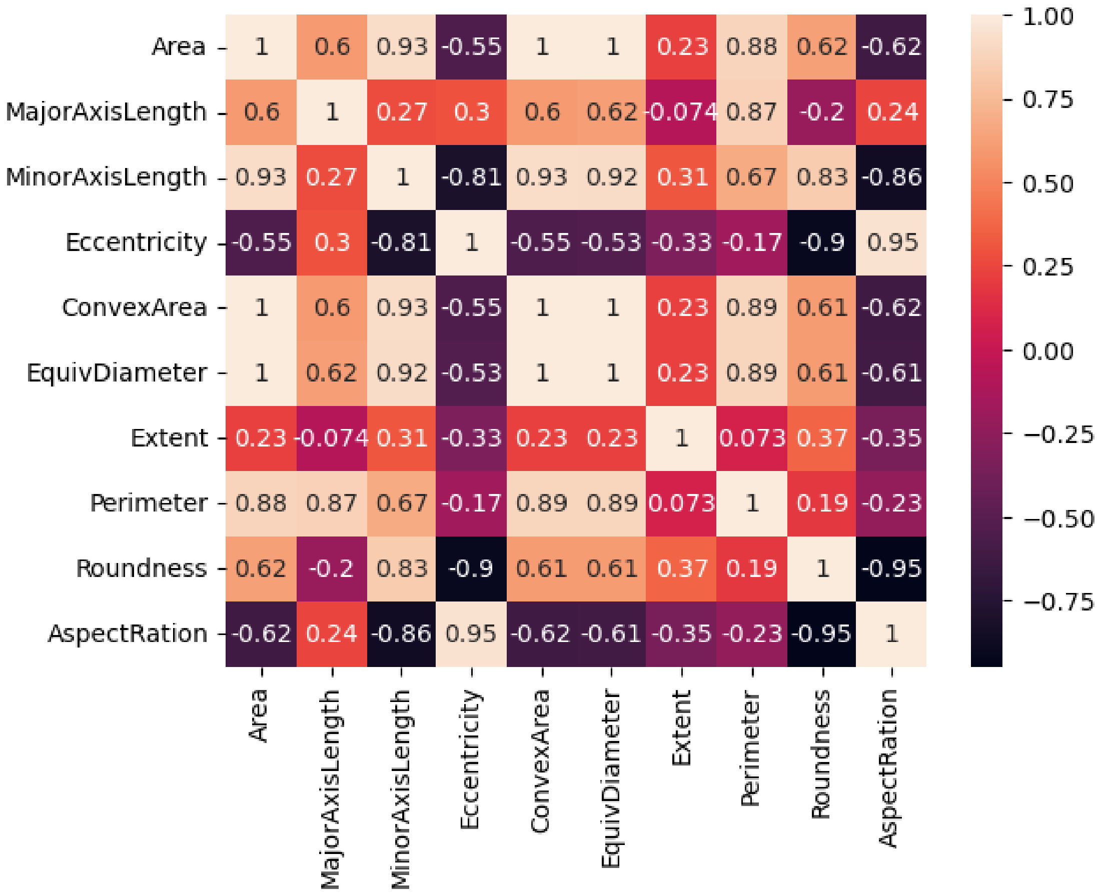
1.5 Quick Thought Stop

- Are they correlated?
- Any other potential correlations?

1.6 Correlation

[7]:
```
correlation = data.corr(numeric_only=True)
sns.heatmap(correlation, annot=True)
```

[7]: <Axes: >



[8]:
```
import pandas as pd

corr_matrix = data.corr(numeric_only=True).abs()
high_corr = corr_matrix[corr_matrix > 0.85]

high_corr_pairs = (
    corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
```

```
    .stack()
    .reset_index()
)
high_corr_pairs.columns = ["Feature 1", "Feature 2", "Correlation"]

high_corr_pairs = high_corr_pairs[high_corr_pairs["Correlation"] > 0.85]

print(high_corr_pairs.sort_values(by="Correlation"))
```

```
         Feature 1        Feature 2  Correlation
23  MinorAxisLength      AspectRation     0.860516
14  MajorAxisLength         Perimeter     0.870178
6              Area         Perimeter     0.881540
32       ConvexArea         Perimeter     0.886987
36    EquivDiameter         Perimeter     0.891567
28     Eccentricity         Roundness     0.903657
19  MinorAxisLength     EquivDiameter     0.923790
18  MinorAxisLength        ConvexArea     0.928992
1              Area   MinorAxisLength     0.930215
44        Roundness      AspectRation     0.947875
29     Eccentricity      AspectRation     0.950301
30       ConvexArea     EquivDiameter     0.997403
4              Area     EquivDiameter     0.998158
3              Area        ConvexArea     0.999362
```

1.7 Highly correlated values

For each of the highly correlated feature pairs, one gets dropped, for easier understandability of future diagrams

[9]:
```
cleaned_data = data.drop(columns=["ConvexArea", "EquivDiameter",␣
 ↪"AspectRation"])
```

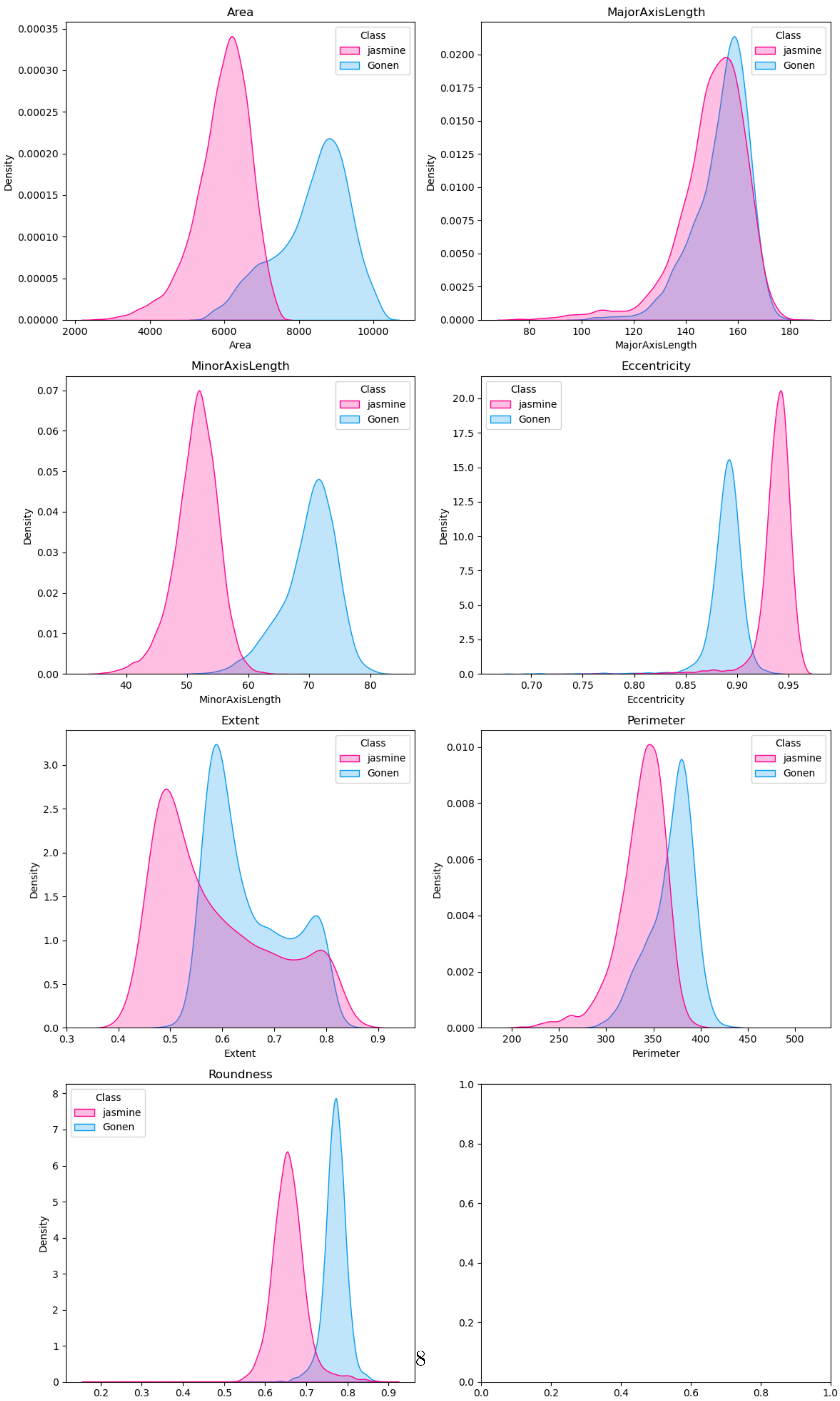
[10]:
```
cols = [
    "Area", "MajorAxisLength", "MinorAxisLength", "Eccentricity",
    "Extent", "Perimeter", "Roundness"
]

fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(12, 20))
axes = axes.flatten()

for i, column in enumerate(cols):
    sns.kdeplot(
        data=cleaned_data,
        hue="Class",
        palette=rice_palette,
        x=column,
        ax=axes[i],
```

```
        fill=True
    )
    axes[i].set_title(column)

plt.tight_layout()
plt.show()
```

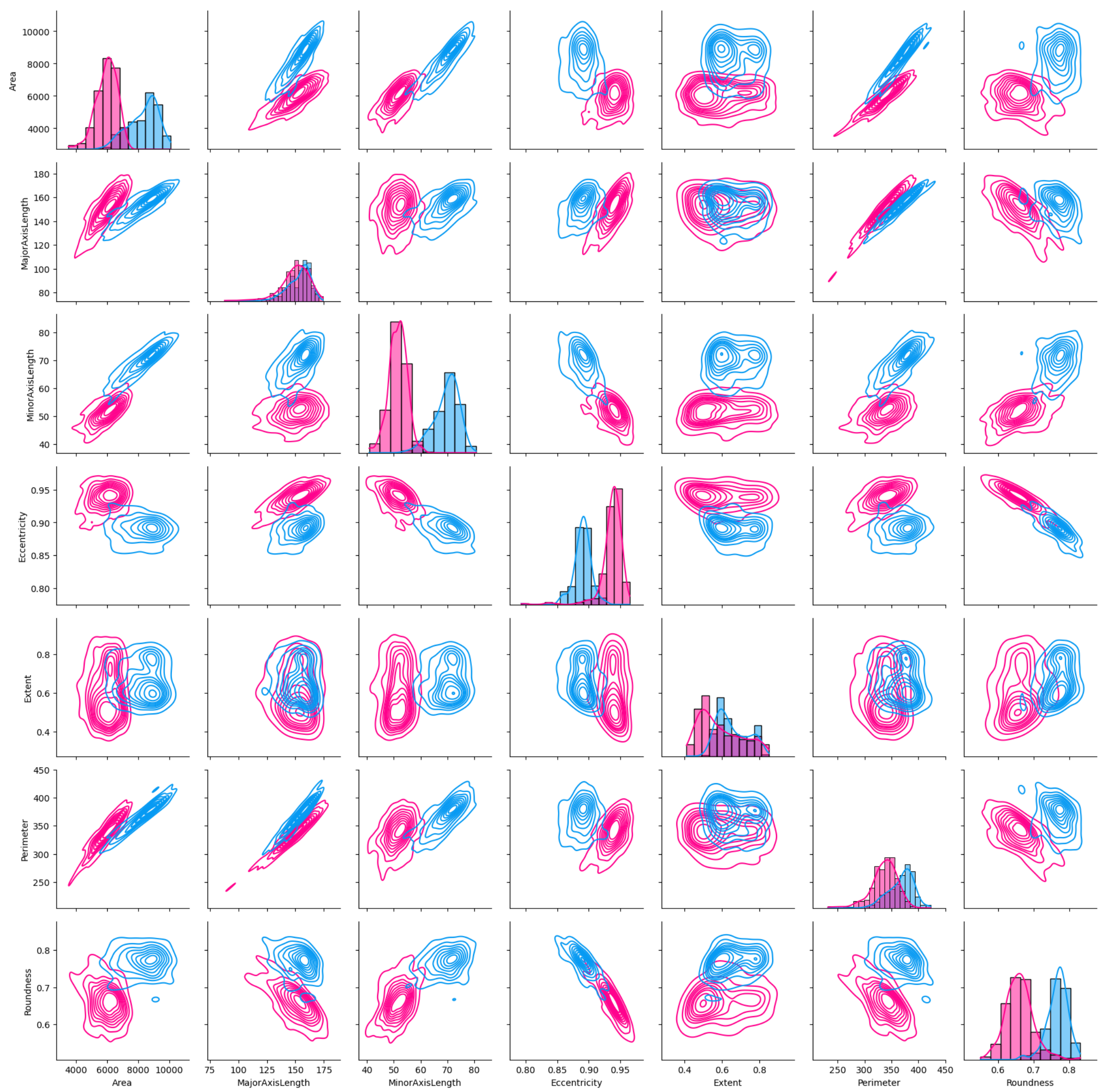

Area
MajorAxisLength
MinorAxisLength
Eccentricity
Extent
Perimeter
Roundness
Class
jasmine
Gonen
Density

1.8 Key-Features

- Roundness
- Eccentricity
- Minor-Axis-Length

[11]:
```
pair_grid = sns.PairGrid(data=cleaned_data.sample(500), hue='Class',␣
↪palette=rice_palette)
pair_grid.map_diag(sns.histplot, kde=True)
pair_grid.map_offdiag(sns.kdeplot)
```

[11]: <seaborn.axisgrid.PairGrid at 0x2a8e7126f90>



1.9 Back to the questions

- What is the best feature to differentiate between `jasmine` and `baldo` rice?
  - the key feature is the `minor-axis-length`
- Are `length` and `roundness` the key features to differentiate them?
  - `roundness` and `minor-axis-length` are decent
  - but `area` and `roundness` would also work