Accuracy_analysis

May 8, 2019

1 Import necessary dependencies

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

2 Load datasets and Reviews features

```
In [2]: data = pd.read_csv('./accuracy_full.csv')

In [3]: data.head()

Out[3]:                              Unnamed: 0  \
        0  7c81560b1f077f25e0dd594f5bf4ad86
        1  1d516aebeabbf2a07ca7e8ebe18d97c8
        2  aa8e22e74a528ca8c34f022da26e6b6e
        3  e4703dbfb0fd5afe7abb4d354a9d37f0
        4  caf621af10216ec1210297567df473e1

                                clf name & configuration      AP  MagicTelescope  \
        0          weka.classifiers.bayes.NaiveBayes-['-K']  0.9615          0.9967
        1  weka.classifiers.bayes.BayesNet-['-Q', 'weka.c...     NaN          0.8395
        2              weka.classifiers.bayes.NaiveBayes-[]  0.9594          0.8944
        3                weka.classifiers.bayes.BayesNet-[]     NaN          0.9984
        4  weka.classifiers.bayes.BayesNet-['-Q', 'weka.c...     NaN             NaN

           abalone  anneal     ar1  arrhythmia  audiology   autos  ...  soybean  \
        0   0.6253  0.8608  0.8843      0.6504     0.7168  0.6780  ...   0.9444
        1   0.5688     NaN  0.9256         NaN        NaN     NaN  ...      NaN
        2   0.5808  0.6882  0.8595      0.6173     0.7168  0.6098  ...   0.9312
        3   0.6299  0.9131  0.9256      0.7168     0.7478  0.7073  ...   0.9531
        4   0.6775  0.9432  0.9256         NaN        NaN  0.7854  ...   0.9327

           spambase  splice  teachingAssistant  tic-tac-toe    vote   vowel  \
        0    0.9854  0.9991             0.5497       0.9958  0.9011  0.6909
```

```
1       NaN     NaN             0.5166        0.9019  0.9655  0.7374
2    0.8133  0.9925             0.5298        0.9916  0.9011  0.6303
3       NaN     NaN             0.9073        0.9990  0.9011  0.6253
4       NaN     NaN             0.9205        0.9990  0.9563  0.8303

   waveform-5000   yeast     zoo
0         0.8012  0.6098  0.9604
1            NaN  0.5761  0.9505
2         0.7998  0.5856  0.9406
3            NaN  0.6004  0.9307
4            NaN  0.6024     NaN

[5 rows x 74 columns]
```

In [4]:
```
# Prepare a new data inlcude only features datasets ( begin from column 2)
data_history = data.iloc[:, 2:].copy()
```

2.1 Descriptive Statistics

In [5]:
```
data_history.describe()
```

Out[5]:
```
              AP  MagicTelescope    abalone     anneal        ar1  arrhythmia  \
count  49.000000       57.000000  61.000000  60.000000  62.000000   57.000000
mean    0.924343        0.914574   0.632536   0.852503   0.905879    0.610765
std     0.046357        0.090206   0.037053   0.063289   0.026954    0.068615
min     0.735000        0.701100   0.536000   0.688200   0.760300    0.440300
25%     0.925200        0.851100   0.601600   0.798400   0.900800    0.559700
50%     0.933800        0.894400   0.645700   0.870800   0.913250    0.623900
75%     0.953000        0.999900   0.657200   0.905600   0.925600    0.661500
max     0.961500        1.000000   0.690200   0.943200   0.933900    0.743400

       audiology      autos   badges2  balance-scale  ...    soybean  \
count  57.000000  60.000000  61.00000      61.000000  ...  60.000000
mean    0.656184   0.669097   0.99883       0.791790  ...   0.849243
std     0.160168   0.139438   0.00425       0.084076  ...   0.201654
min     0.252200   0.326800   0.96940       0.462400  ...   0.131800
25%     0.535400   0.620750   1.00000       0.776000  ...   0.889125
50%     0.716800   0.695150   1.00000       0.800000  ...   0.925300
75%     0.787600   0.763425   1.00000       0.838400  ...   0.941400
max     0.840700   0.863400   1.00000       0.904000  ...   0.994100

        spambase     splice  teachingAssistant  tic-tac-toe       vote  \
count  54.000000  55.000000          61.000000    61.000000  61.000000
mean    0.930785   0.869207           0.522961     0.942564   0.950913
std     0.072013   0.188026           0.150465     0.090268   0.021099
min     0.730700   0.243600           0.324500     0.699400   0.894300
25%     0.884550   0.782750           0.410600     0.915400   0.949400
50%     0.929900   0.942000           0.529800     0.988500   0.956300
```

```
75%      0.999250   0.998900           0.582800     0.999000   0.965500
max      0.999600   0.999400           0.927200     1.000000   0.974700

             vowel  waveform-5000      yeast        zoo
count  61.000000      54.000000  61.000000  59.000000
mean    0.677630       0.793074   0.541989   0.795780
std     0.249163       0.080794   0.084657   0.184834
min     0.090900       0.513200   0.303200   0.405900
25%     0.630300       0.763150   0.510100   0.643600
50%     0.755600       0.796600   0.571400   0.901000
75%     0.819200       0.859950   0.593000   0.920800
max     0.991900       0.868800   0.651600   0.970300

[8 rows x 72 columns]
```

3 I. Analyze each dataset (columns)

3.1 1. The best dataset

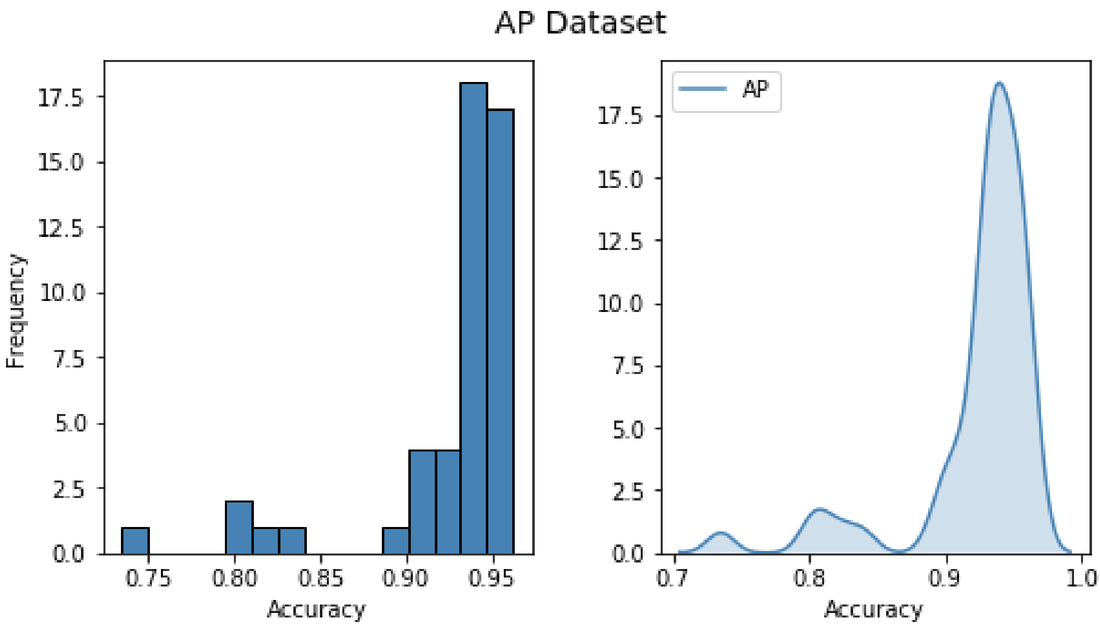
The first time, we will review each datasets. Corresponding to each this dataset, we wanna know how many algorithms apply to it for the most optimal results. A dataset is called "the best dataset" if it has many algorithms which give high accuracy.

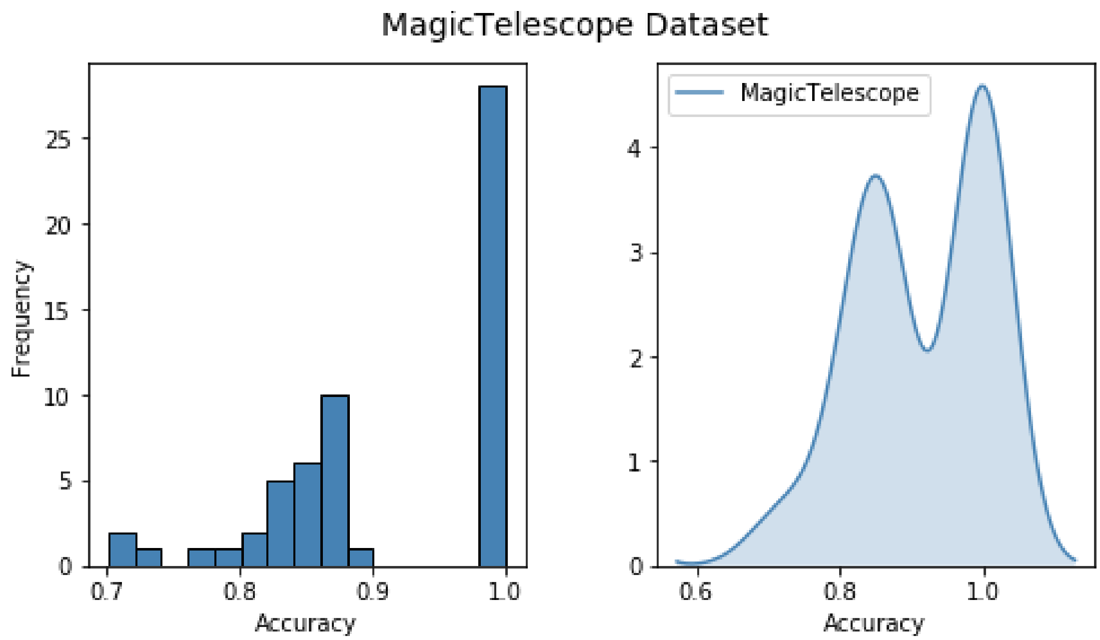
One of the most effective wayss to visualize the numeric attributes is to use a histogram or a density plot works quit well in understanding how the data is distributed for that attribute.

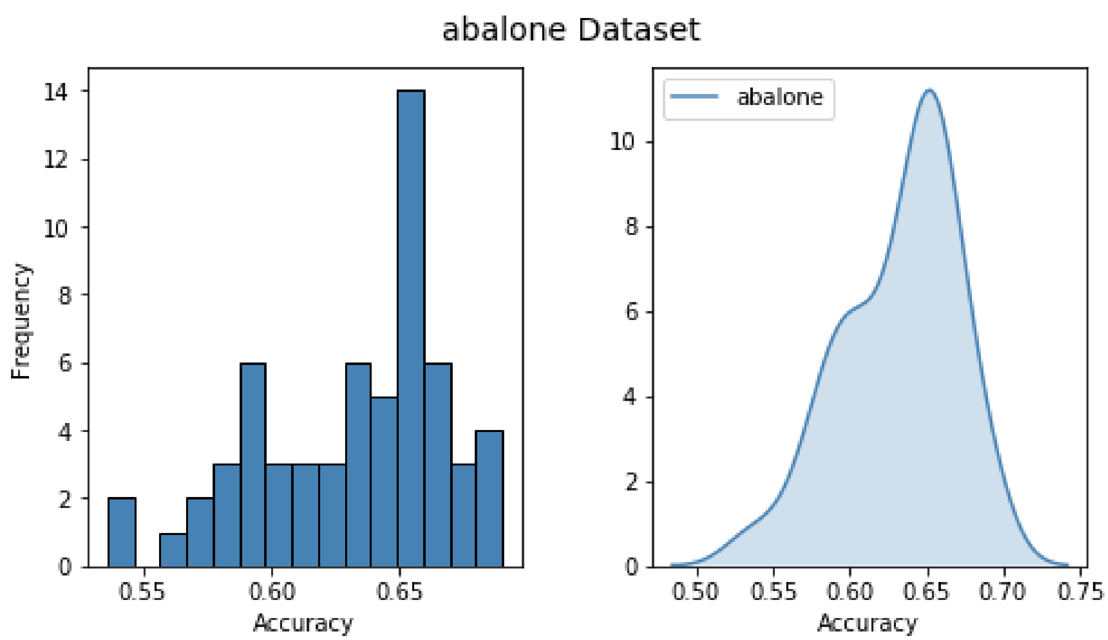
```
In [6]: for i in range(72):
            # Histogram

            fig = plt.figure(figsize=(8, 4)) # Create a new figure with the
            # size 8x4 (unit:inch)
            title = fig.suptitle( data_history.columns.values[i]
                                 + ' Dataset', fontsize=14) # Set title
            fig.subplots_adjust(top=0.9, wspace=0.3) # Set the position of title
            # We'll have 2 subplot, histogram plot is on the left
            ax = fig.add_subplot(1,2,1)
            ax.set_xlabel('Accuracy') # Set the name axis-x
            ax.set_ylabel('Frequency') # Set the name axis-y
            freq, bins, patches = ax.hist(data_history.iloc[:,i],
                color='steelblue', bins=15, edgecolor='black', linewidth=1)

            # Density Plot
            fig.subplots_adjust(top=0.9, wspace=0.3)
            ax1 = fig.add_subplot(1,2,2) # density Plot is on the right
            ax1.set_xlabel('Accuracy')
            warning = sns.kdeplot(data_history.iloc[:,i], ax=ax1,
                                  shade=True, color='steelblue')
```

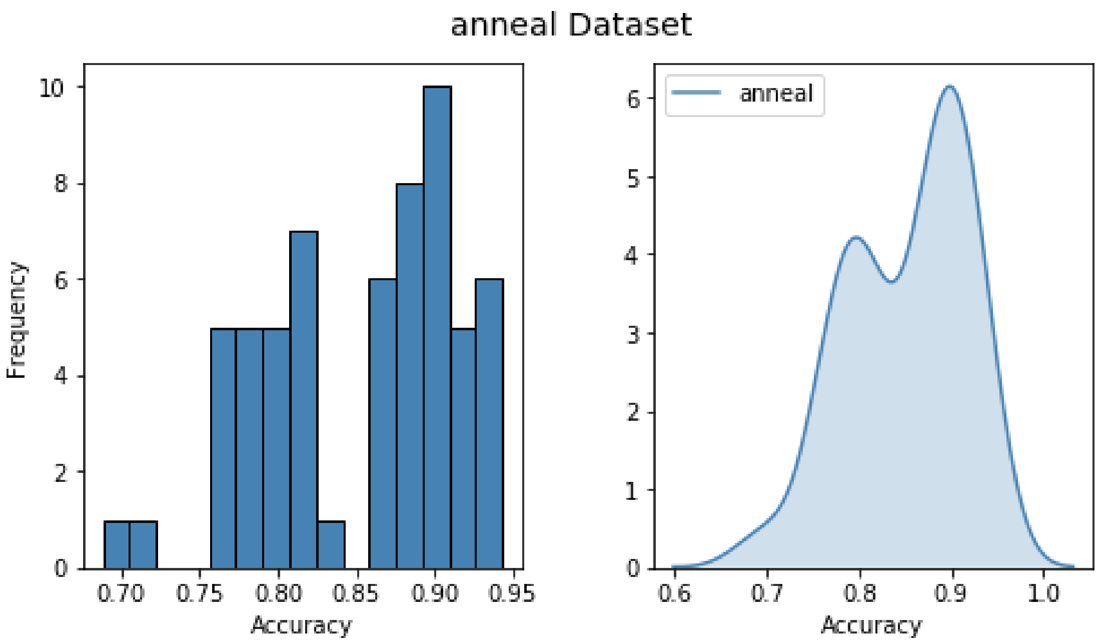
```
/home/haipro/anaconda3/lib/python3.7/site-packages/numpy/lib/histograms.py:824: RuntimeWarning
  keep = (tmp_a >= first_edge)
```

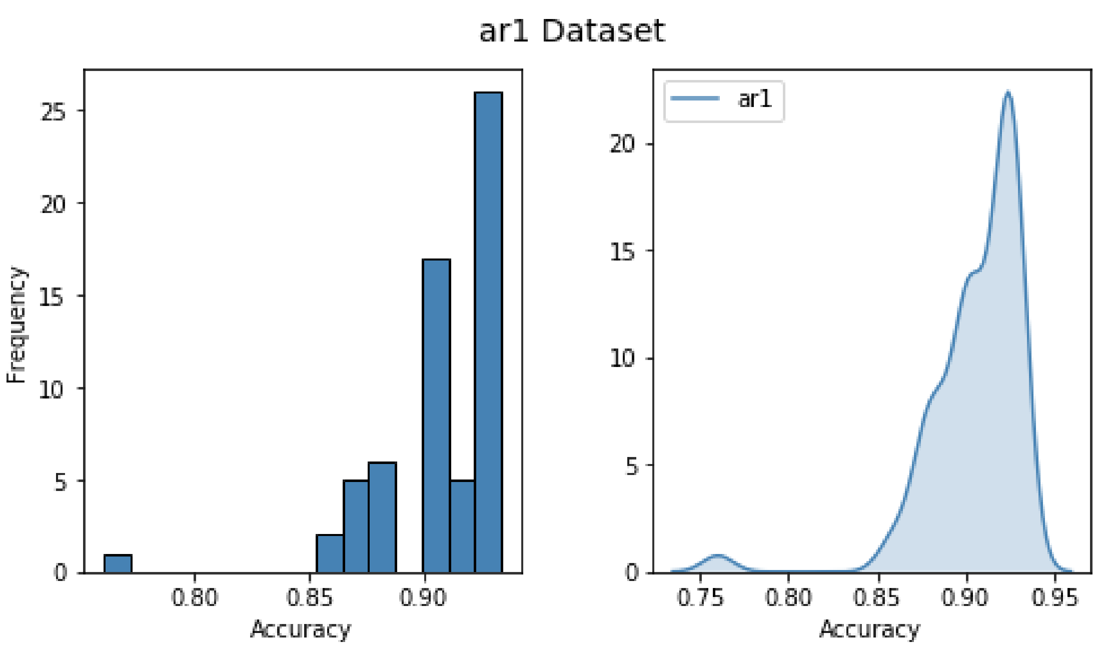
```
/home/haipro/anaconda3/lib/python3.7/site-packages/numpy/lib/histograms.py:825: RuntimeWarning
  keep &= (tmp_a <= last_edge)
/home/haipro/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kde.py:448: Runtin
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
/home/haipro/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kde.py:448: Runtin
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
/home/haipro/anaconda3/lib/python3.7/site-packages/matplotlib/pyplot.py:514: RuntimeWarning: Mo
  max_open_warning, RuntimeWarning)
```

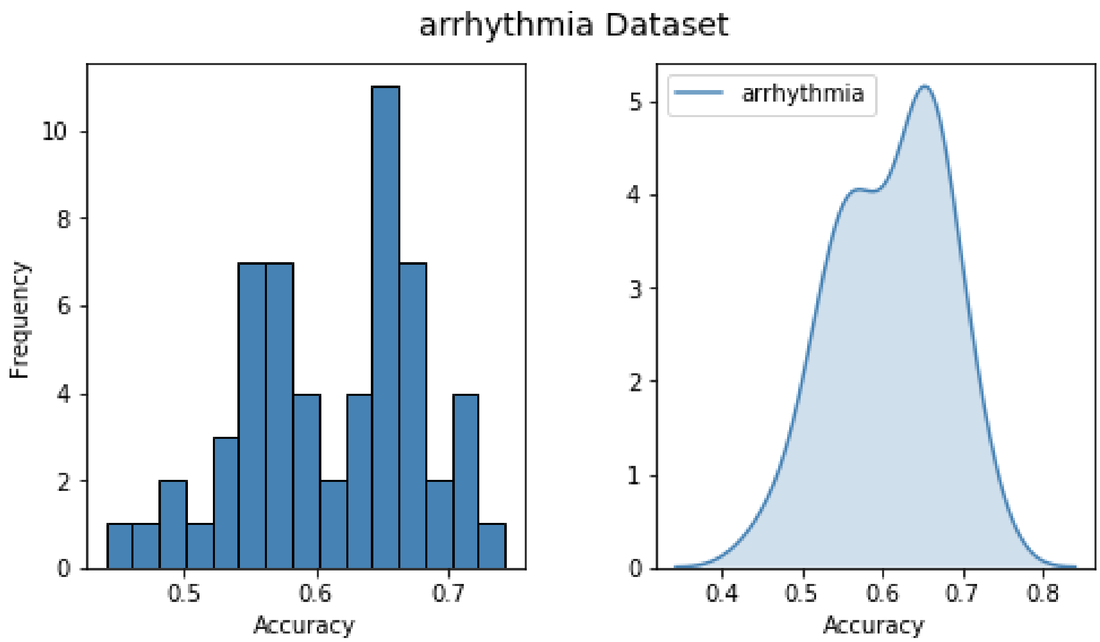


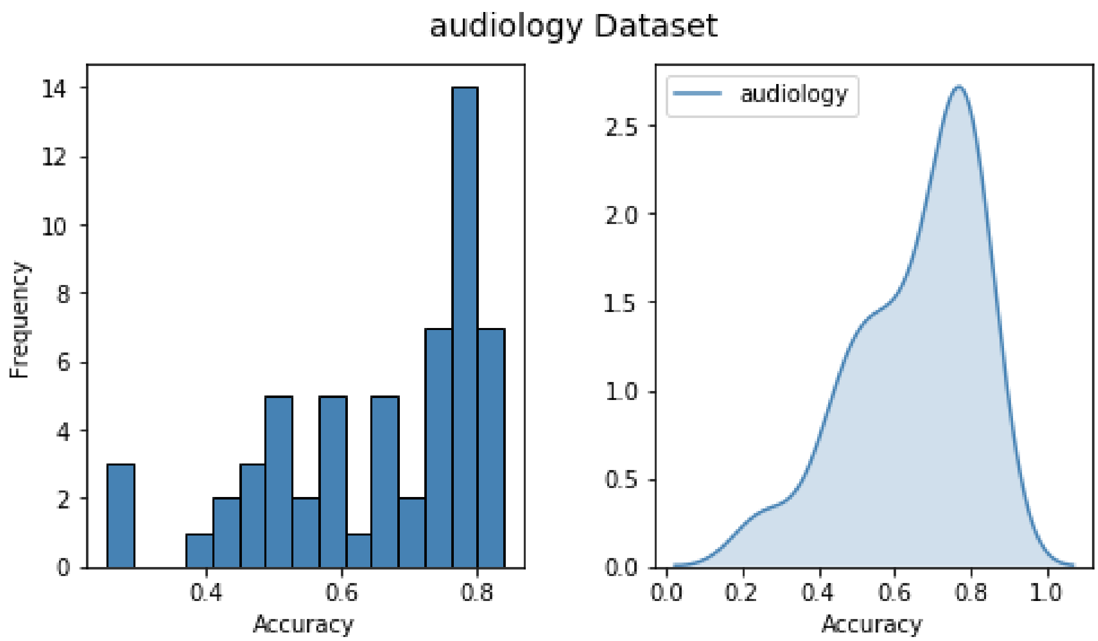

MagicTelescope Dataset
Frequency
Accuracy
MagicTelescope
Accuracy

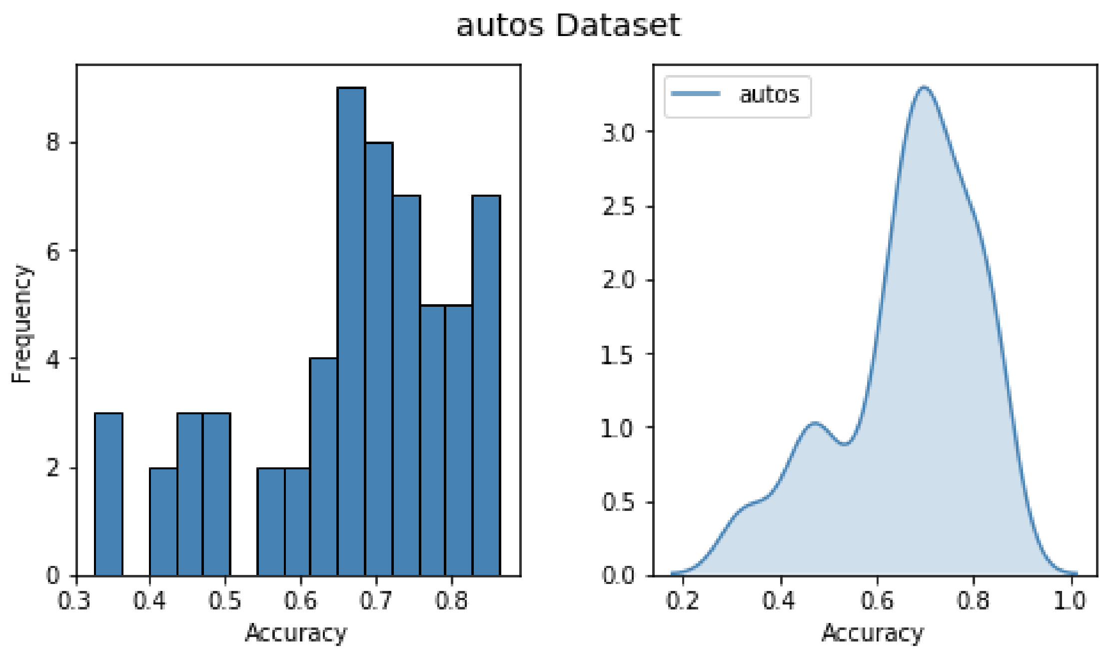

abalone Dataset
Frequency
Accuracy
abalone
Accuracy

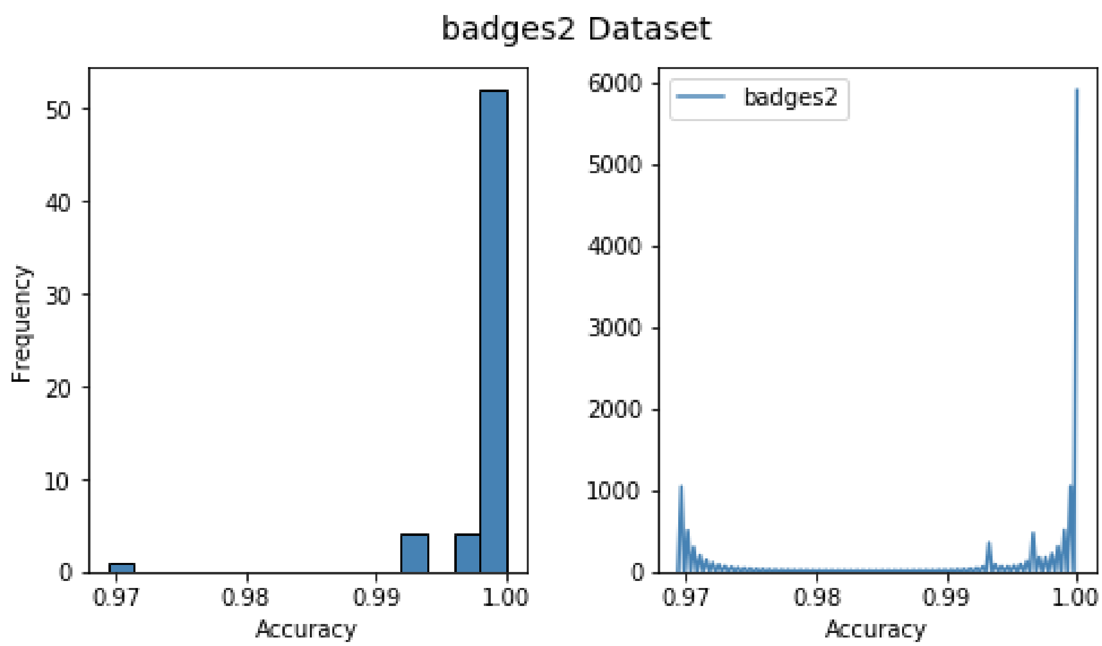

anneal Dataset
Frequency
Accuracy
anneal
0.70 0.75 0.80 0.85 0.90 0.95
0.6 0.7 0.8 0.9 1.0

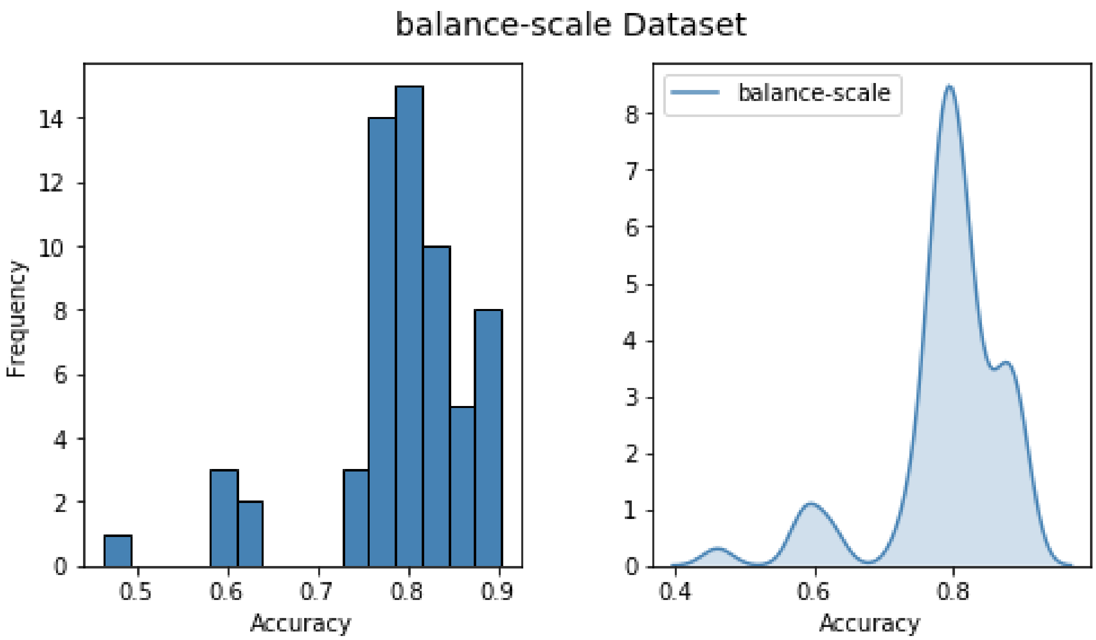

ar1 Dataset
Frequency
Accuracy
ar1
0.80 0.85 0.90
0.75 0.80 0.85 0.90 0.95

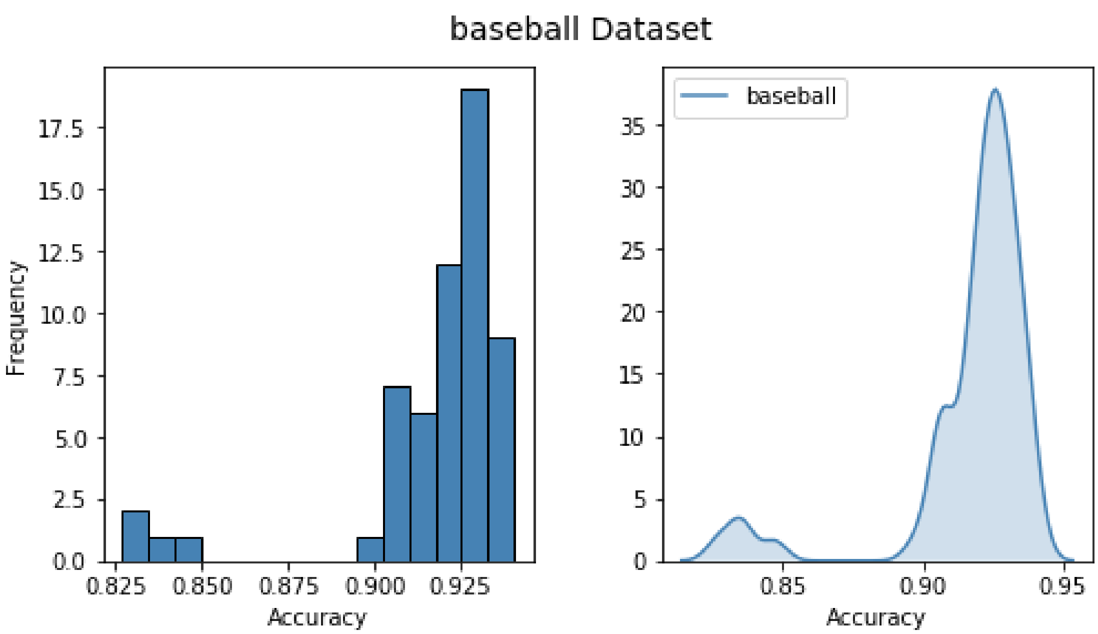

arrhythmia Dataset
Frequency
Accuracy
0
2
4
6
8
10
0.5
0.6
0.7
arrhythmia
0
1
2
3
4
5
0.4
0.5
0.6
0.7
0.8
Accuracy

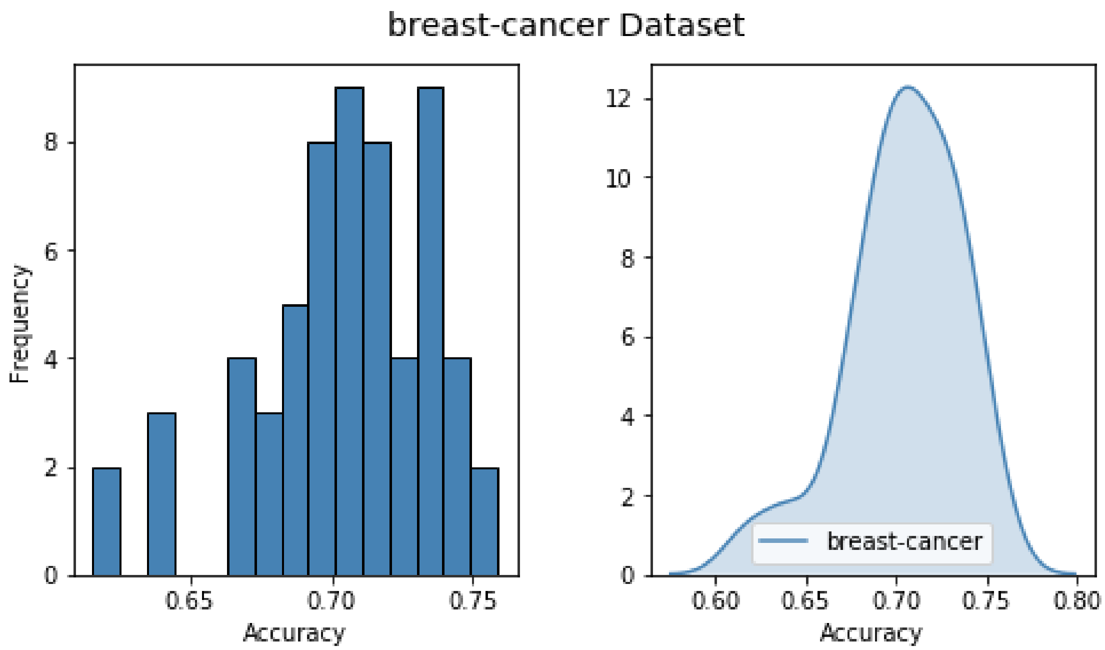

audiology Dataset
Frequency
Accuracy
0
2
4
6
8
10
12
14
0.4
0.6
0.8
audiology
0.0
0.5
1.0
1.5
2.0
2.5
0.0
0.2
0.4
0.6
0.8
1.0
Accuracy

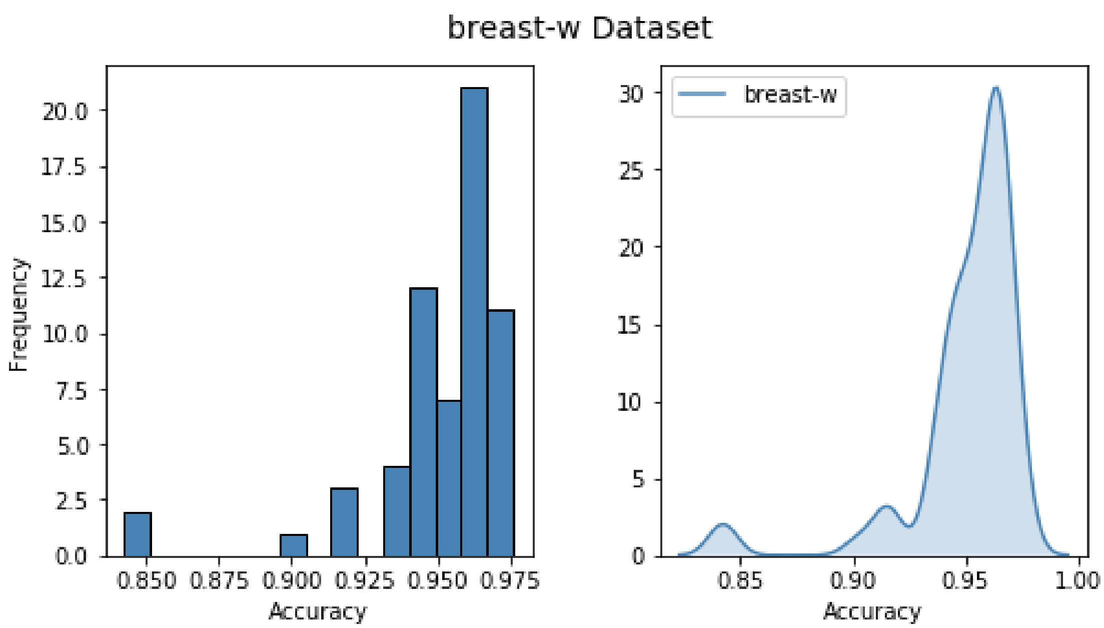

autos Dataset
Frequency
Accuracy
autos
0
2
4
6
8
0.3
0.4
0.5
0.6
0.7
0.8
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.2
0.4
0.6
0.8
1.0


badges2 Dataset
Frequency
Accuracy
badges2
0
10
20
30
40
50
0.97
0.98
0.99
1.00
0
1000
2000
3000
4000
5000
6000

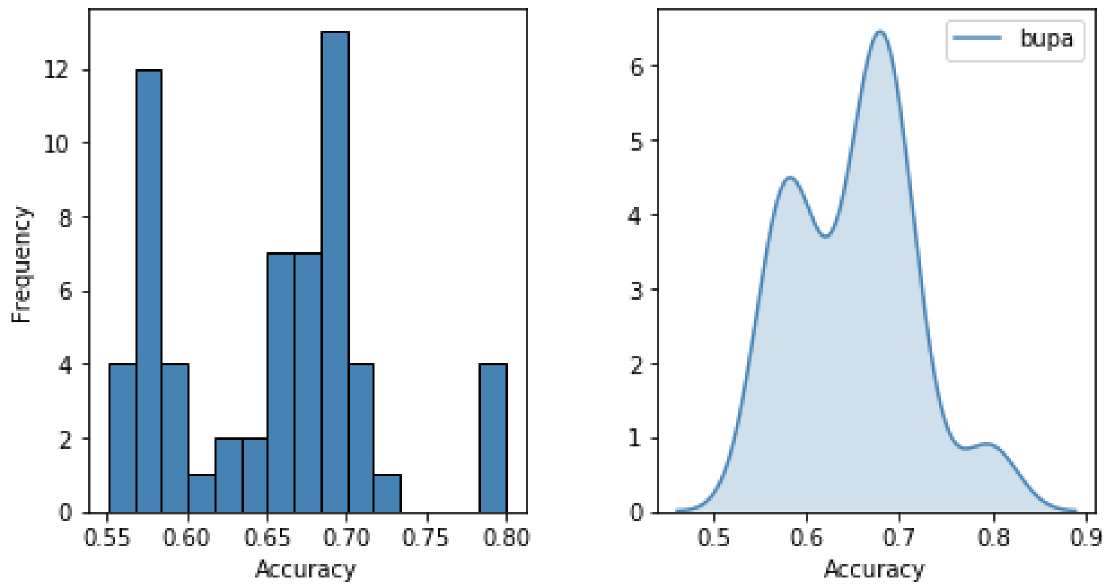

balance-scale Dataset
Frequency
Accuracy
balance-scale
Accuracy


baseball Dataset
Frequency
Accuracy
baseball
Accuracy

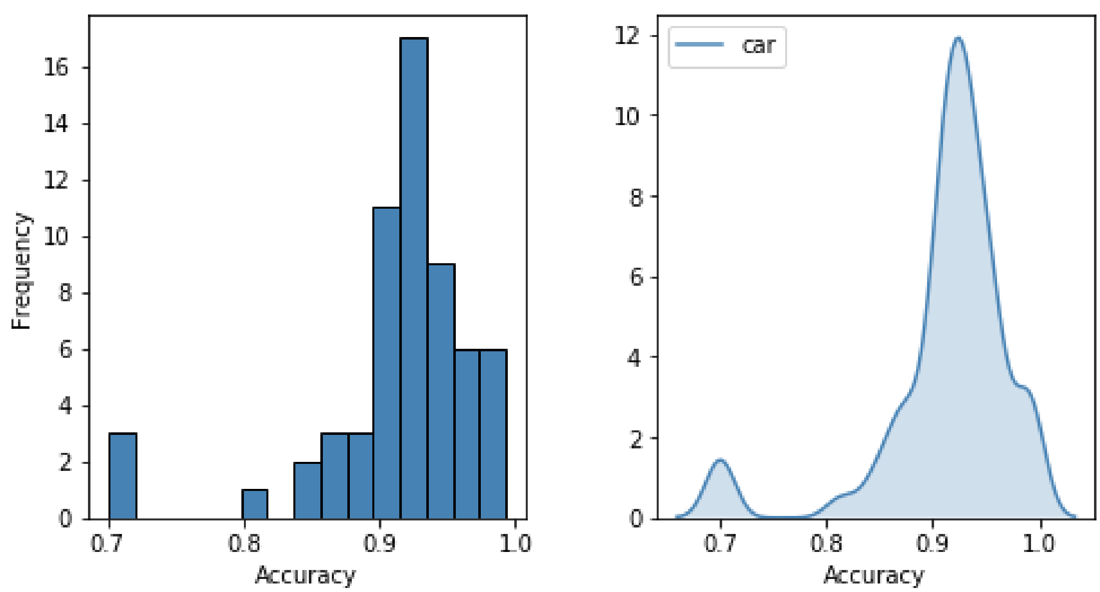

breast-cancer Dataset
Frequency
Accuracy
breast-cancer

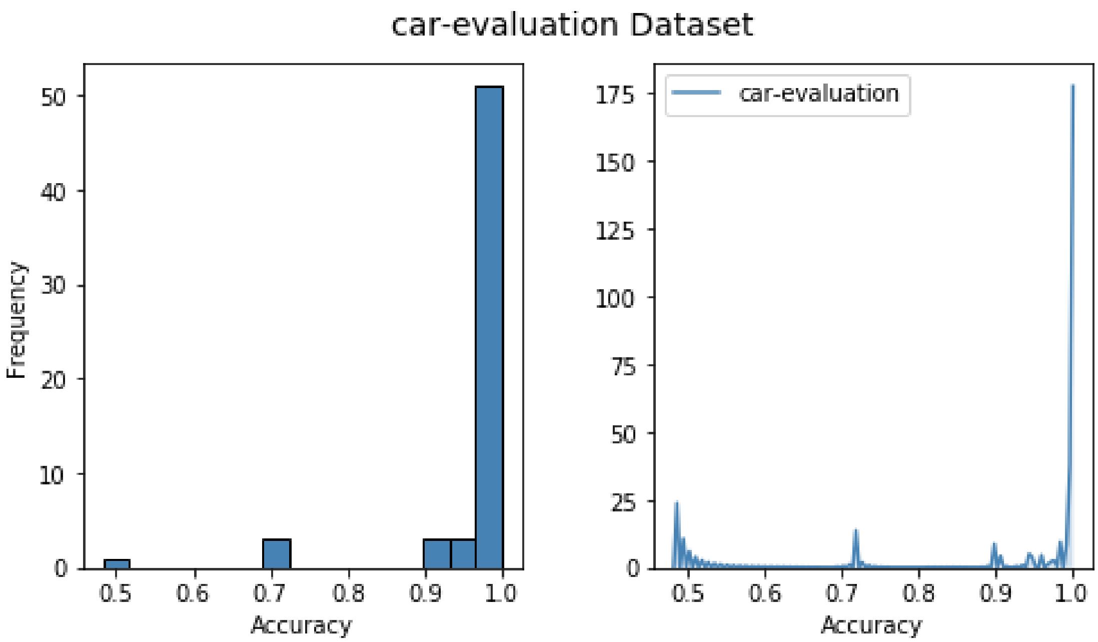

breast-w Dataset
Frequency
Accuracy
breast-w

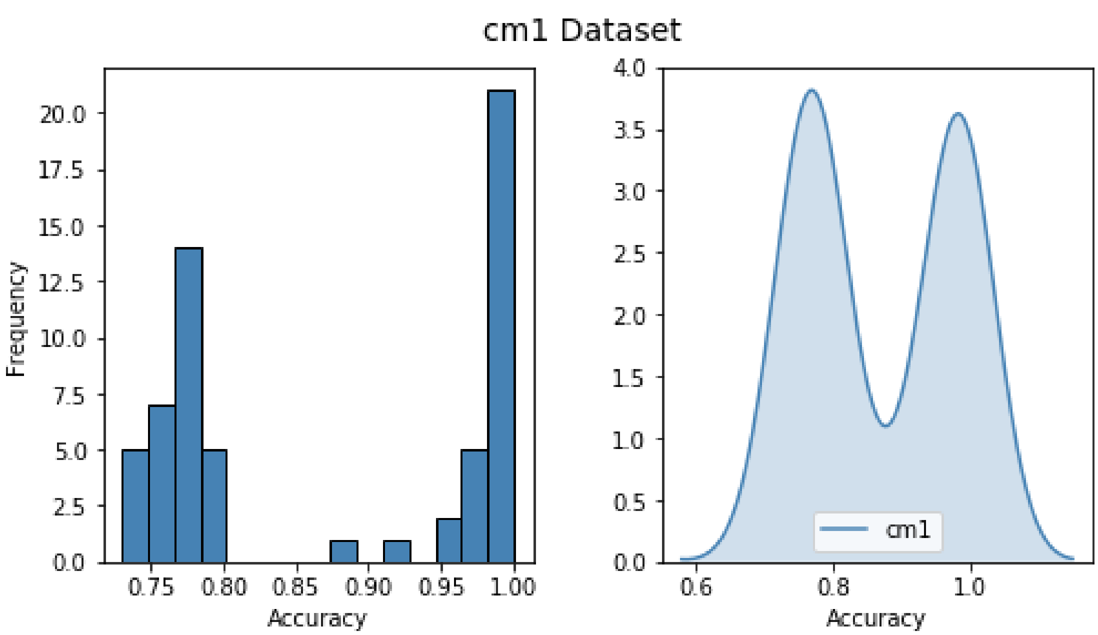
bupa Dataset



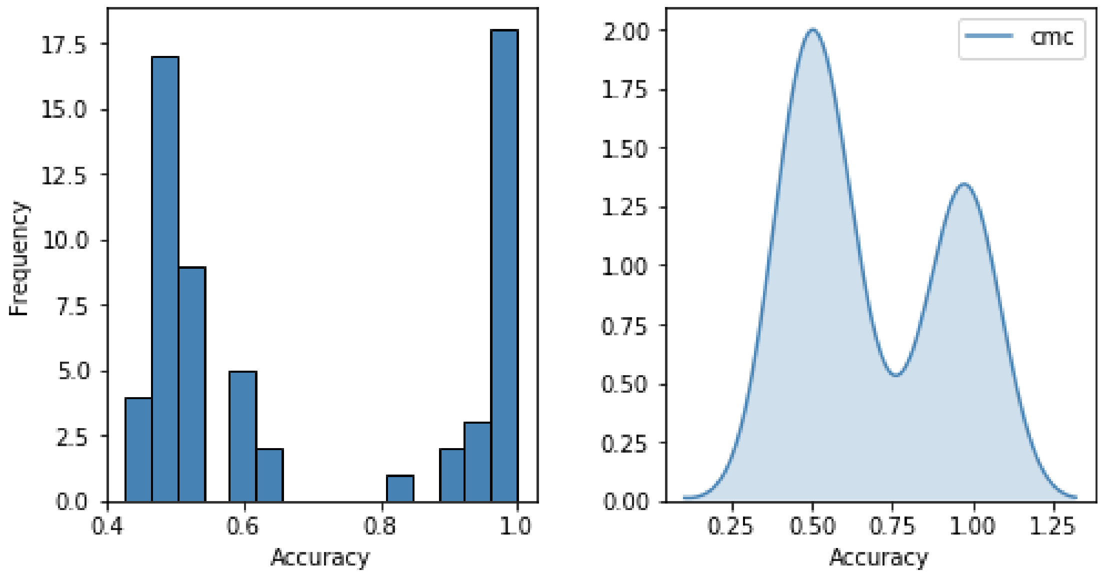
car Dataset



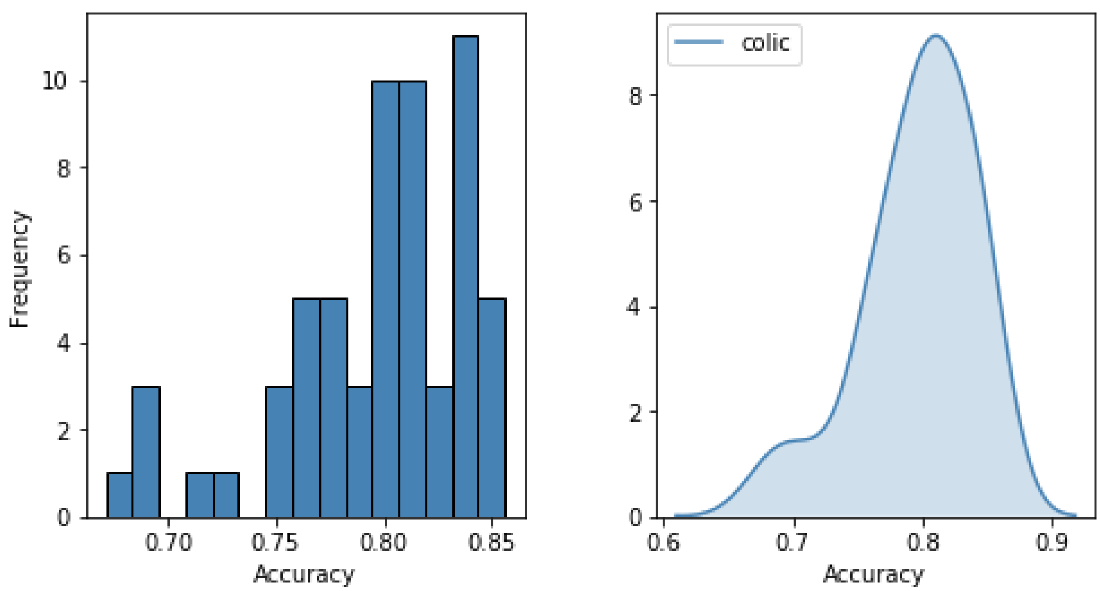

car-evaluation Dataset
Frequency
Accuracy
car-evaluation
0
10
20
30
40
50
0.5
0.6
0.7
0.8
0.9
1.0
25
75
100
125
150
175


cm1 Dataset
Frequency
Accuracy
cm1
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
0.75
0.80
0.85
0.90
0.95
1.00
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0.6
0.8

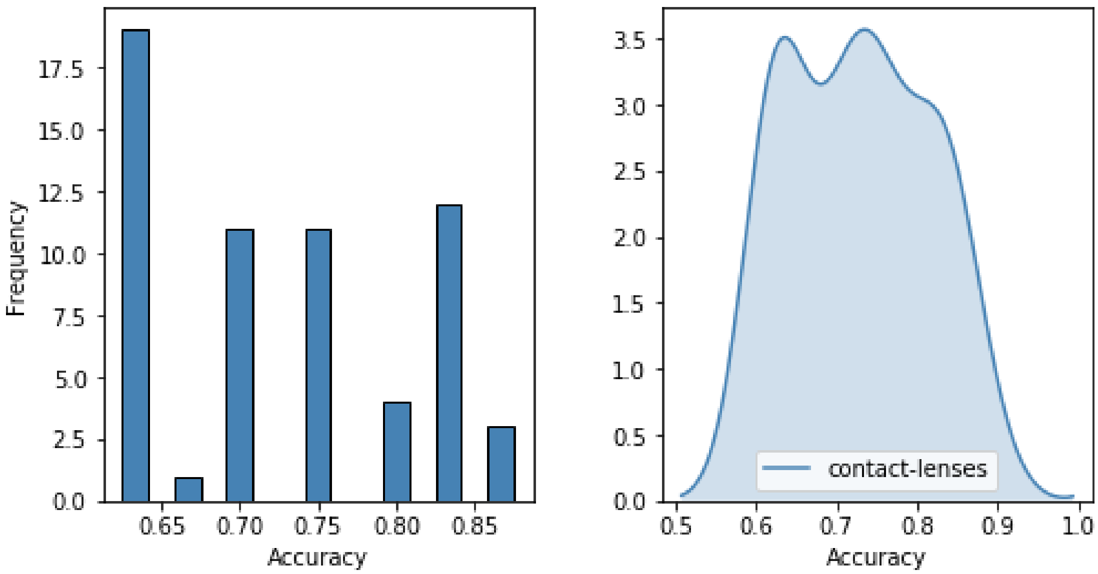
cmc Dataset



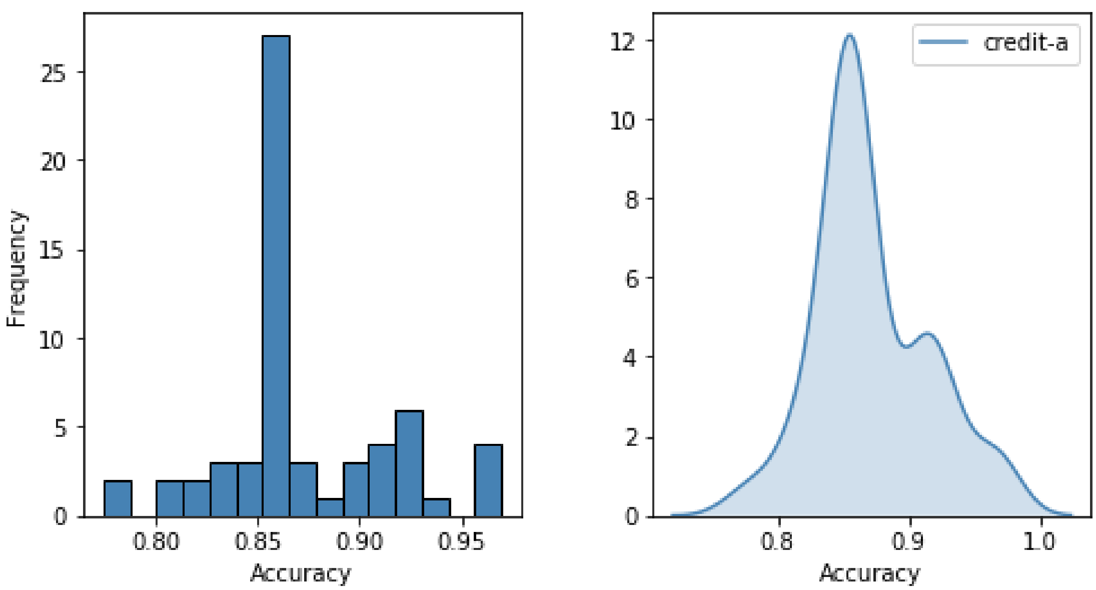
colic Dataset

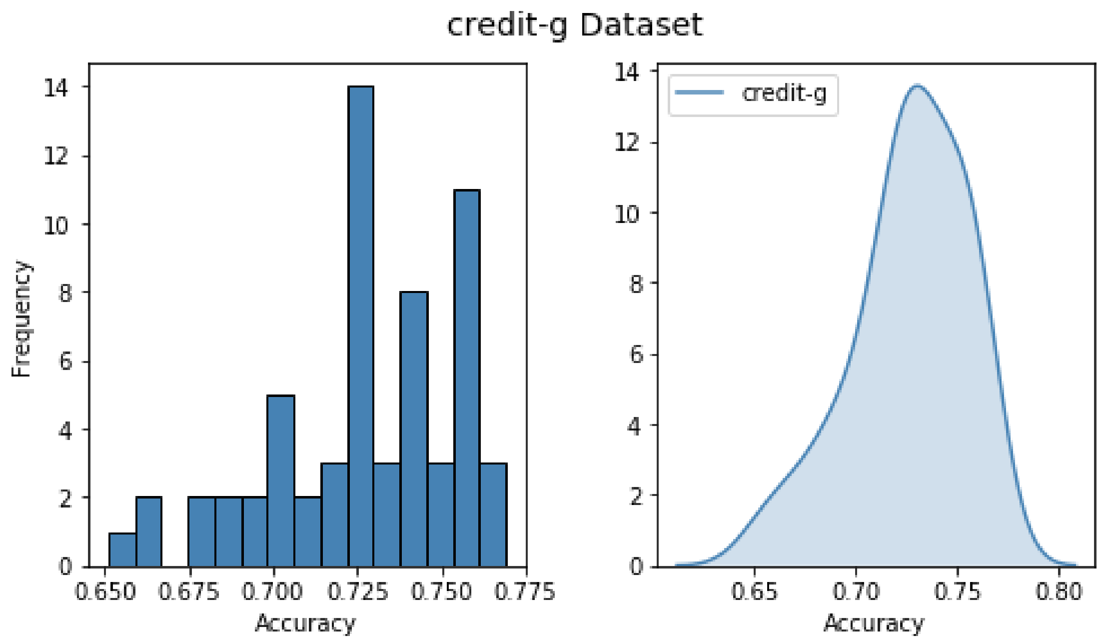


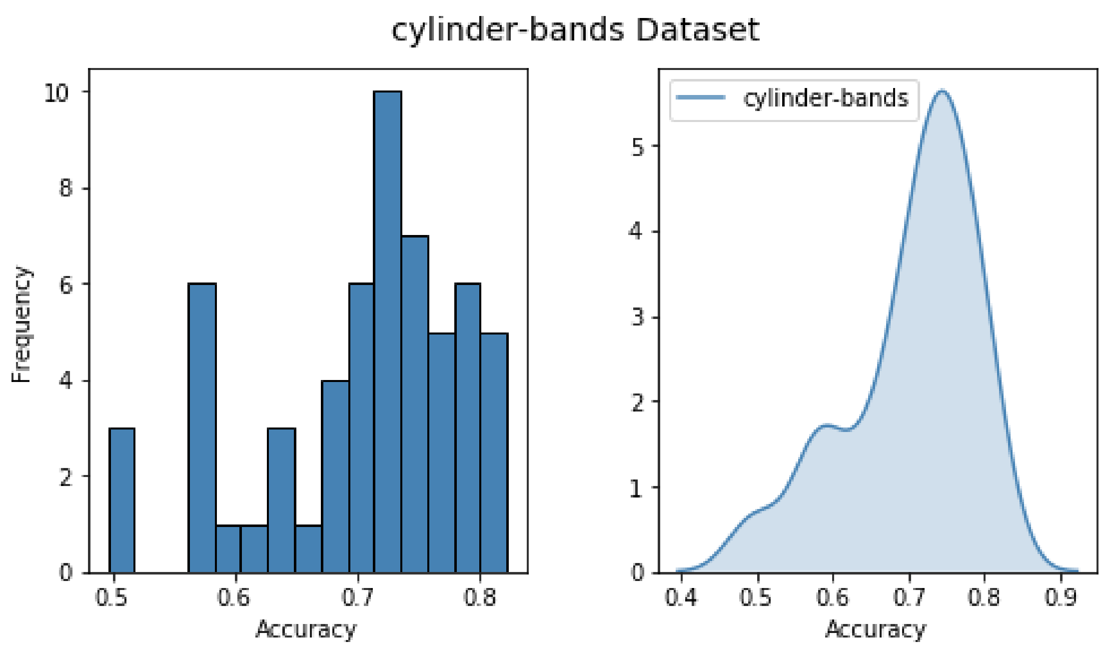
contact-lenses Dataset

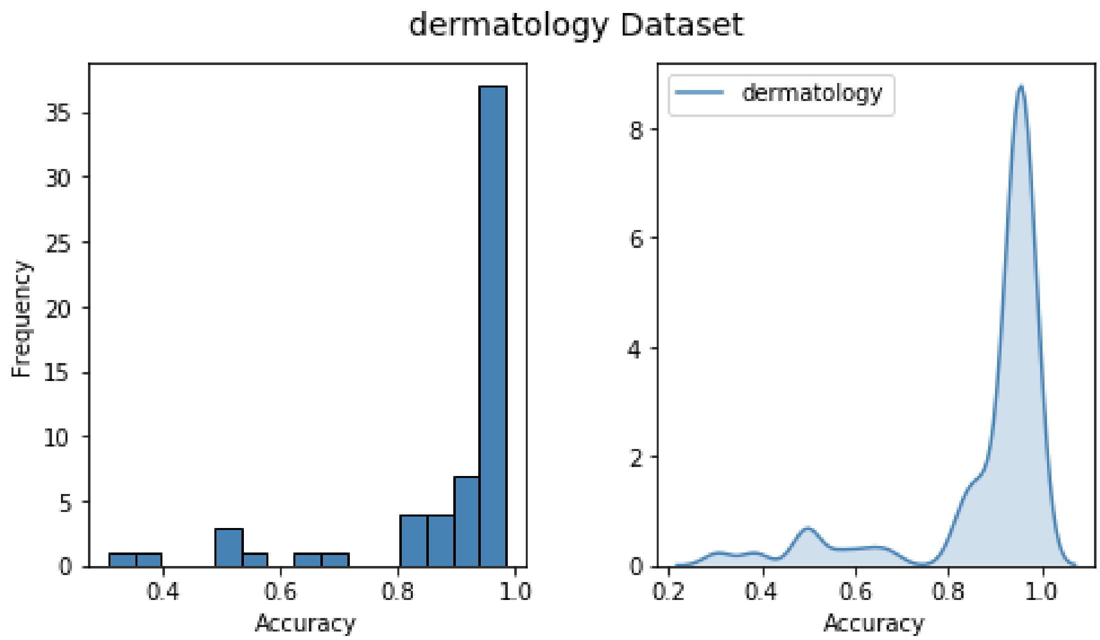


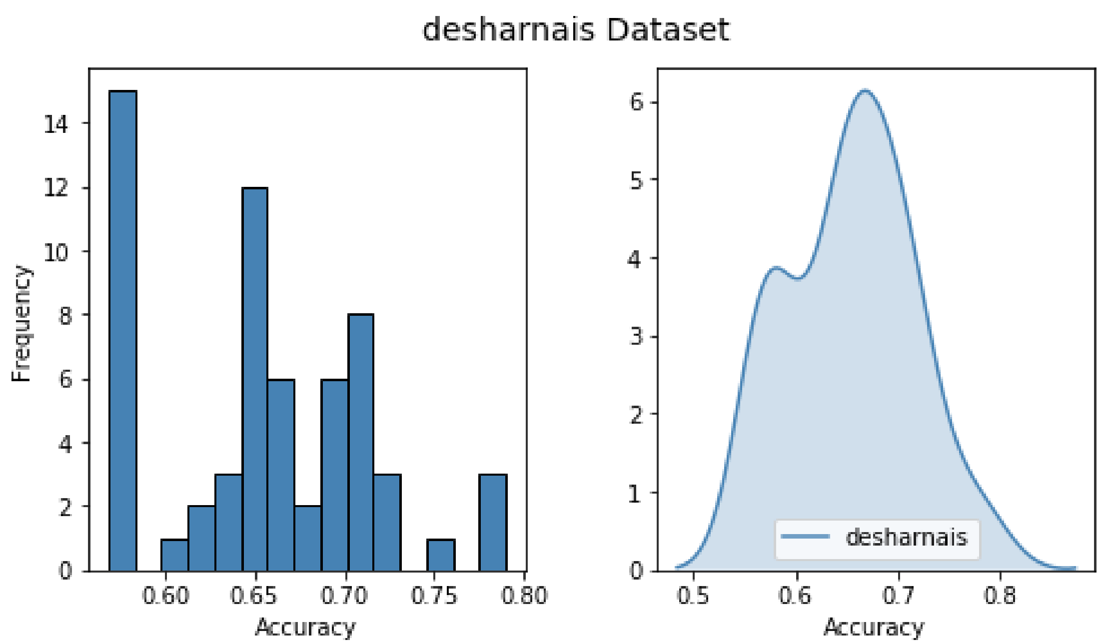
credit-a Dataset

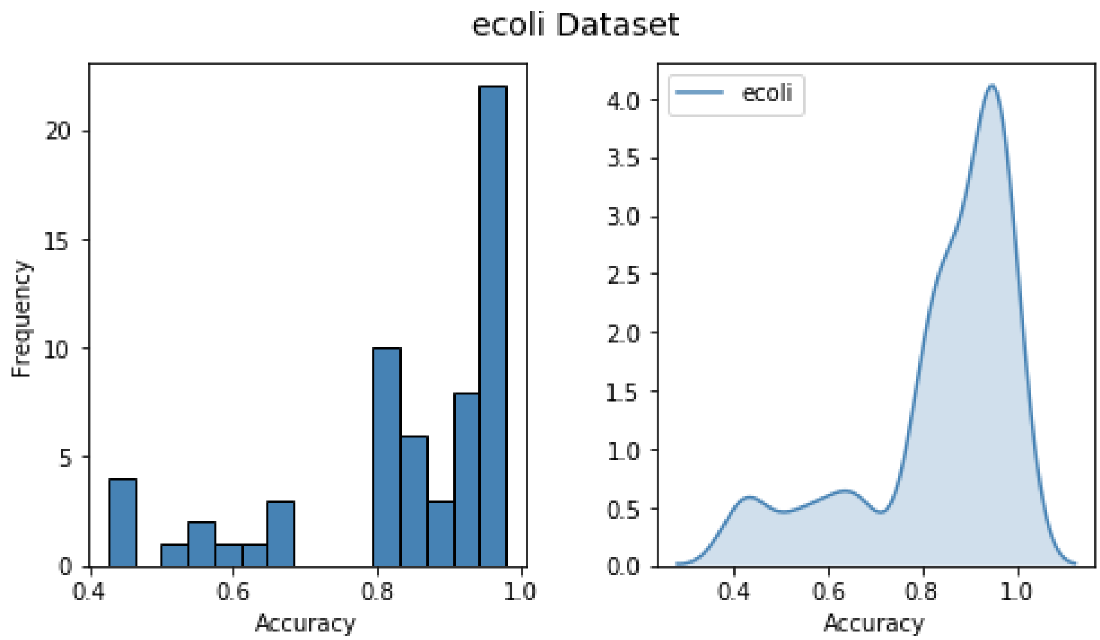


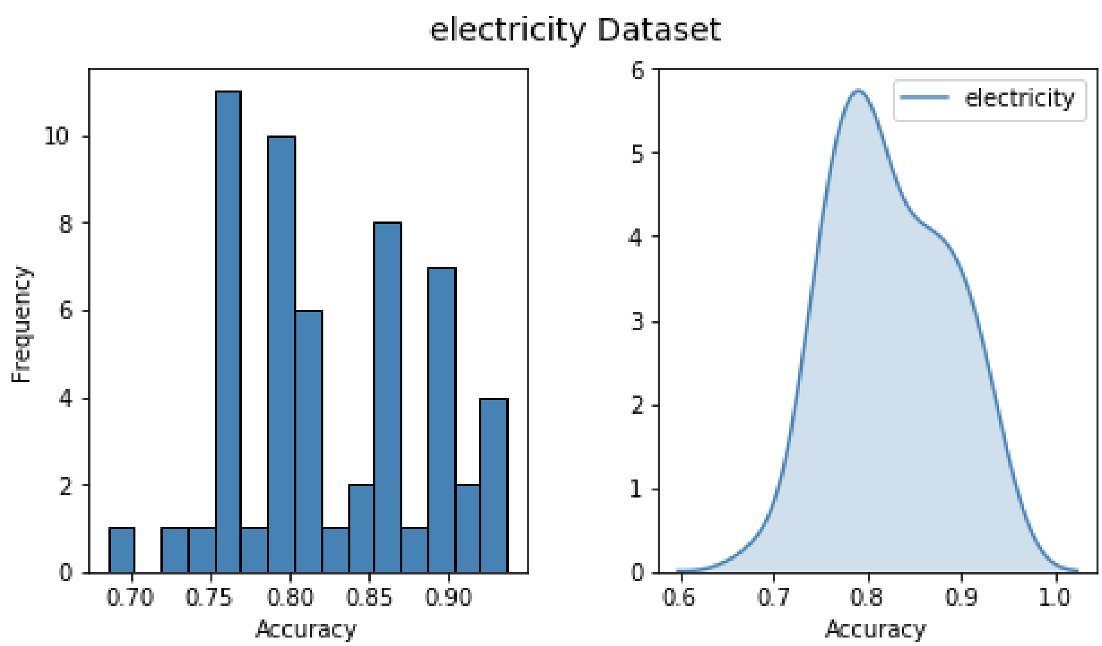

credit-g Dataset
Frequency
Accuracy
0.650
0.675
0.700
0.725
0.750
0.775
credit-g
Accuracy
0.65
0.70
0.75
0.80

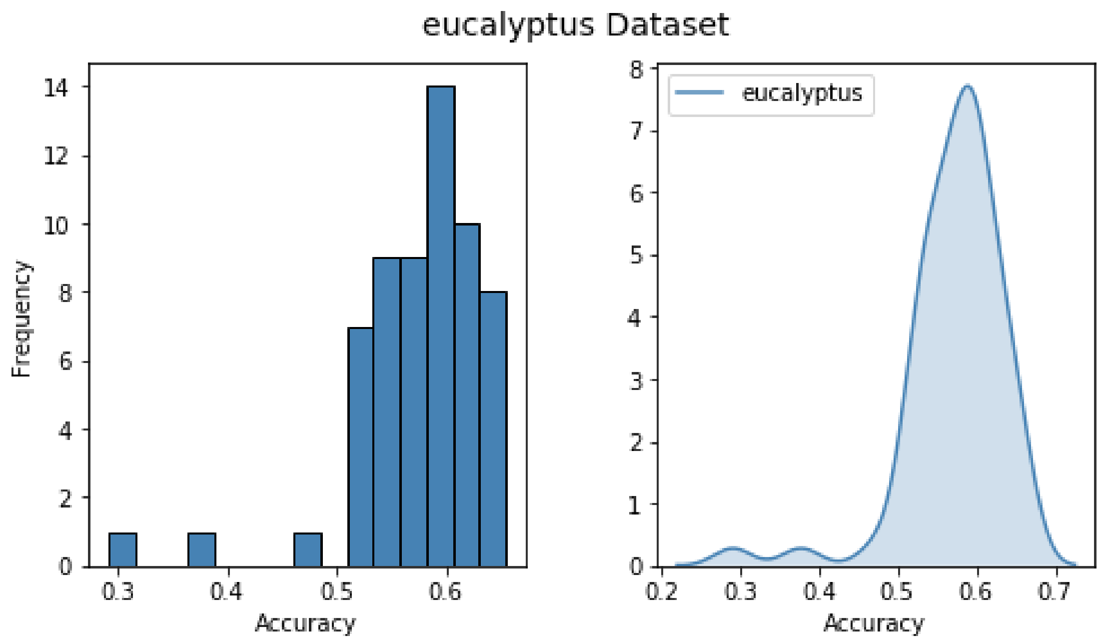

cylinder-bands Dataset
Frequency
Accuracy
0.5
0.6
0.7
0.8
cylinder-bands
Accuracy
0.4
0.5
0.6
0.7
0.8
0.9

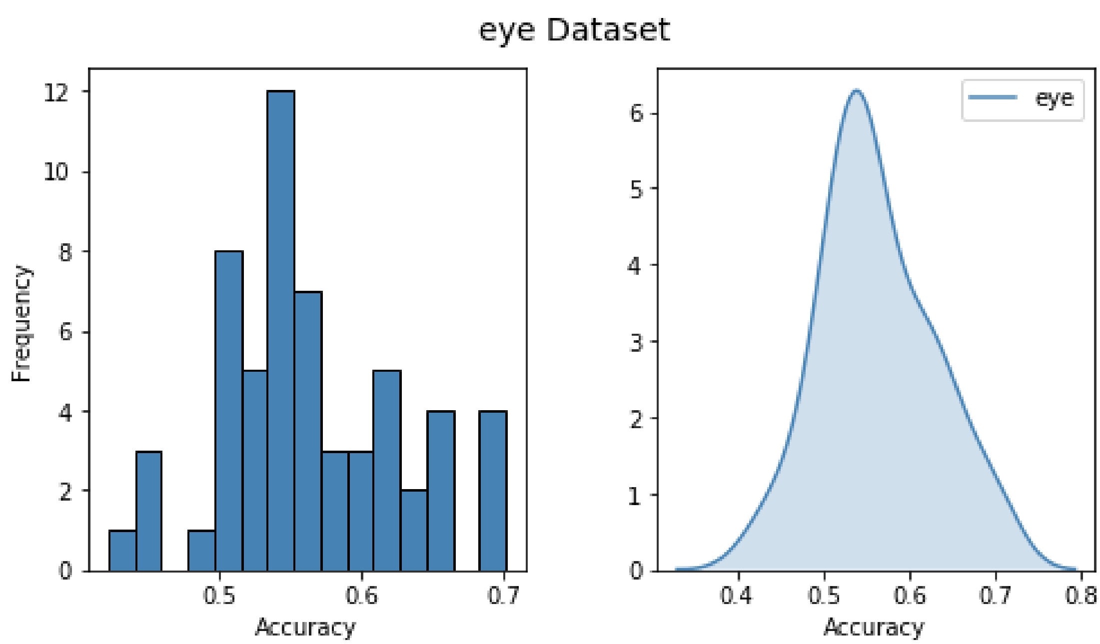

dermatology Dataset
Frequency
Accuracy
dermatology
Accuracy

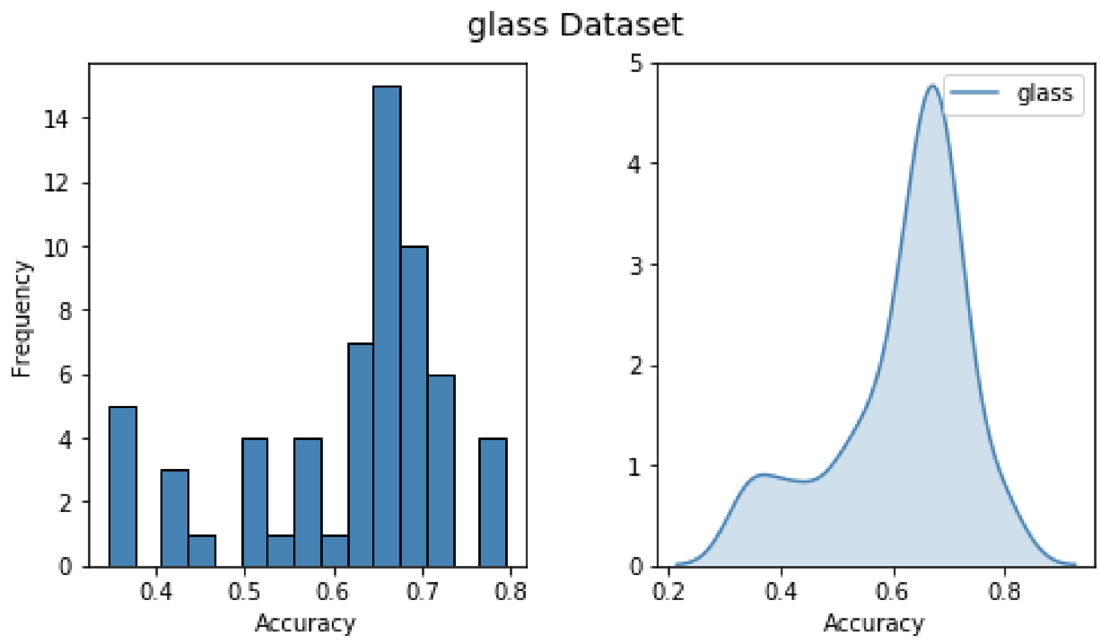

desharnais Dataset
Frequency
Accuracy
desharnais
Accuracy

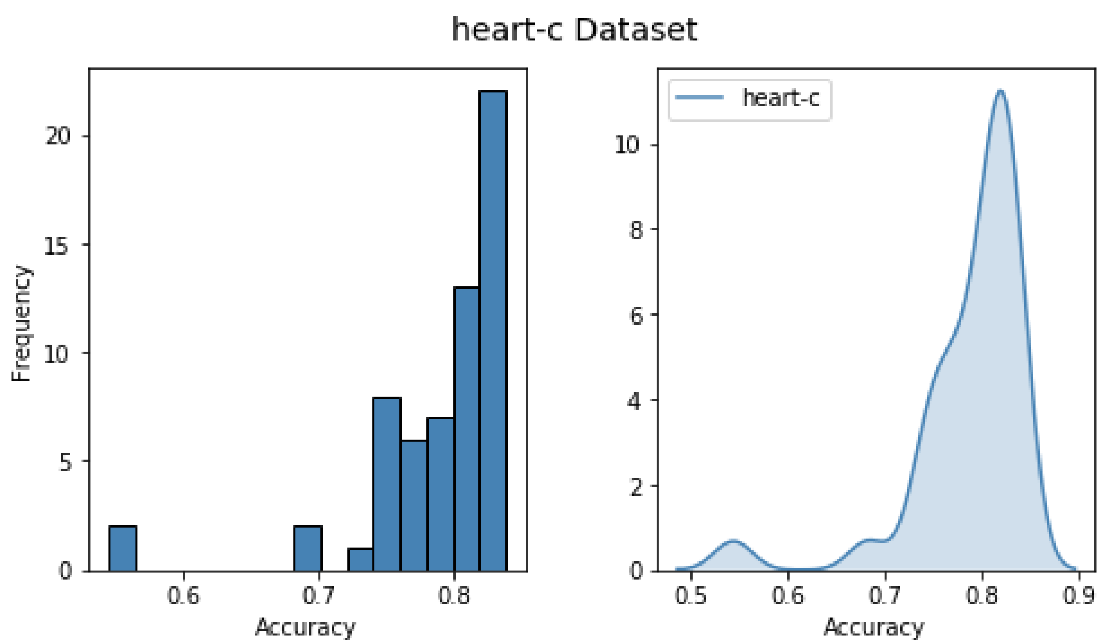

ecoli Dataset
Frequency
Accuracy
ecoli
0
5
10
15
20
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

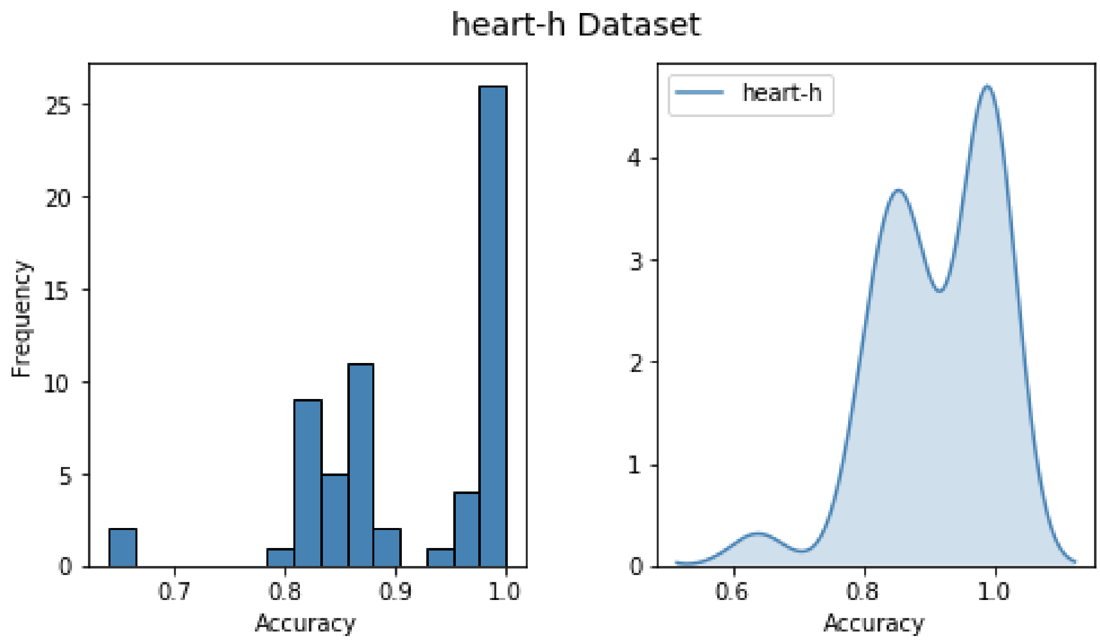

electricity Dataset
Frequency
Accuracy
electricity
0
2
4
6
8
10
0.70
0.75
0.80
0.85
0.90
0.6
0.7
0.8
0.9
1.0
1
3
5

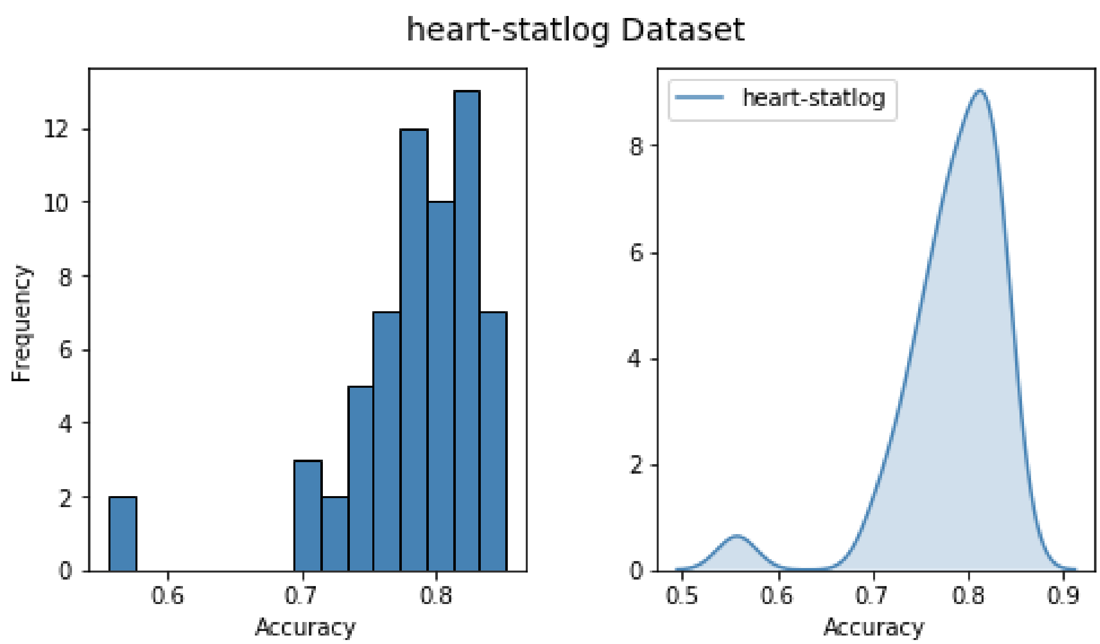

eucalyptus Dataset
Frequency
Accuracy
eucalyptus
Accuracy

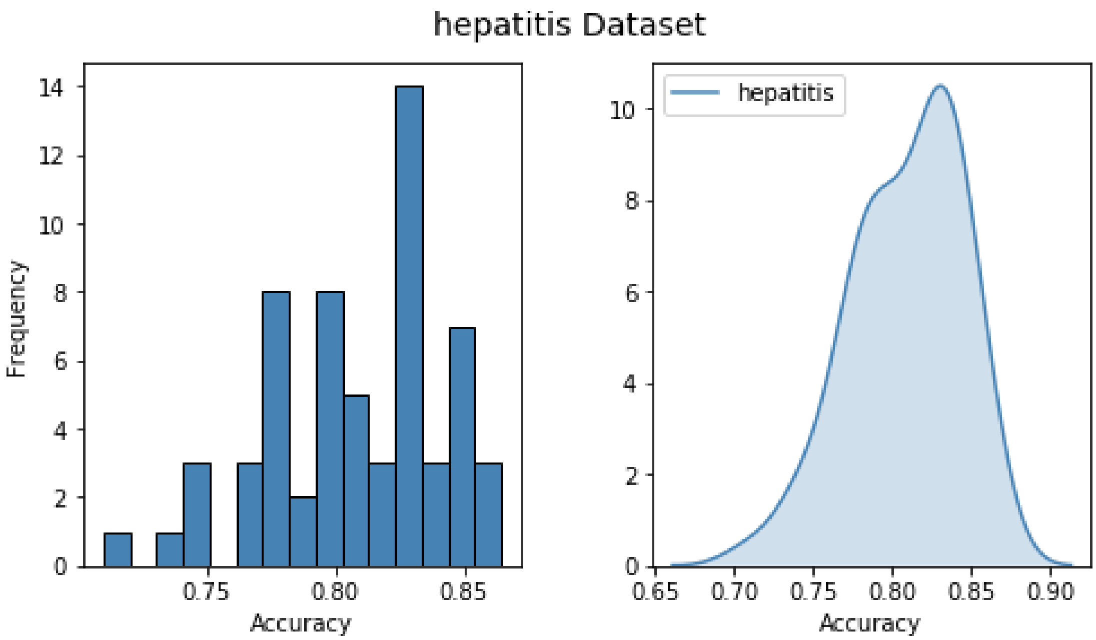

eye Dataset
Frequency
Accuracy
eye
Accuracy

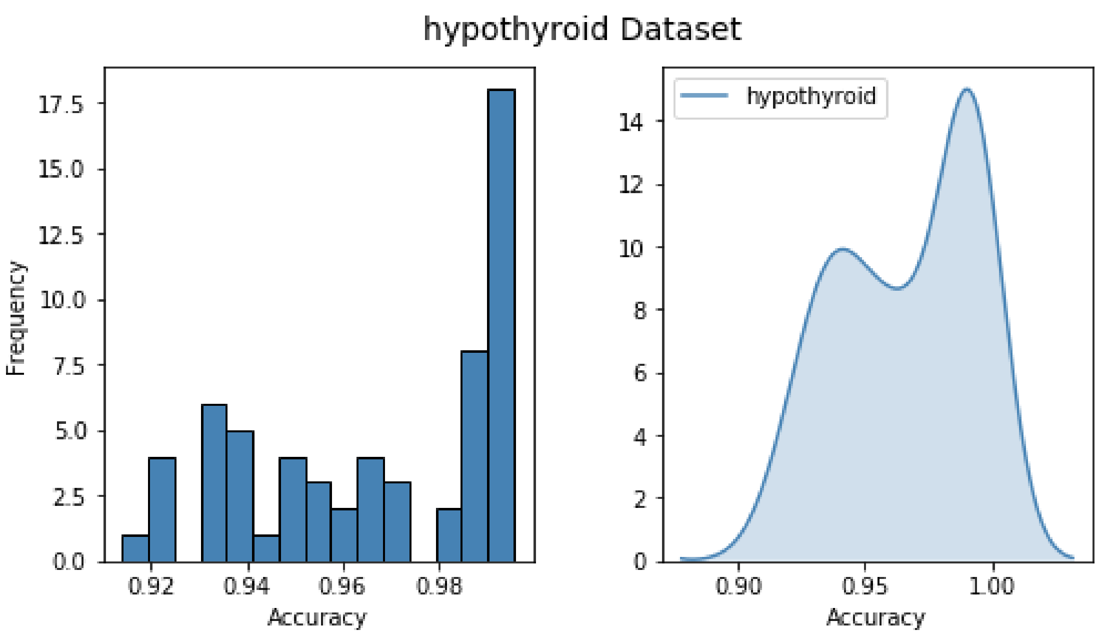

glass Dataset
Frequency
Accuracy
Accuracy
glass

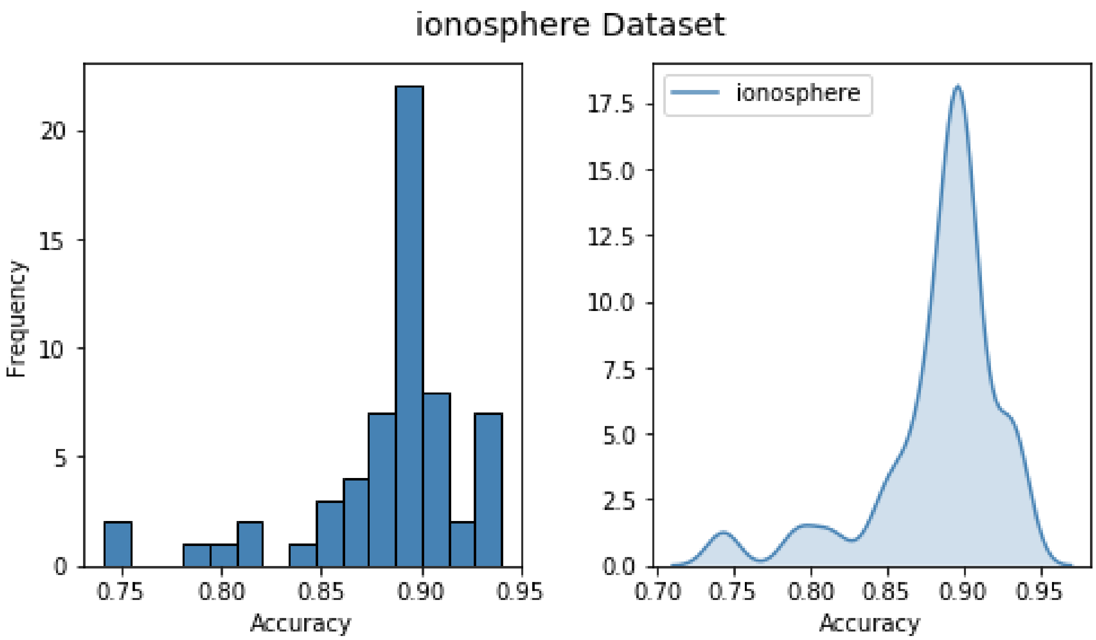

heart-c Dataset
Frequency
Accuracy
Accuracy
heart-c

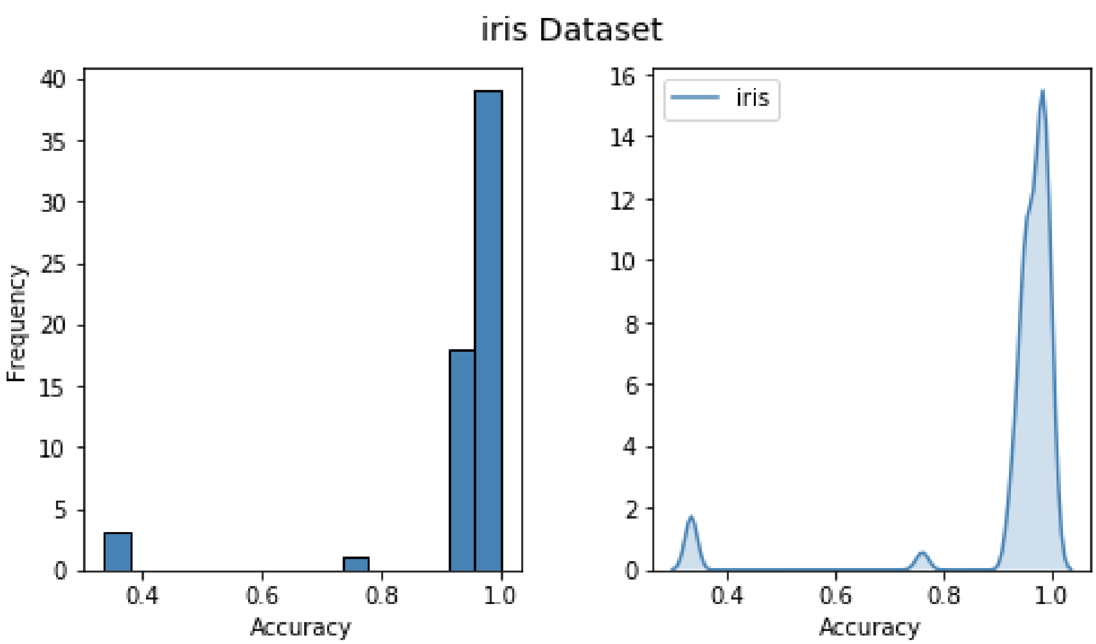

heart-h Dataset
Frequency
Accuracy
heart-h
Accuracy

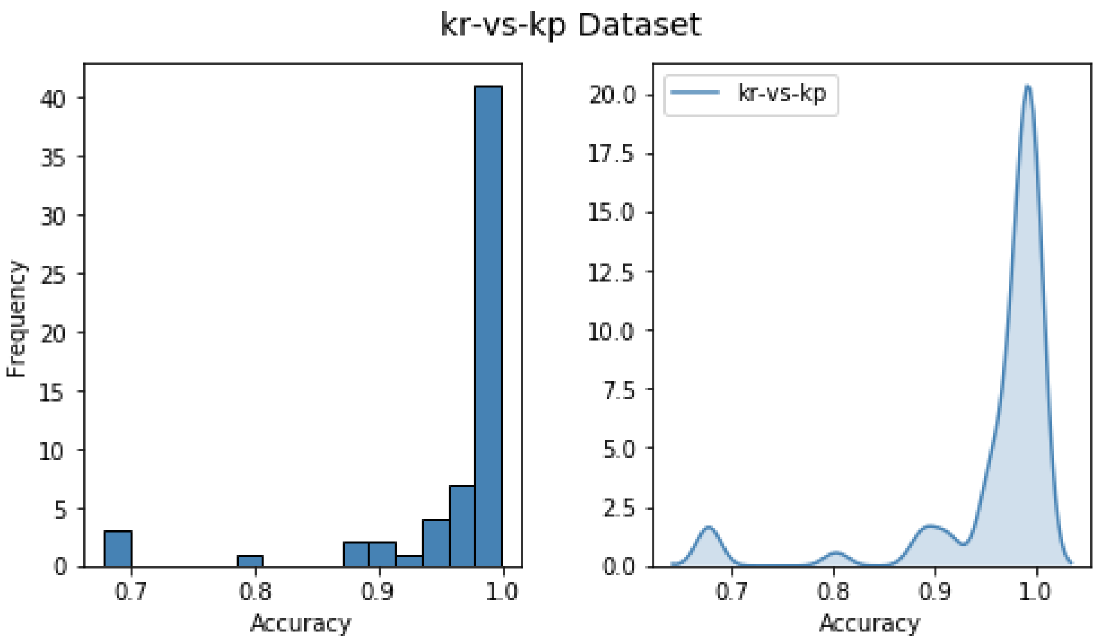

heart-statlog Dataset
Frequency
Accuracy
heart-statlog
Accuracy

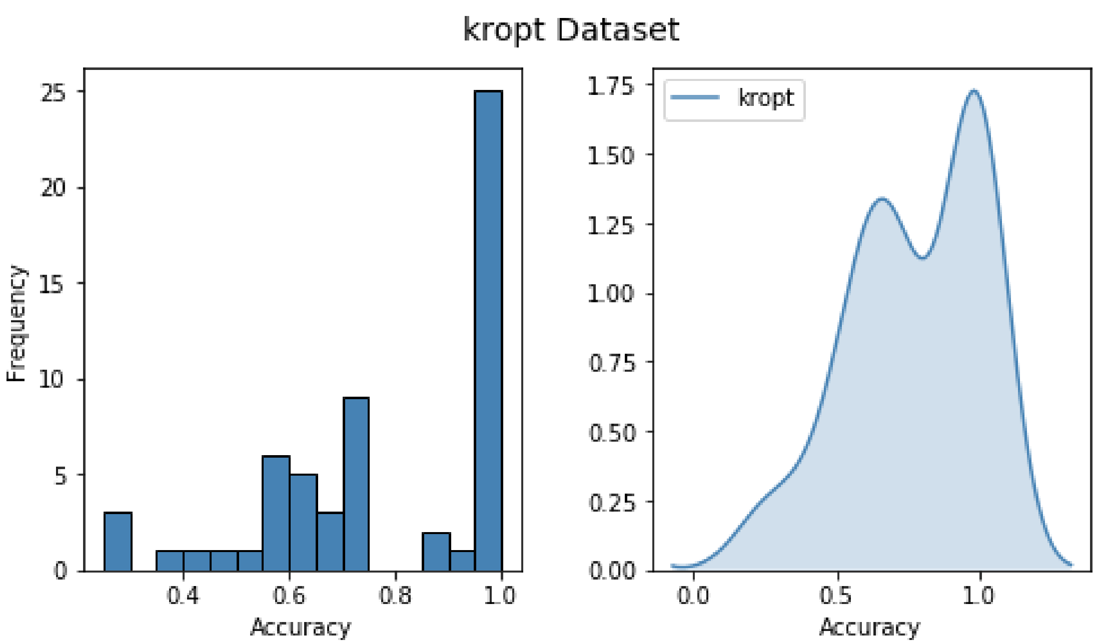

hepatitis Dataset
Frequency
Accuracy
0
2
4
6
8
10
12
14
0.75
0.80
0.85
hepatitis
0.65
0.70
0.90

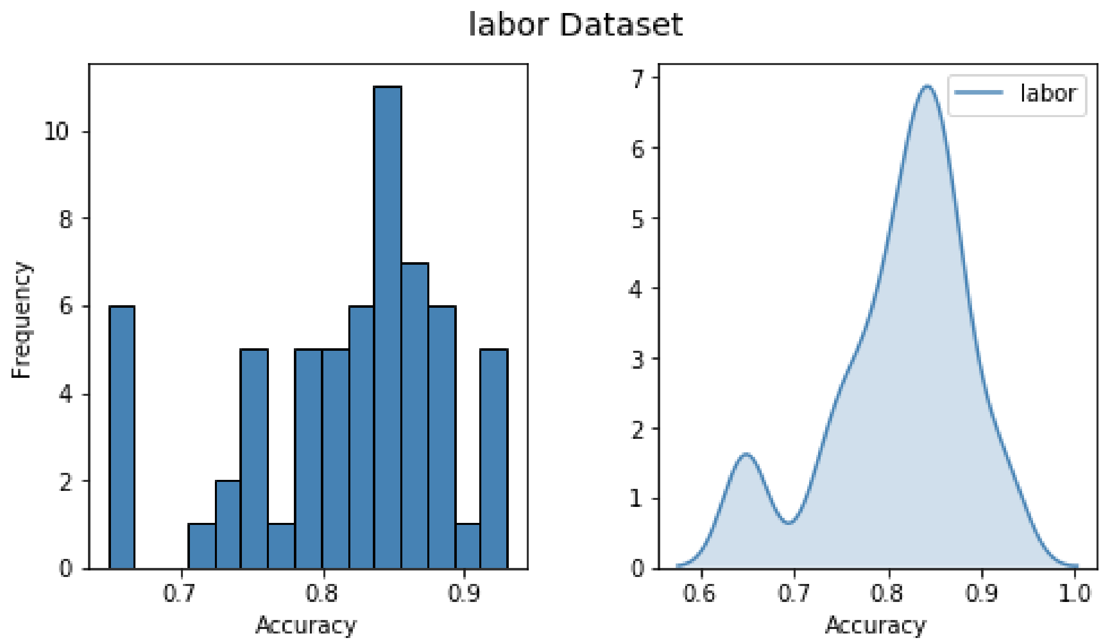

hypothyroid Dataset
Frequency
Accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0.92
0.94
0.96
0.98
hypothyroid
0
2
4
6
8
10
12
14
0.90
0.95
1.00

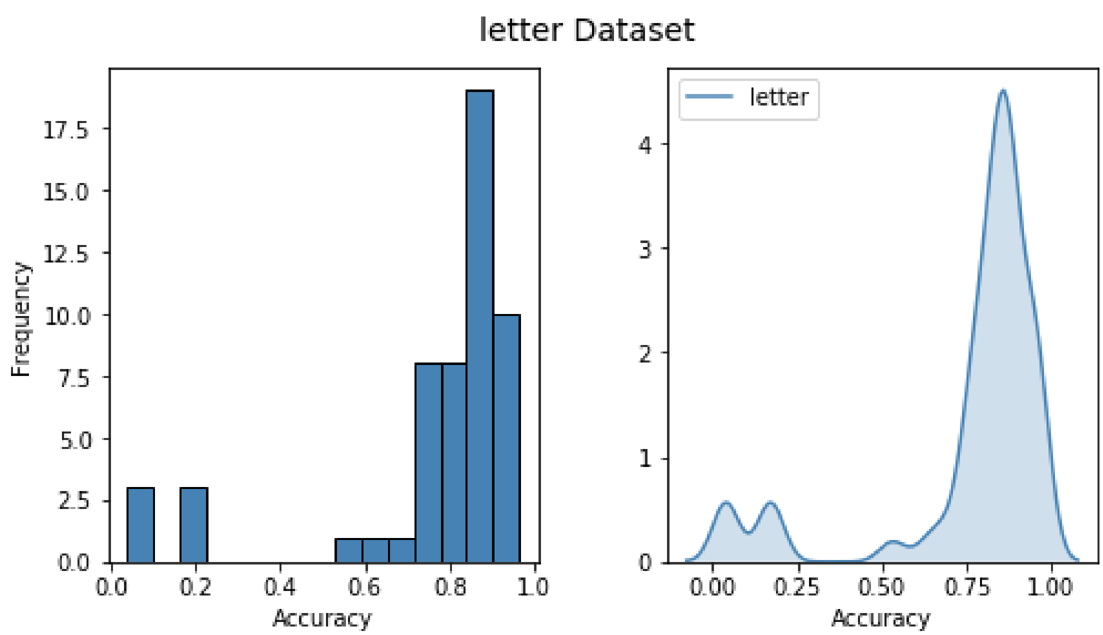

ionosphere Dataset
Frequency
Accuracy
ionosphere
0 5 10 15 20
0.75 0.80 0.85 0.90 0.95
0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5
0.70 0.75 0.80 0.85 0.90 0.95


iris Dataset
Frequency
Accuracy
iris
0 5 10 15 20 25 30 35 40
0.4 0.6 0.8 1.0
0 2 4 6 8 10 12 14 16

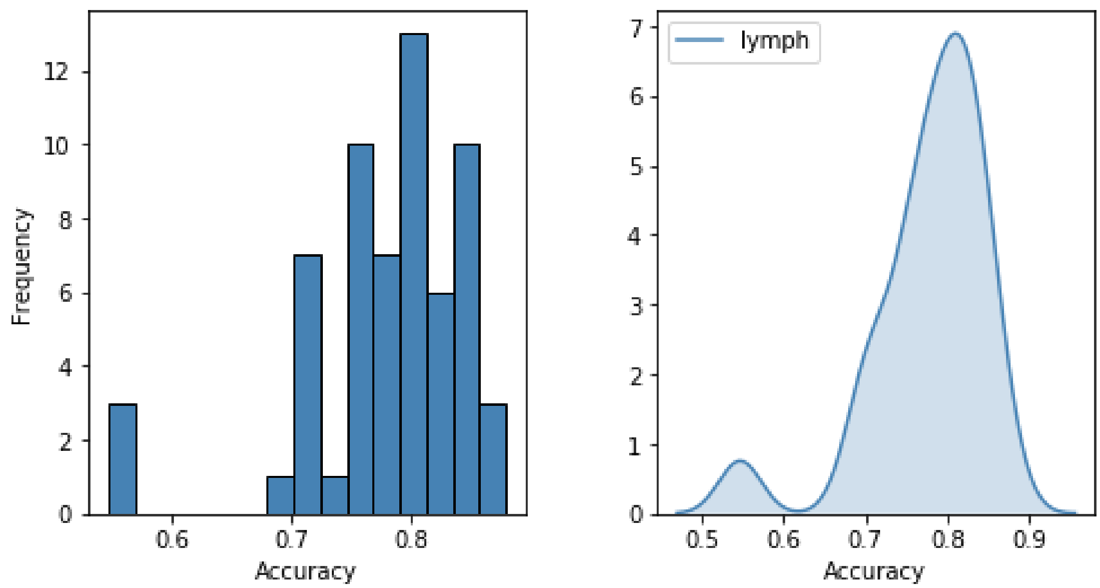

kr-vs-kp Dataset
Frequency
Accuracy
0.7
0.8
0.9
1.0
kr-vs-kp


kropt Dataset
Frequency
Accuracy
0.4
0.6
0.8
1.0
0.0
0.5
kropt

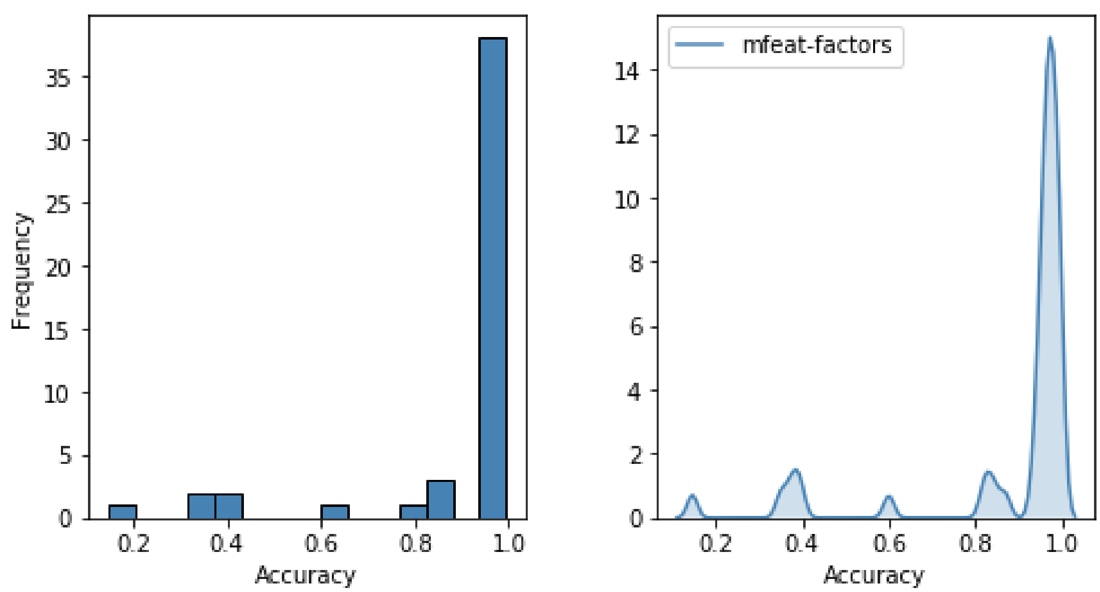

labor Dataset
Frequency
Accuracy
labor

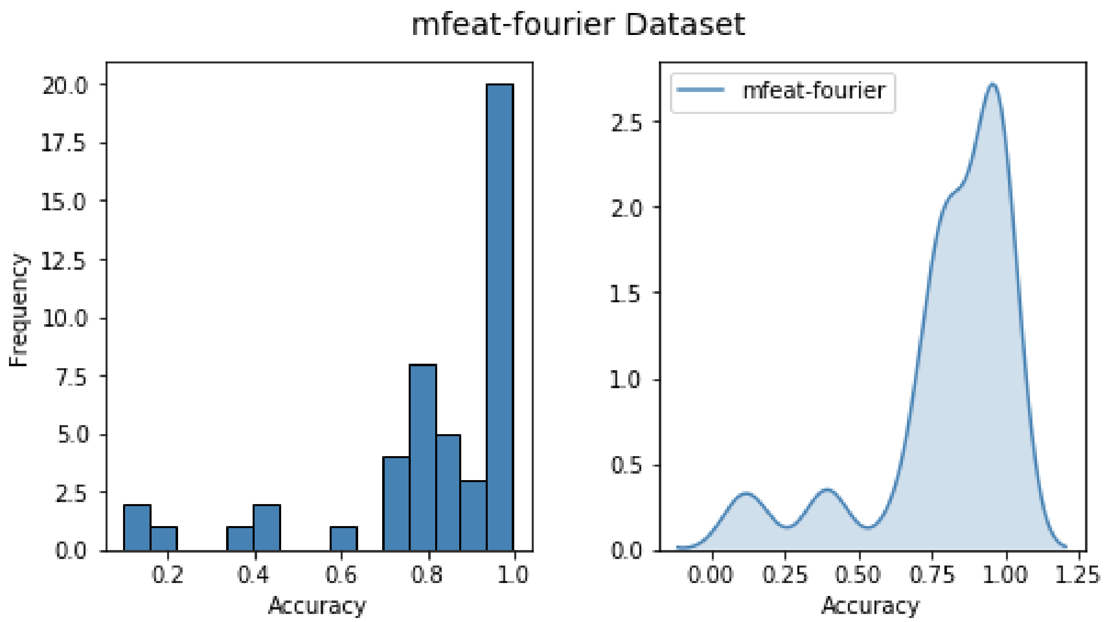

letter Dataset
Frequency
Accuracy
letter

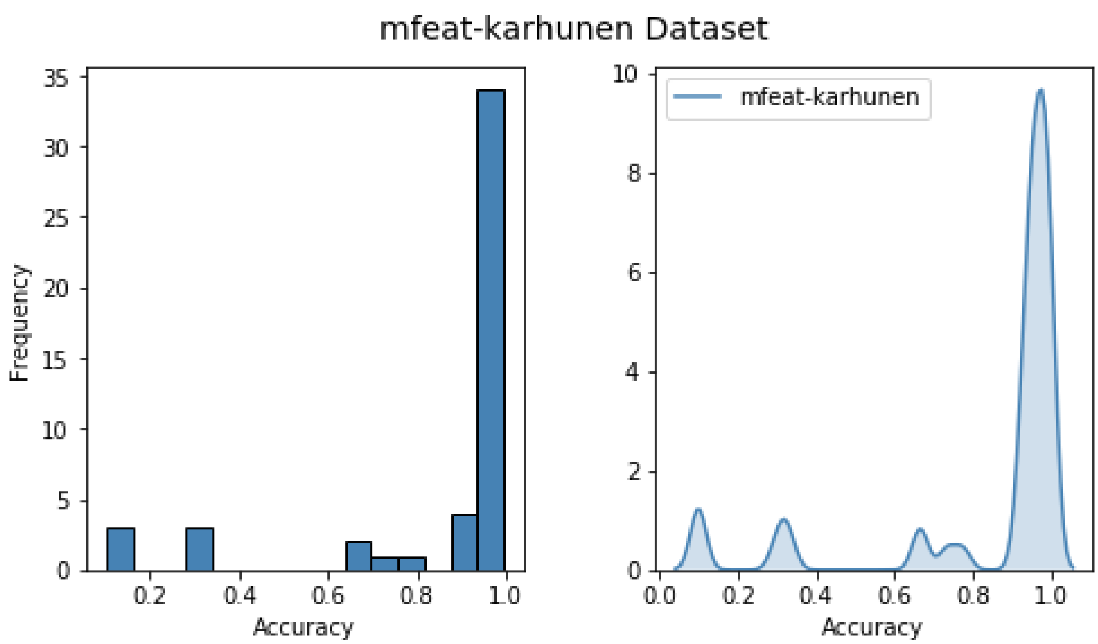
lymph Dataset

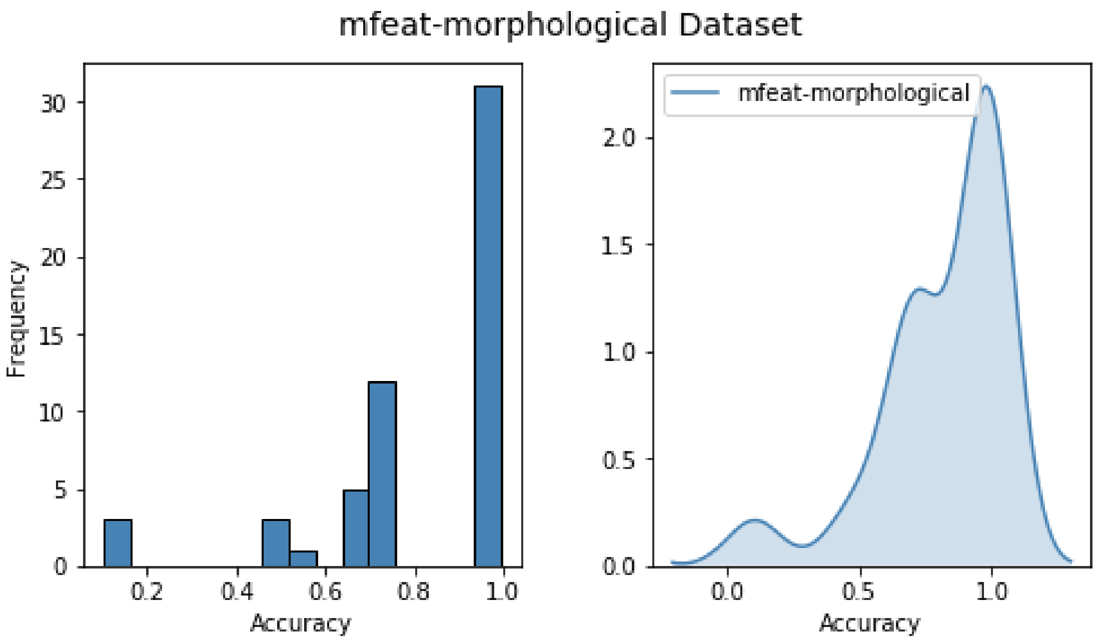


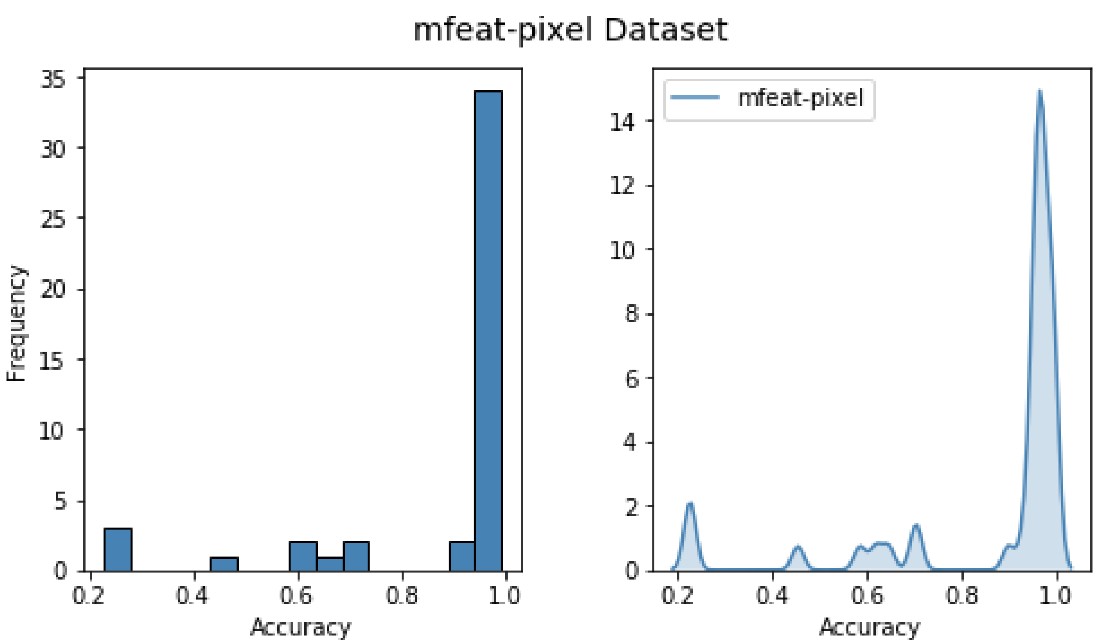
mfeat-factors Dataset

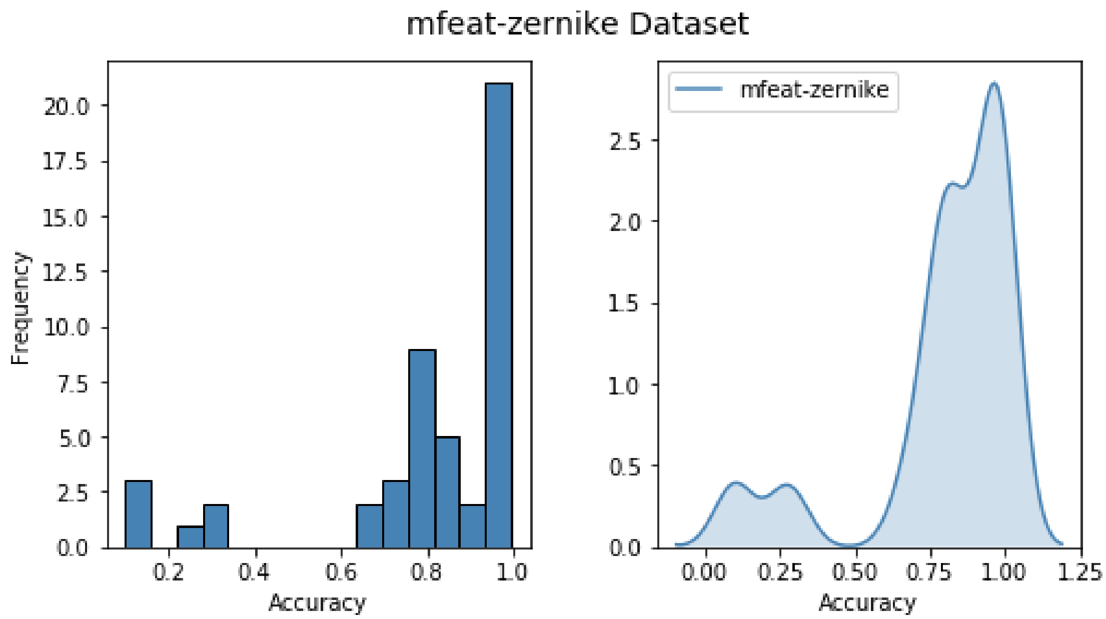


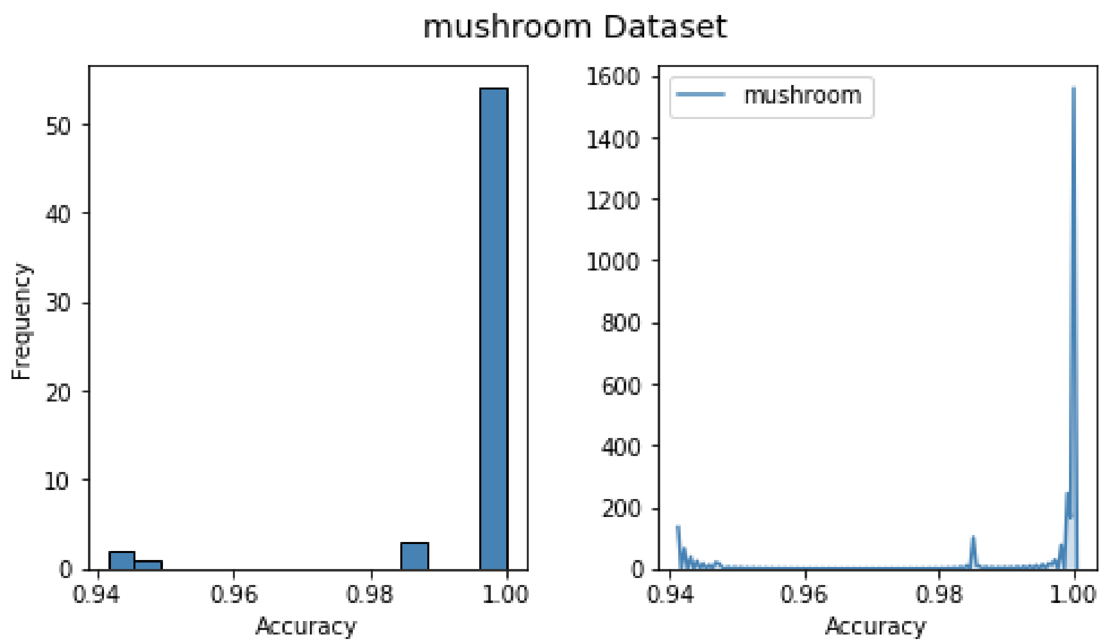

mfeat-fourier Dataset
Frequency
Accuracy
mfeat-fourier
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.2
0.4
0.6
0.8
1.0
2.5
2.0
1.5
1.0
0.5
0.0
0.00
0.25
0.50
0.75
1.00
1.25

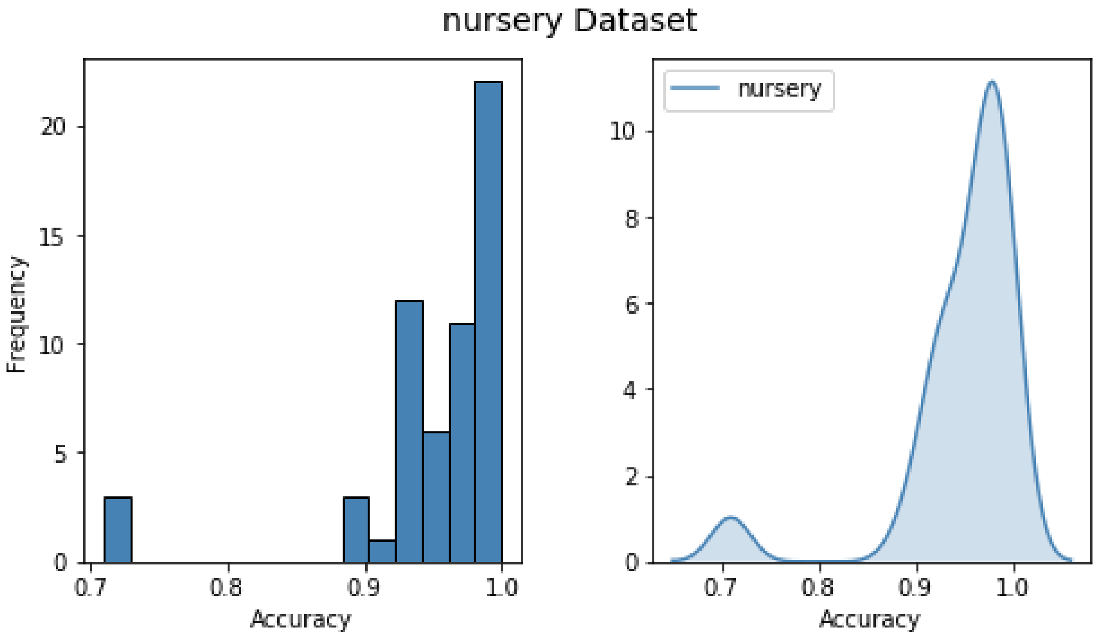

mfeat-karhunen Dataset
Frequency
Accuracy
mfeat-karhunen
35
30
25
20
15
10
5
0
0.2
0.4
0.6
0.8
1.0
10
8
6
4
2
0
0.0
0.2
0.4
0.6
0.8
1.0

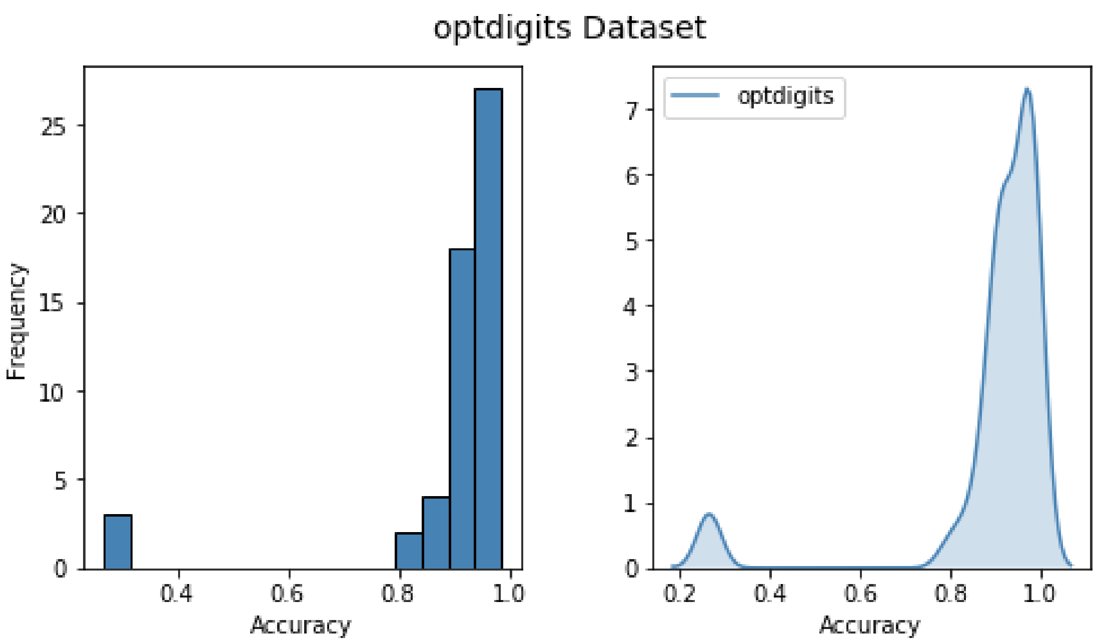

mfeat-morphological Dataset
Frequency
Accuracy
mfeat-morphological
Accuracy

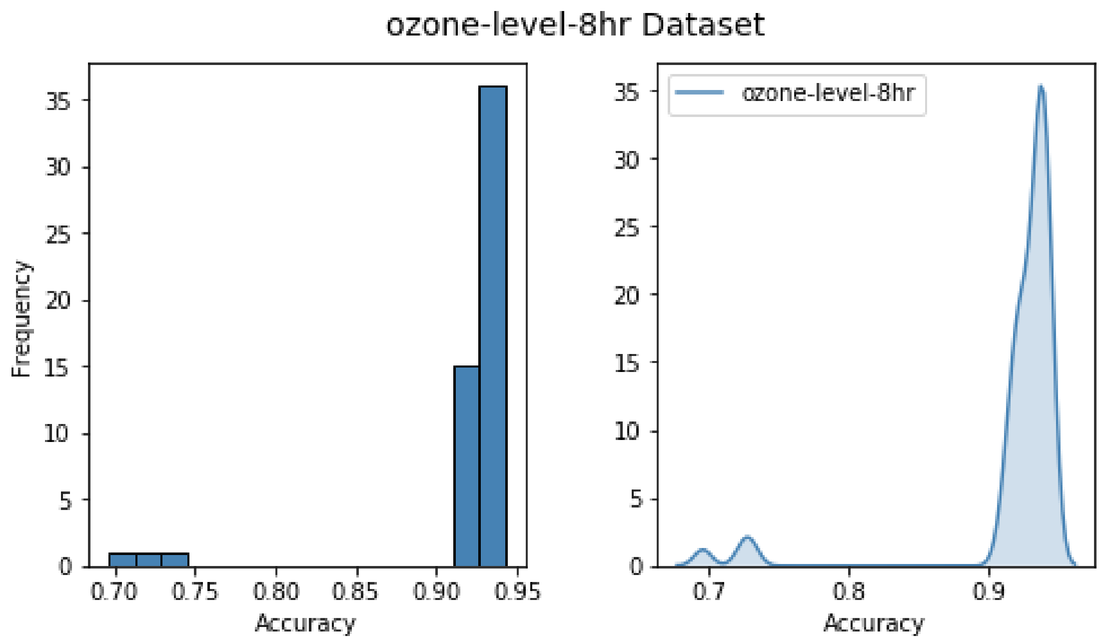

mfeat-pixel Dataset
Frequency
Accuracy
mfeat-pixel
Accuracy

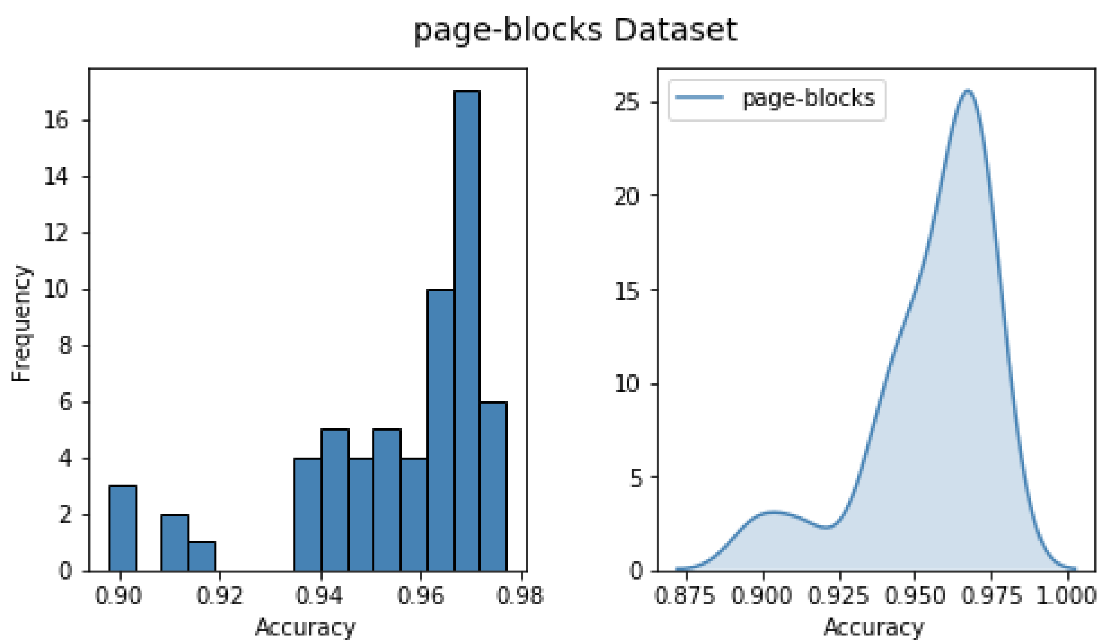

mfeat-zernike Dataset
Frequency
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.2
0.4
0.6
0.8
1.0
Accuracy
mfeat-zernike
2.5
2.0
1.5
1.0
0.5
0.0
0.00
0.25
0.50
0.75
1.00
1.25
Accuracy

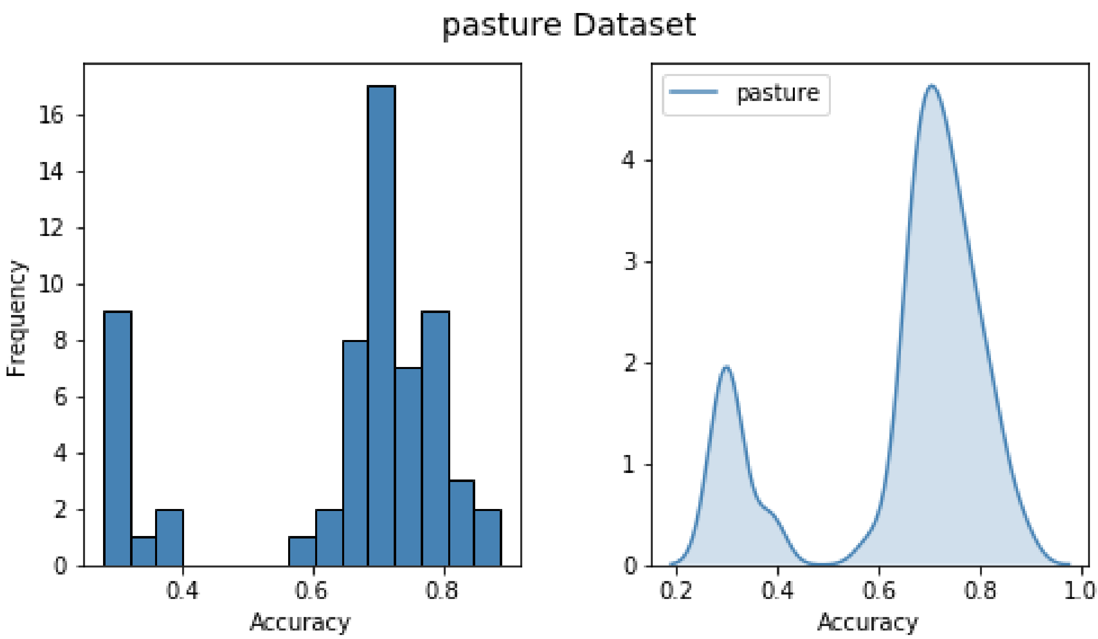

mushroom Dataset
Frequency
50
40
30
20
10
0
0.94
0.96
0.98
1.00
Accuracy
mushroom
1600
1400
1200
1000
800
600
400
200
0
0.94
0.96
0.98
1.00
Accuracy

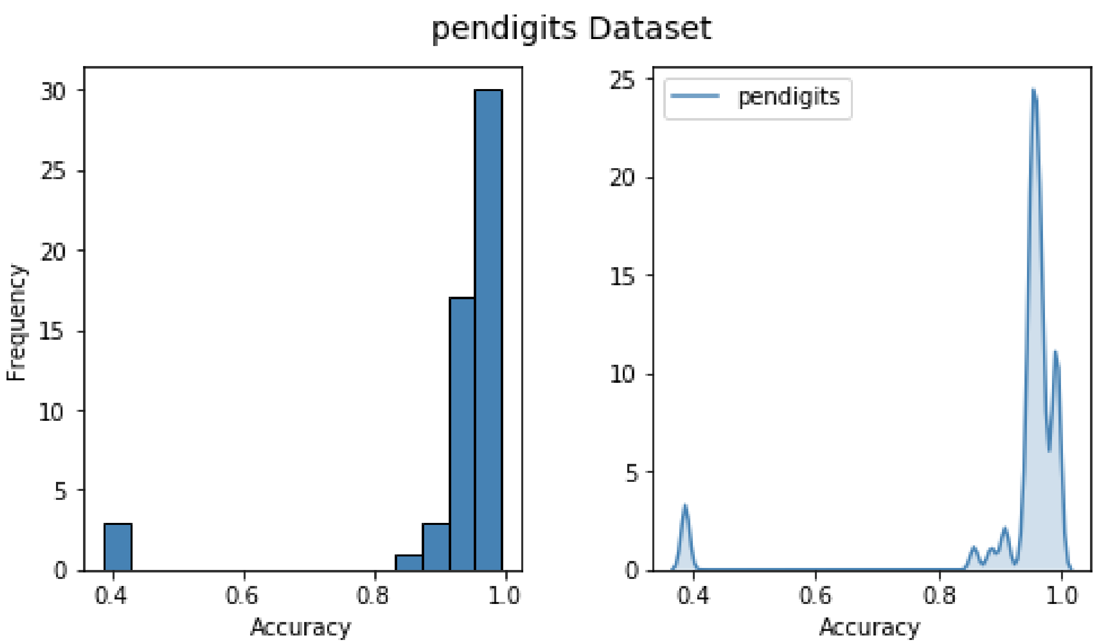

nursery Dataset
Frequency
Accuracy
nursery
0
5
10
15
20
0.7
0.8
0.9
1.0
2
4
6
8

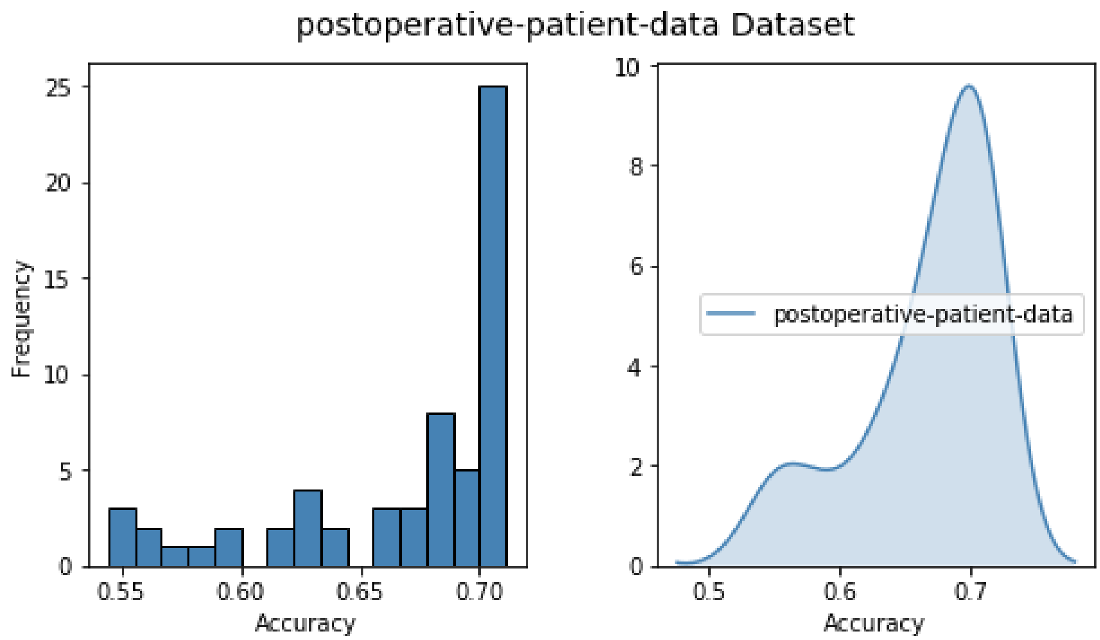

optdigits Dataset
Frequency
Accuracy
optdigits
0
5
10
15
20
25
0.4
0.6
0.8
1.0
0.2
1
2
3
4
6
7

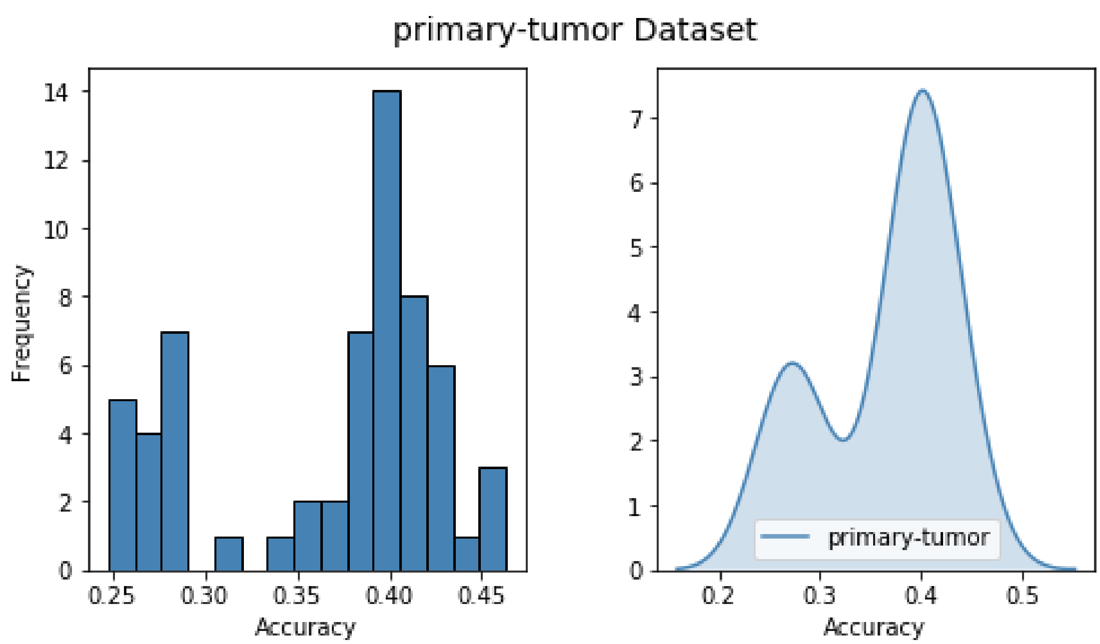

ozone-level-8hr Dataset
Frequency
Accuracy
ozone-level-8hr

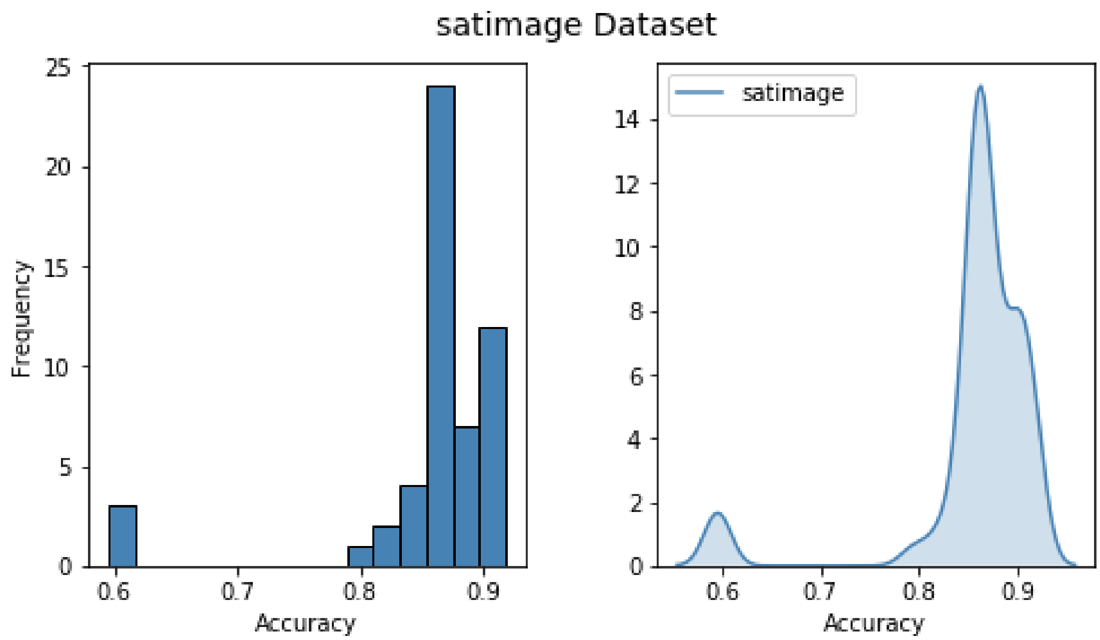

page-blocks Dataset
Frequency
Accuracy
page-blocks

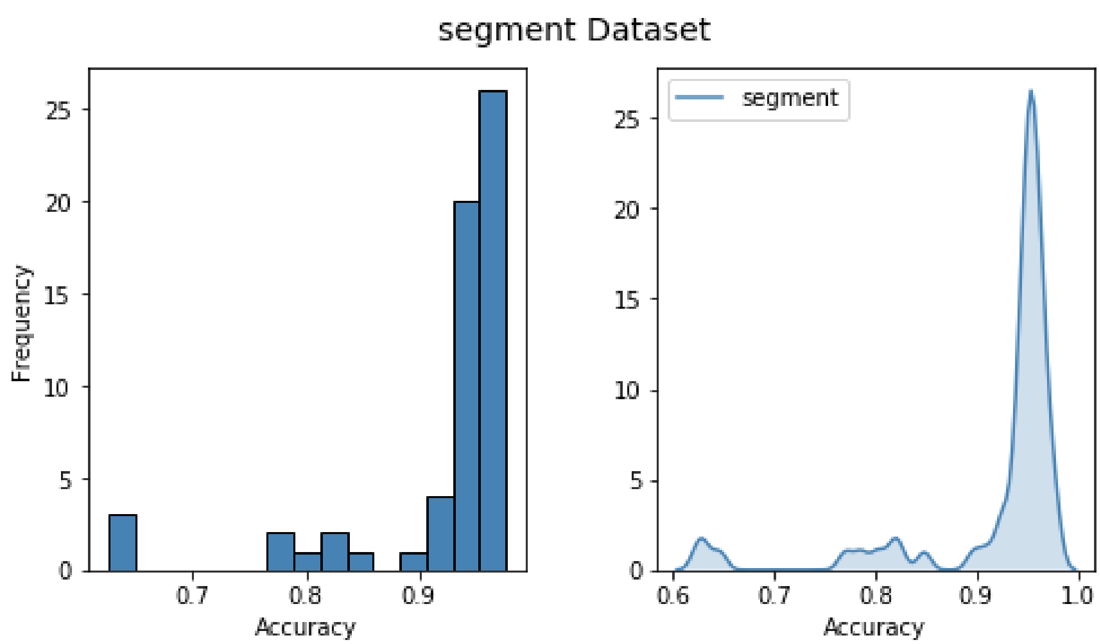

pasture Dataset
Frequency
Accuracy
pasture
0.2
0.4
0.6
0.8
1.0

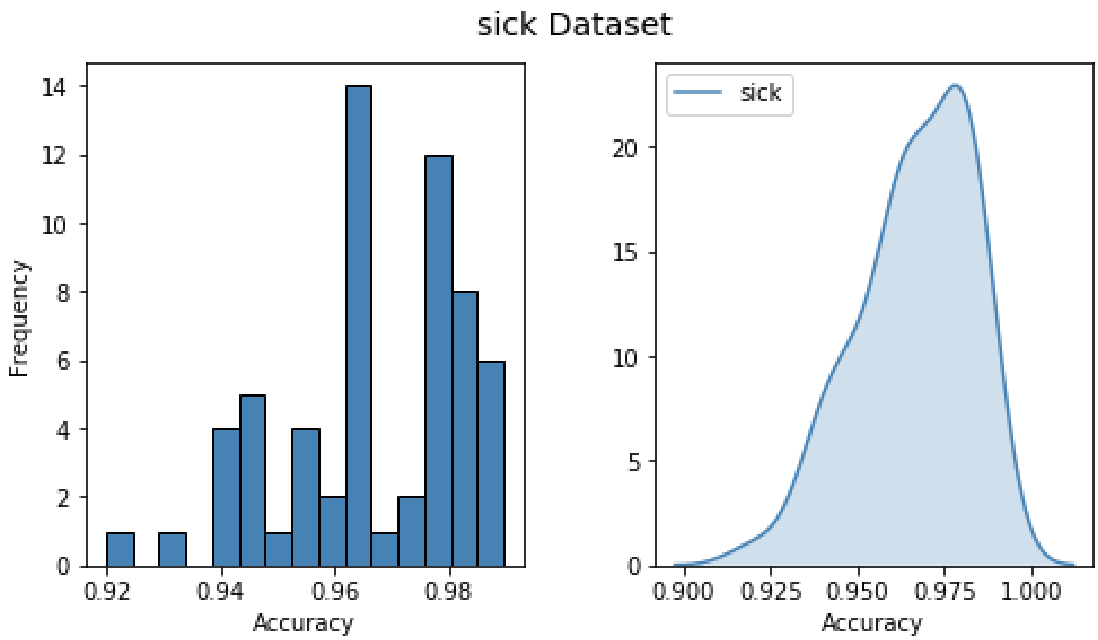

pendigits Dataset
Frequency
Accuracy
pendigits
0.4
0.6
0.8
1.0

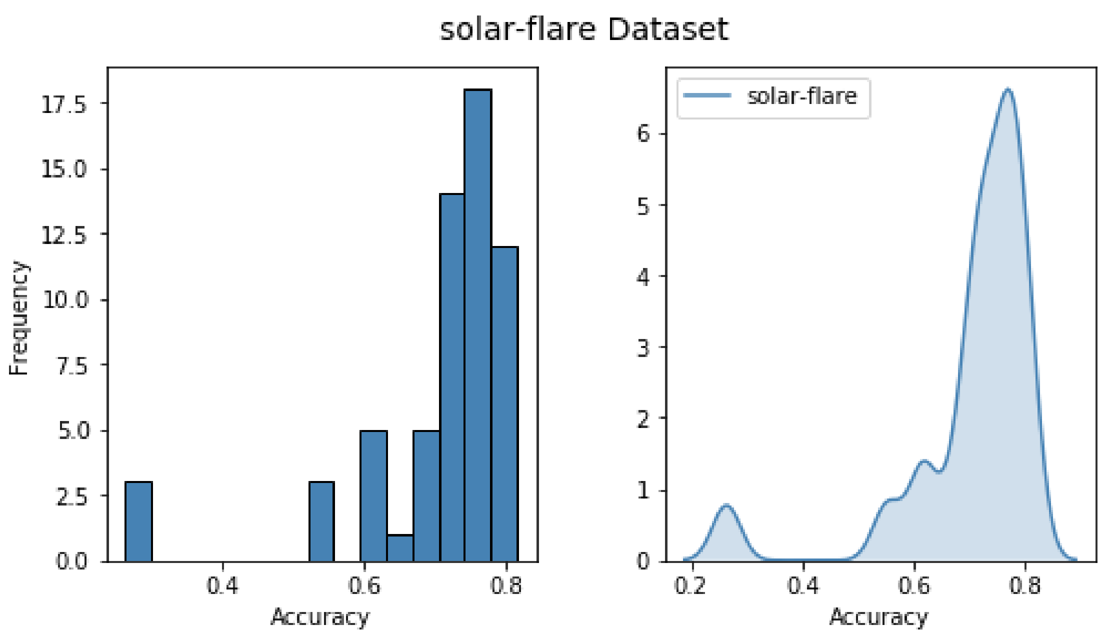

postoperative-patient-data Dataset
Frequency
Accuracy
0
5
10
15
20
25
0.55
0.60
0.65
0.70
postoperative-patient-data
0
2
4
6
8
10
0.5
0.6
0.7
Accuracy

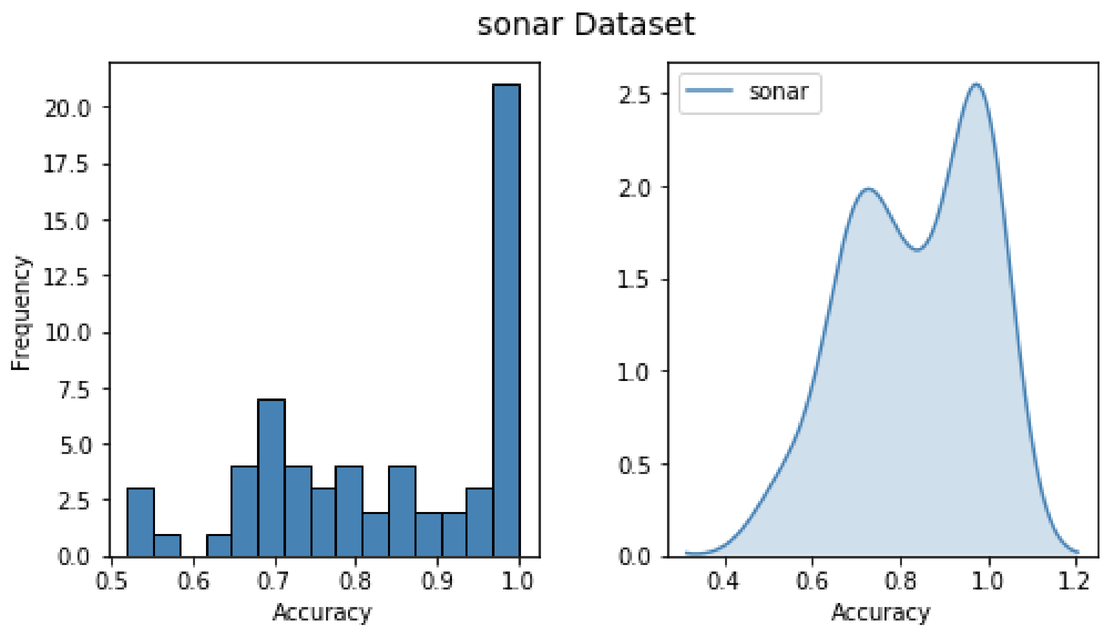

primary-tumor Dataset
Frequency
Accuracy
0
2
4
6
8
10
12
14
0.25
0.30
0.35
0.40
0.45
primary-tumor
0
1
2
3
4
5
6
7
0.2
0.3
0.4
0.5
Accuracy

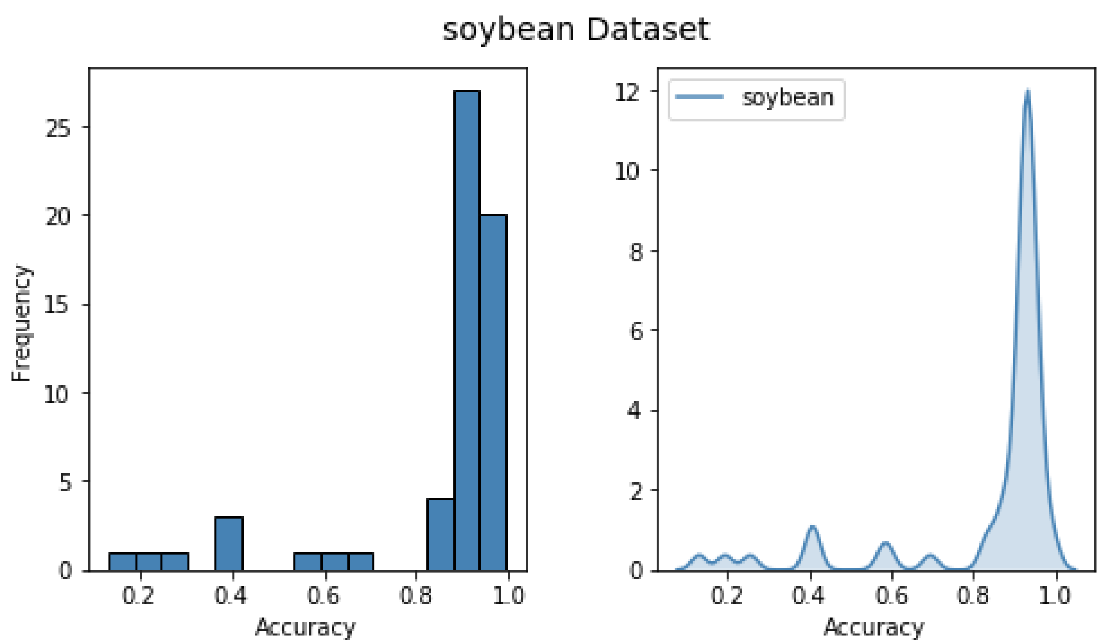

satimage Dataset
Frequency
Accuracy
satimage
0.6
0.7
0.8
0.9
0
5
10
15
20
25
2
4
6
8
12
14

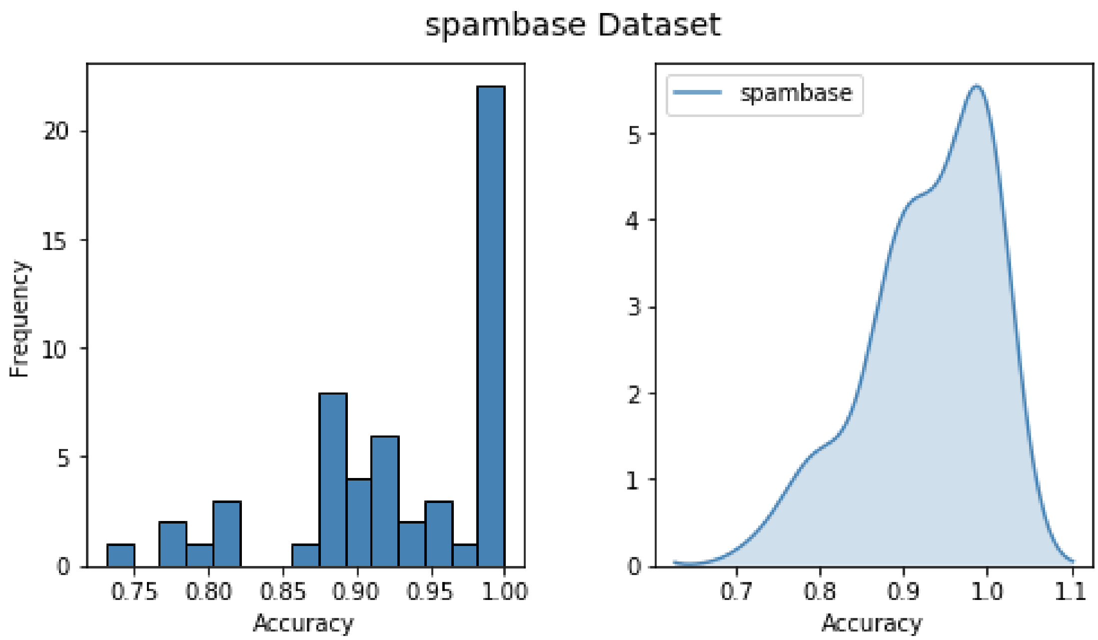

segment Dataset
Frequency
Accuracy
segment
0.6
0.7
0.8
0.9
1.0
0
5
10
15
20
25

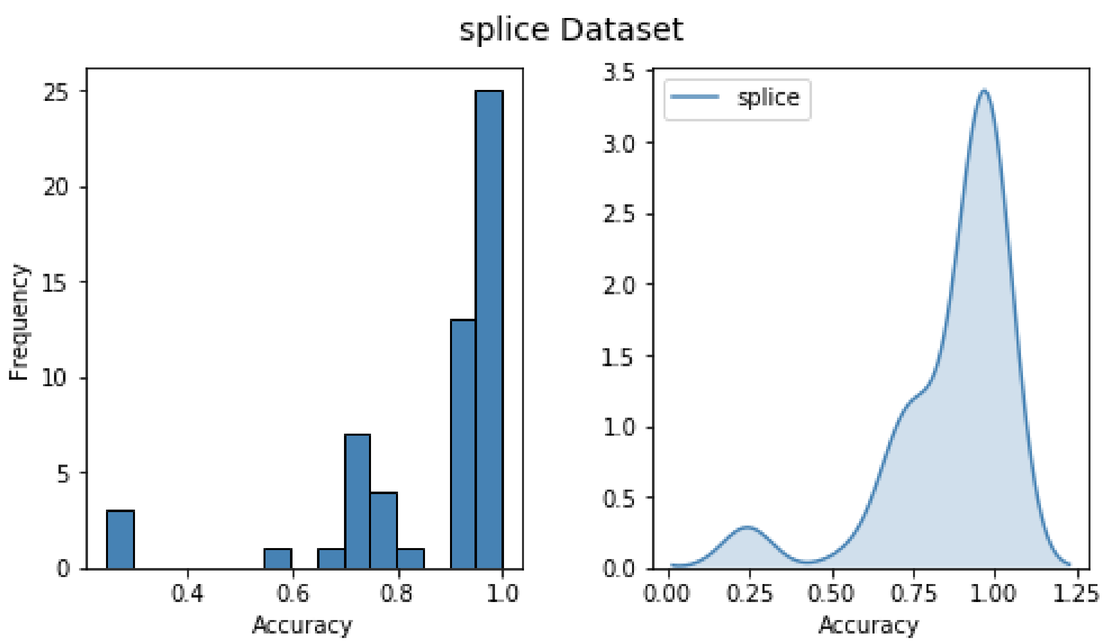

sick Dataset
Frequency
Accuracy
sick
0.92
0.94
0.96
0.98
0.900
0.925
0.950
0.975
1.000

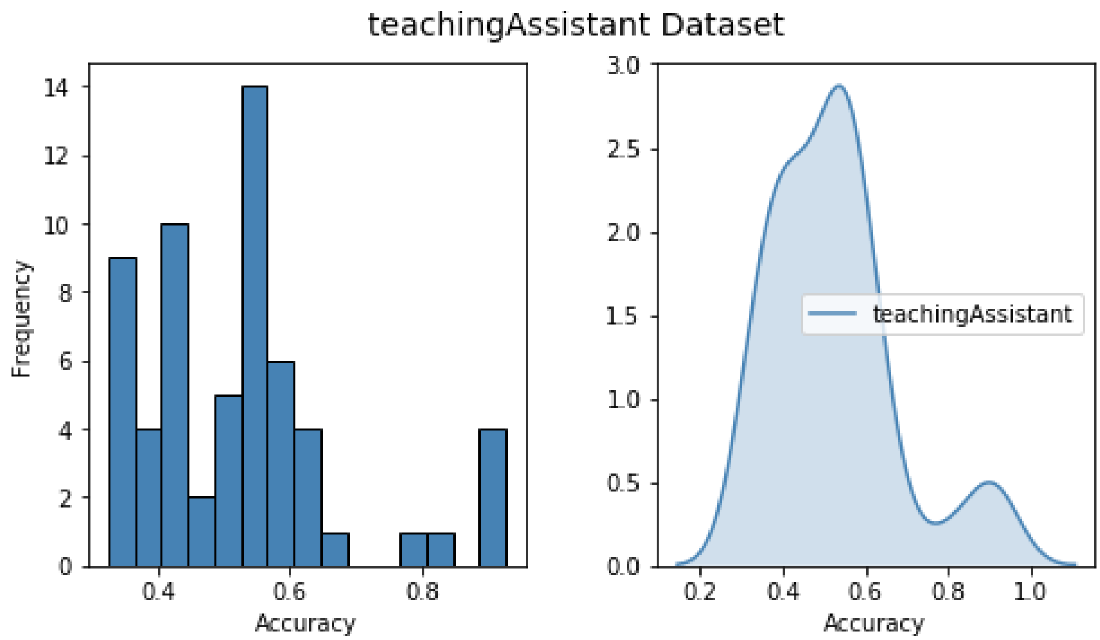

solar-flare Dataset
Frequency
Accuracy
solar-flare
0.2
0.4
0.6
0.8

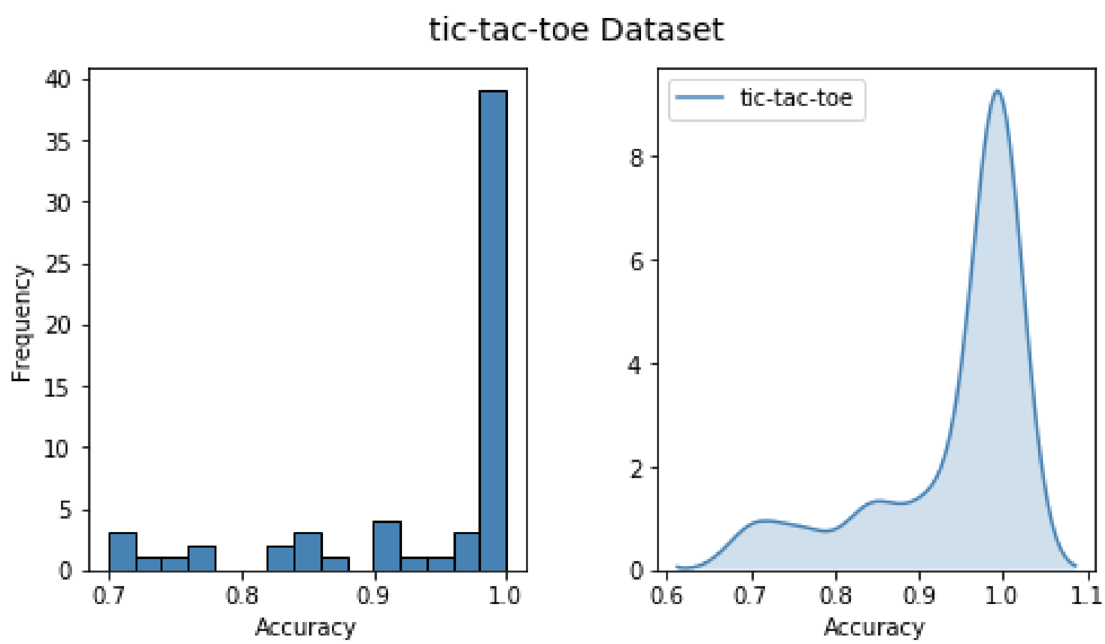

sonar Dataset
Frequency
Accuracy
sonar
Accuracy

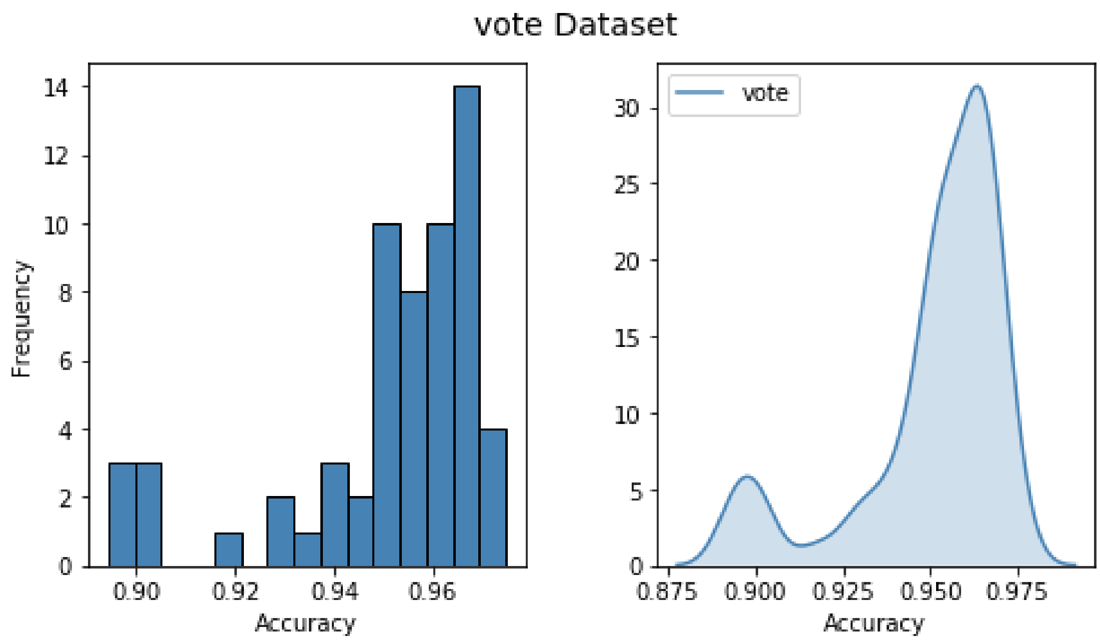

soybean Dataset
Frequency
Accuracy
soybean
Accuracy

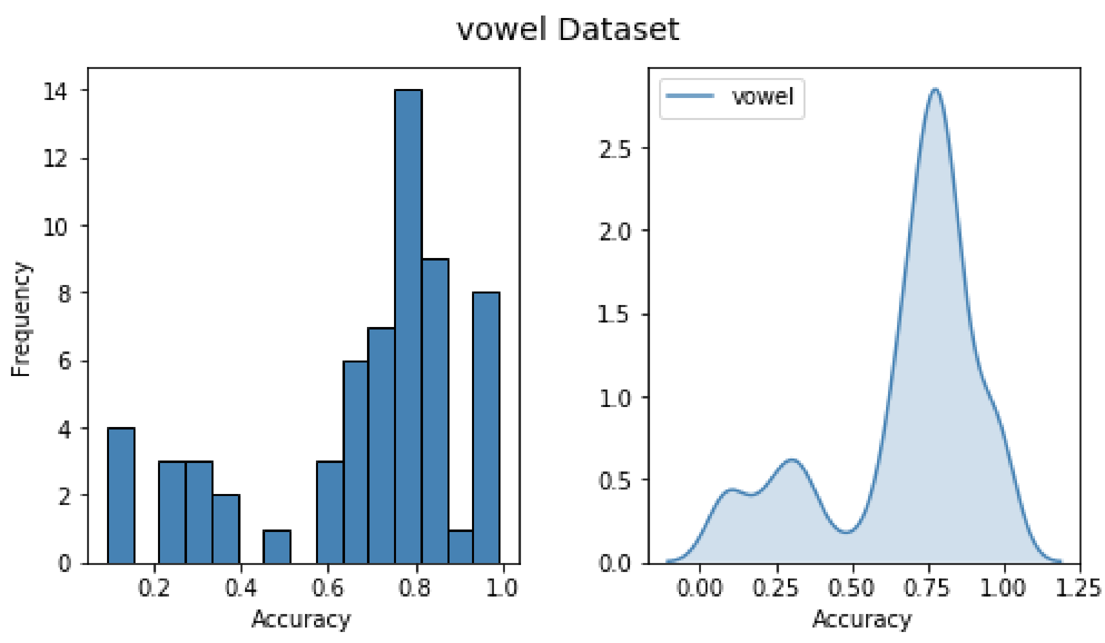

spambase Dataset
Frequency
Accuracy
spambase
0
5
10
15
20
0.75
0.80
0.85
0.90
0.95
1.00
0
1
2
3
4
5
0.7
0.8
0.9
1.0
1.1

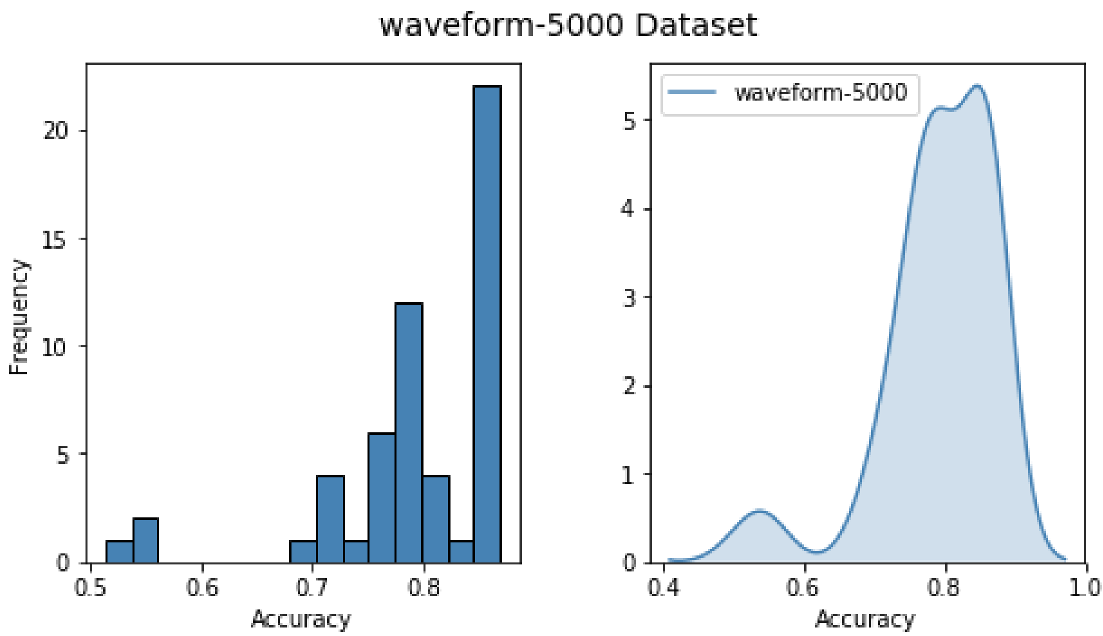

splice Dataset
Frequency
Accuracy
splice
0
5
10
15
20
25
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.00
0.25
0.50
0.75
1.00
1.25

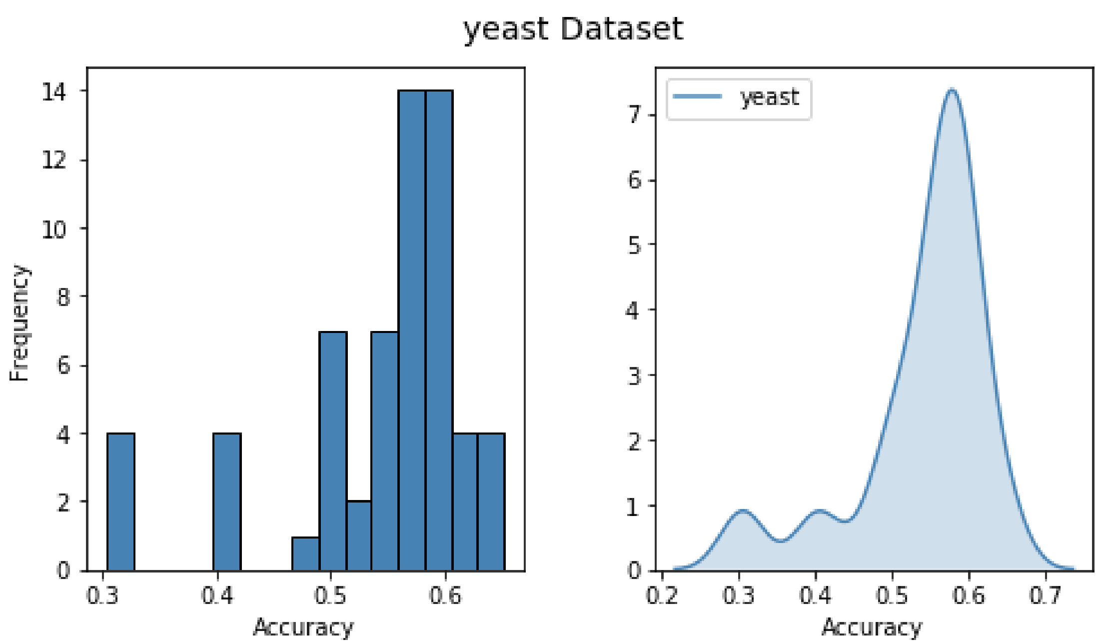

teachingAssistant Dataset
Frequency
Accuracy
teachingAssistant
0.4
0.6
0.8
0.2
1.0

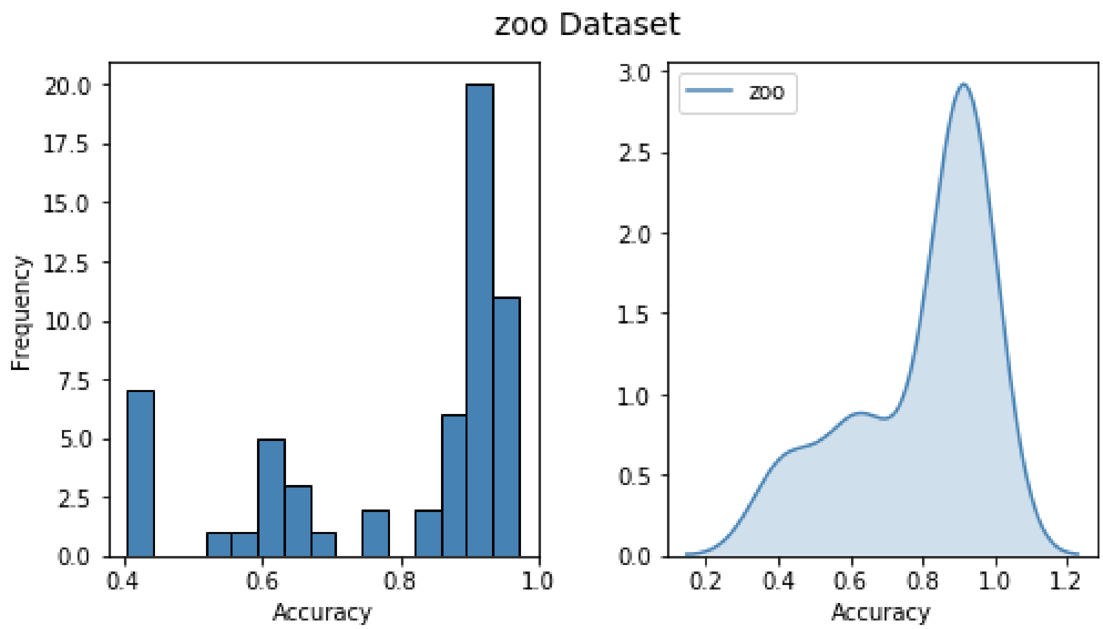

tic-tac-toe Dataset
Frequency
Accuracy
tic-tac-toe
0.7
0.8
0.9
1.0
0.6
1.1


vote Dataset
Frequency
Accuracy
vote
0.90
0.92
0.94
0.96
0.875
0.900
0.925
0.950
0.975
0
2
4
6
8
10
12
14
5
15
20
25
30


vowel Dataset
Frequency
Accuracy
vowel
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00
1.25
0
2
4
6
8
10
12
14
0.0
0.5
1.0
1.5
2.0
2.5


waveform-5000 Dataset
Frequency
Accuracy
waveform-5000
Accuracy


yeast Dataset
Frequency
Accuracy
yeast
Accuracy



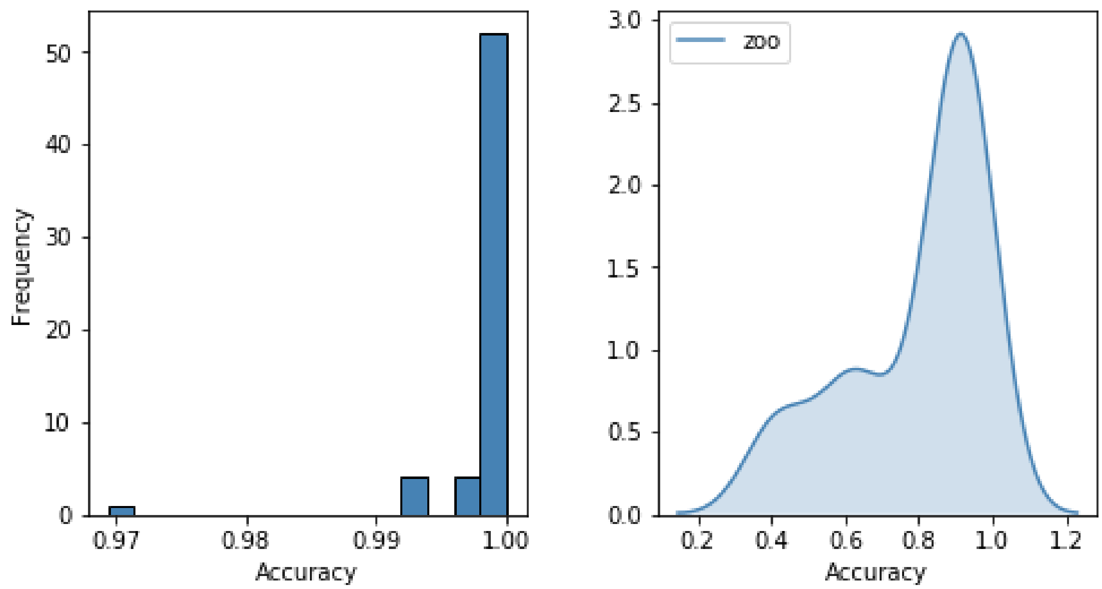
Based on the above graphs, we check the value mean for each datasets. It's easy to do it.

```
In [7]: data_history.mean().idxmax()
```

```
Out[7]: 'badges2'
```

The dataset 'badges2' is the highest mean accuracy. Let's look at the plot of it.

```
In [8]: # Histogram

        fig = plt.figure(figsize=(8, 4)) # Create a new figure with the size 8x4 (unit:inch)
        fig.subplots_adjust(top=0.9, wspace=0.3) # Set the position of title
        ax = fig.add_subplot(1,2,1) # We'll have 2 subplot, histogram plot is on the left
        ax.set_xlabel('Accuracy') # Set the name axis-x
        ax.set_ylabel('Frequency') # Set the name axis-y
        freq, bins, patches = ax.hist(data_history['badges2'], color='steelblue',
                                      bins=15, edgecolor='black', linewidth=1)

        # Density Plot
        fig.subplots_adjust(top=0.9, wspace=0.3)
        ax1 = fig.add_subplot(1,2,2) # density Plot is on the right
        ax1.set_xlabel('Accuracy')
        warning = sns.kdeplot(data_history.iloc[:,i], ax=ax1, shade=True, color='steelblue')
```



That's great, it has about 50 algorithms apply for it which has a high accuracy (approximately 1). We have only 62 algorithms so this result is very well. However I do not believe in that, because I see that there are many value NaN. We need to review these values

3.2 2. Check the value null in each dataset

In [9]:
```
# Check the sum of value null in each dataset and sort it in descending
data_null = data_history.isnull().sum()
data_null.sort_values(ascending=False).head(10)
```

Out[9]:
```
mfeat-pixel         17
mfeat-fourier       15
mfeat-zernike       14
mfeat-karhunen      14
mfeat-factors       14
AP                  13
satimage             9
ozone-level-8hr      8
spambase             8
optdigits            8
dtype: int64
```

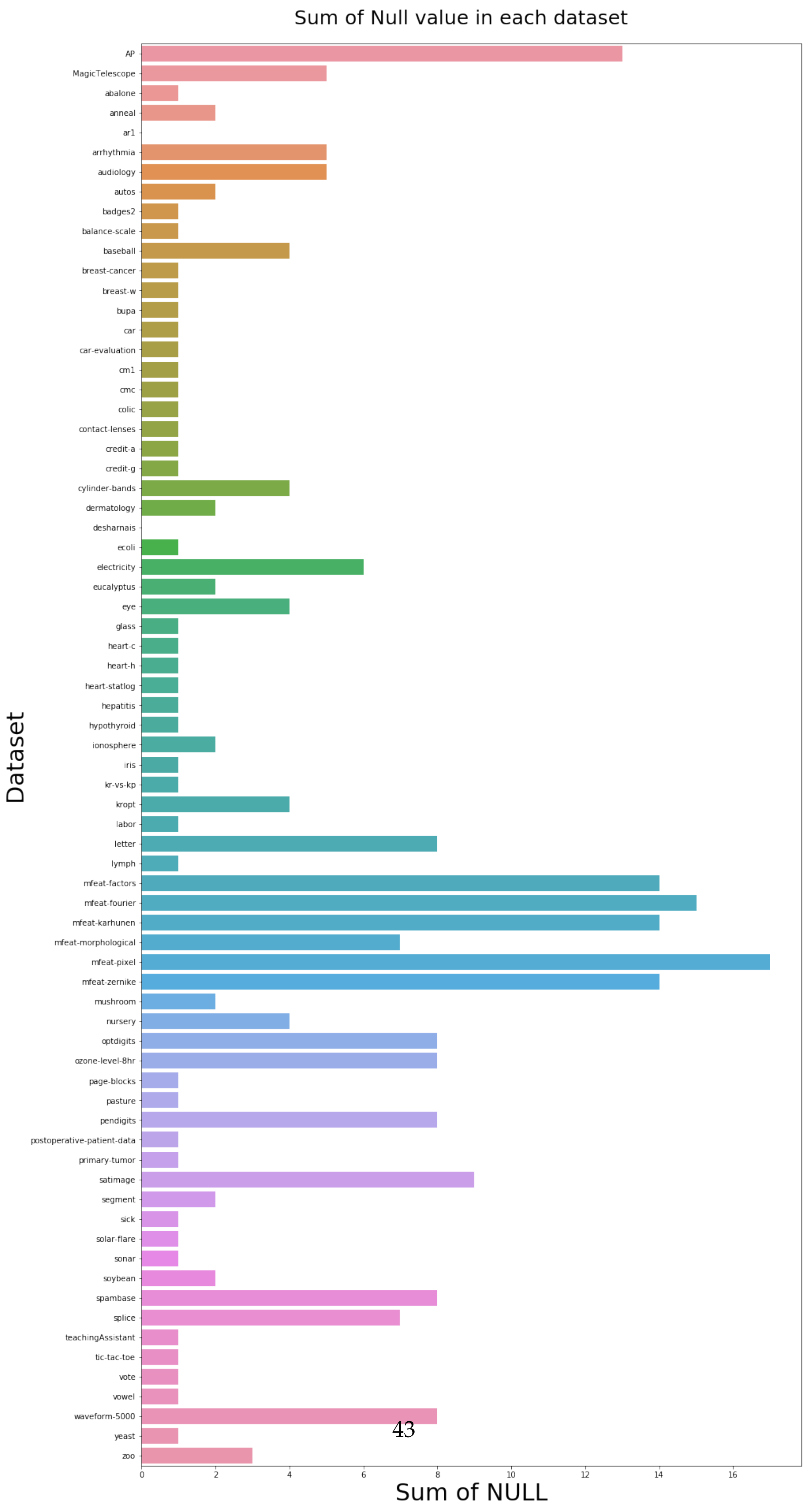
In [10]:
```
data_null.describe()
```

Out[10]:
```
count    72.000000
mean      3.541667
std       4.110918
min       0.000000
```

```
25%       1.000000
50%       1.000000
75%       5.000000
max      17.000000
dtype: float64
```

```
In [11]: data_null = pd.DataFrame({'Datasets':data_null.index,
                                   'Sum of Null Values':data_null.values})
         fig = plt.figure(figsize=(15,30))
         title = fig.suptitle('Sum of Null value in each dataset', fontsize=25)
         fig.subplots_adjust(top=0.96, wspace=0.3)
         ax = sns.barplot(x='Sum of Null Values', y='Datasets', data=data_null)
         ax.set_xlabel('Sum of NULL', fontsize=30)
         ax.set_ylabel('Dataset', fontsize=30)
```

```
Out[11]: Text(0, 0.5, 'Dataset')
```



Sum of Null value in each dataset
Dataset
Sum of NULL
AP
MagicTelescope
abalone
anneal
ar1
arrhythmia
audiology
autos
badges2
balance-scale
baseball
breast-cancer
breast-w
bupa
car
car-evaluation
cm1
cmc
colic
contact-lenses
credit-a
credit-g
cylinder-bands
dermatology
desharnais
ecoli
electricity
eucalyptus
eye
glass
heart-c
heart-h
heart-statlog
hepatitis
hypothyroid
ionosphere
iris
kr-vs-kp
kropt
labor
letter
lymph
mfeat-factors
mfeat-fourier
mfeat-karhunen
mfeat-morphological
mfeat-pixel
mfeat-zernike
mushroom
nursery
optdigits
ozone-level-8hr
page-blocks
pasture
pendigits
postoperative-patient-data
primary-tumor
satimage
segment
sick
solar-flare
sonar
soybean
spambase
splice
teachingAssistant
tic-tac-toe
vote
vowel
waveform-5000
yeast
zoo
0
2
4
6
8
10
12
14
16

Most datasets have at least 1 value null (50%), and the dataset 'mfeat-pixel' has 17 value null. This number isn't too big so we can accept the above analysis

4 II. Analyze each algorithm (rows)

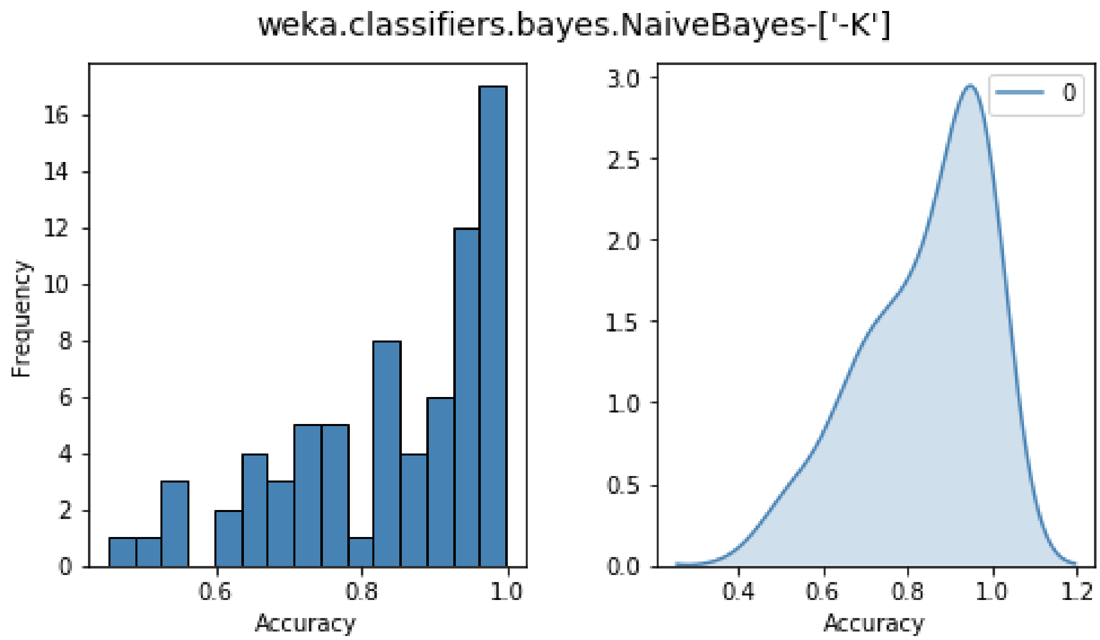
In this part, we also analyze the same method as part I but this time for each row

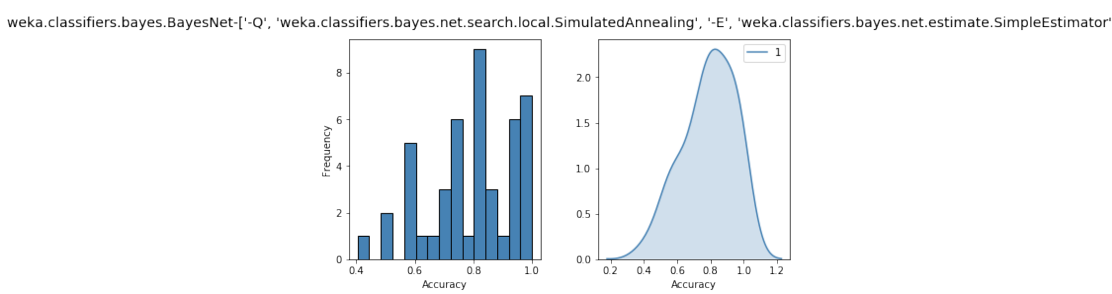
```
In [12]: data_algo = data.drop(columns='Unnamed: 0').copy() # Prepare a new data
         # Drop the colum id 0
```

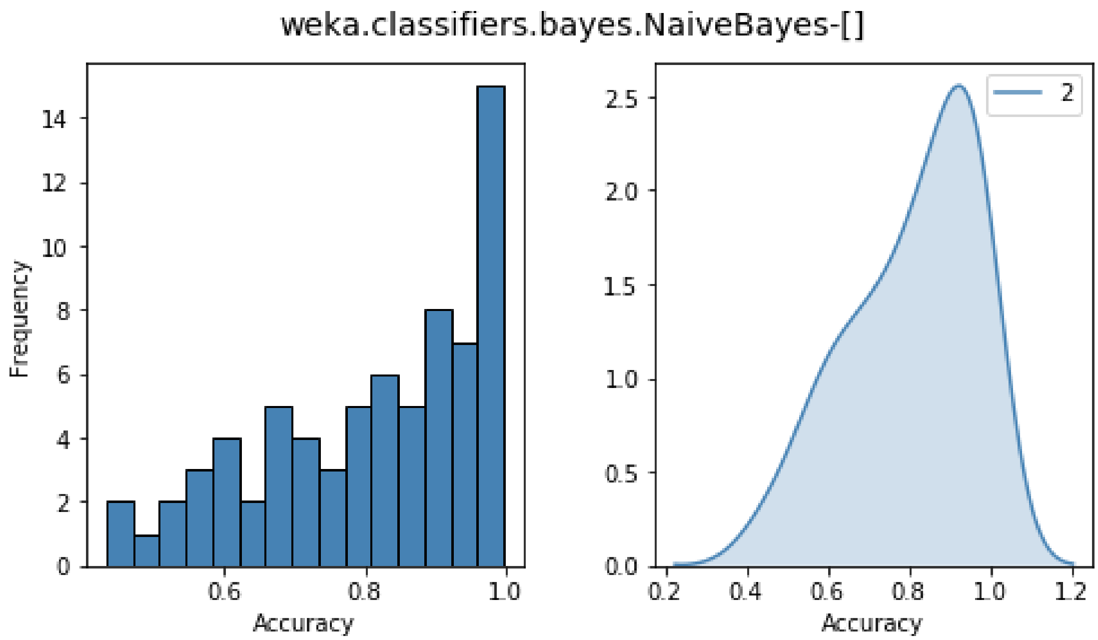
```
In [13]: data_algo.iloc[0,1:].astype('float64').describe()
         # data_history.iloc[:,1]
```

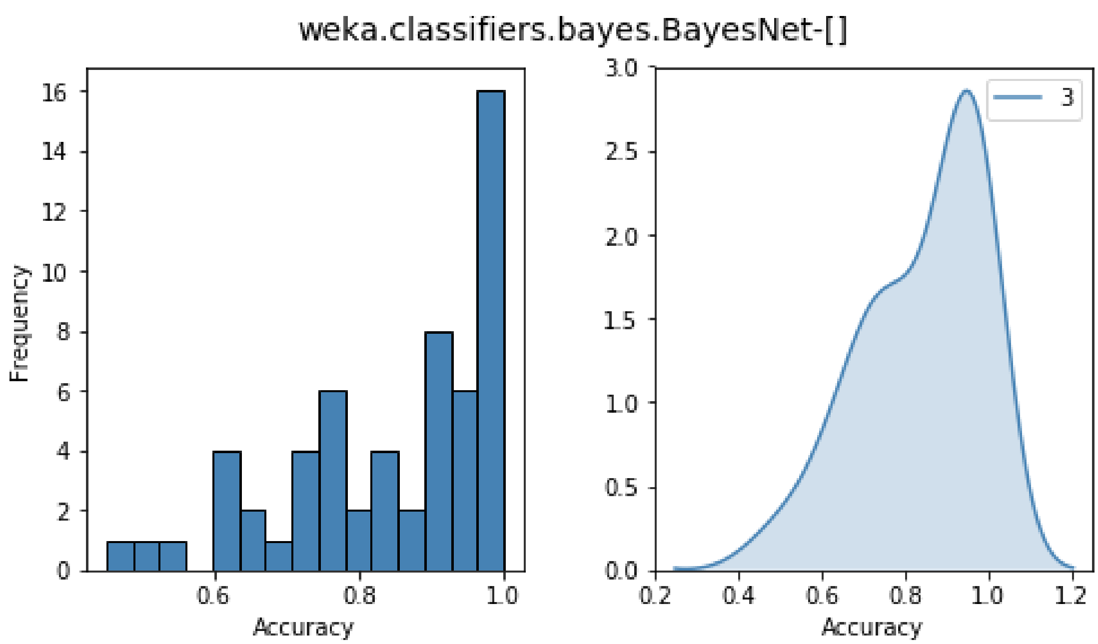
```
Out[13]: count    72.000000
         mean      0.840289
         std       0.145253
         min       0.451300
         25%       0.739900
         50%       0.884850
         75%       0.961575
         max       0.999100
         Name: 0, dtype: float64
```

```
In [14]: for i in range(62):
             # Histogram

             fig = plt.figure(figsize=(8, 4))
             title = fig.suptitle( data_algo['clf name & configuration'][i], fontsize=14)
             fig.subplots_adjust(top=0.9, wspace=0.3)
             ax = fig.add_subplot(1,2,1)
             ax.set_xlabel('Accuracy')
             ax.set_ylabel('Frequency')
             freq, bins, patches = ax.hist(data_algo.iloc[i,1:].astype('float64'),
                                           color='steelblue', bins=15,
                                           edgecolor='black', linewidth=1 )

             # Density Plot

             fig.subplots_adjust(top=0.9, wspace=0.3)
             ax1 = fig.add_subplot(1,2,2)
             ax1.set_xlabel('Accuracy')
             sns.kdeplot(data_algo.iloc[i,1:].astype('float64'),
                         ax=ax1, shade=True, color='steelblue')
```

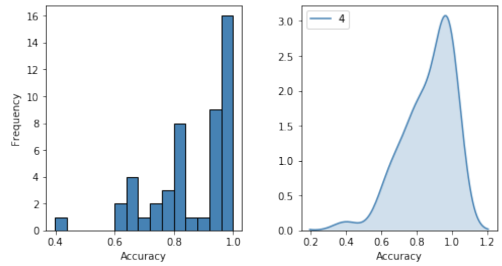

weka.classifiers.bayes.NaiveBayes-['-K']
Frequency
Accuracy
0


weka.classifiers.bayes.BayesNet-['-Q', 'weka.classifiers.bayes.net.search.local.SimulatedAnnealing', '-E', 'weka.classifiers.bayes.net.estimate.SimpleEstimator']
Frequency
Accuracy
1

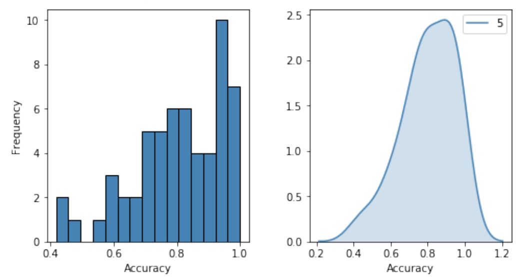

weka.classifiers.bayes.NaiveBayes-[]
Frequency
Accuracy
Accuracy
2


weka.classifiers.bayes.BayesNet-[]
Frequency
Accuracy
Accuracy
3

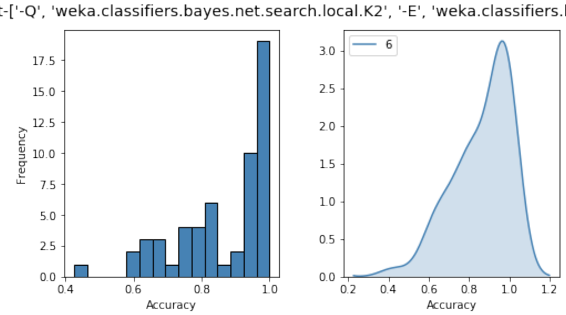
weka.classifiers.bayes.BayesNet-['-Q', 'weka.classifiers.bayes.net.search.local.LAGDHillClimber', '-E', 'weka.classifiers.bayes.net.estimate.SimpleEstimator']



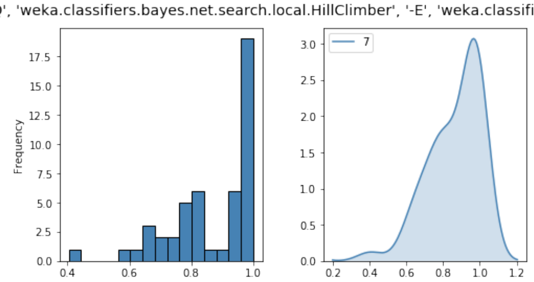
weka.classifiers.bayes.BayesNet-['-Q', 'weka.classifiers.bayes.net.search.local.TabuSearch', '-E', 'weka.classifiers.bayes.net.estimate.SimpleEstimator']



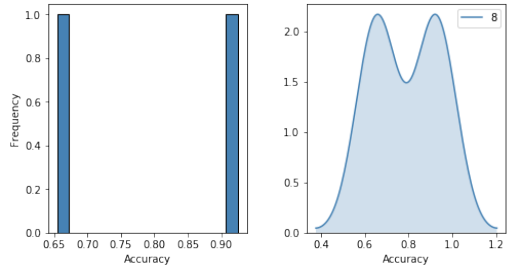
weka.classifiers.bayes.BayesNet-['-Q', 'weka.classifiers.bayes.net.search.local.K2', '-E', 'weka.classifiers.bayes.net.estimate.SimpleEstimator']



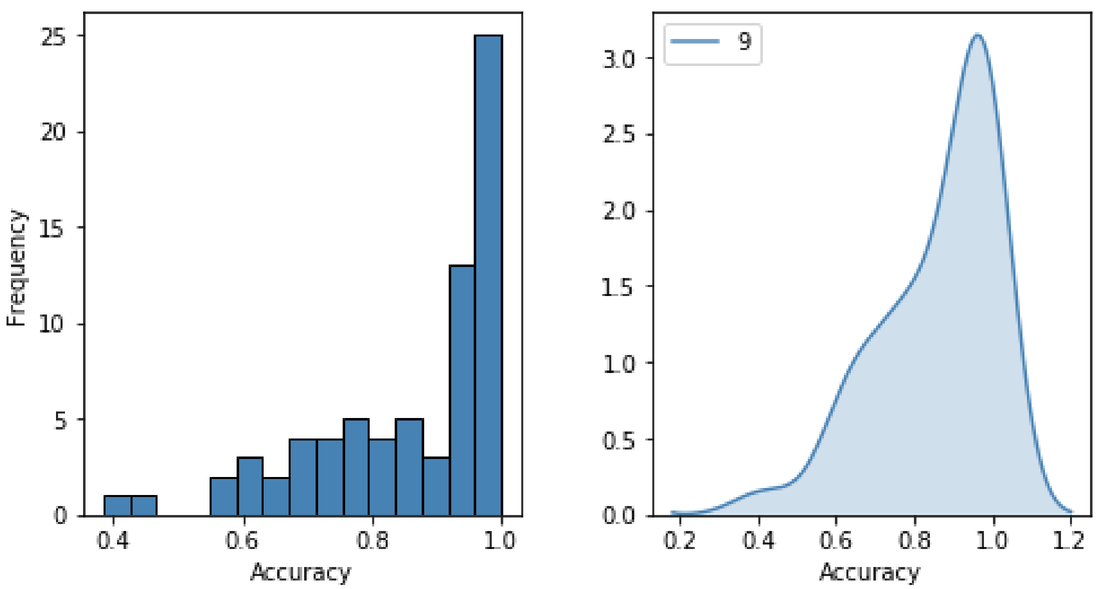
weka.classifiers.bayes.BayesNet-['-Q', 'weka.classifiers.bayes.net.search.local.HillClimber', '-E', 'weka.classifiers.bayes.net.estimate.SimpleEstimator']

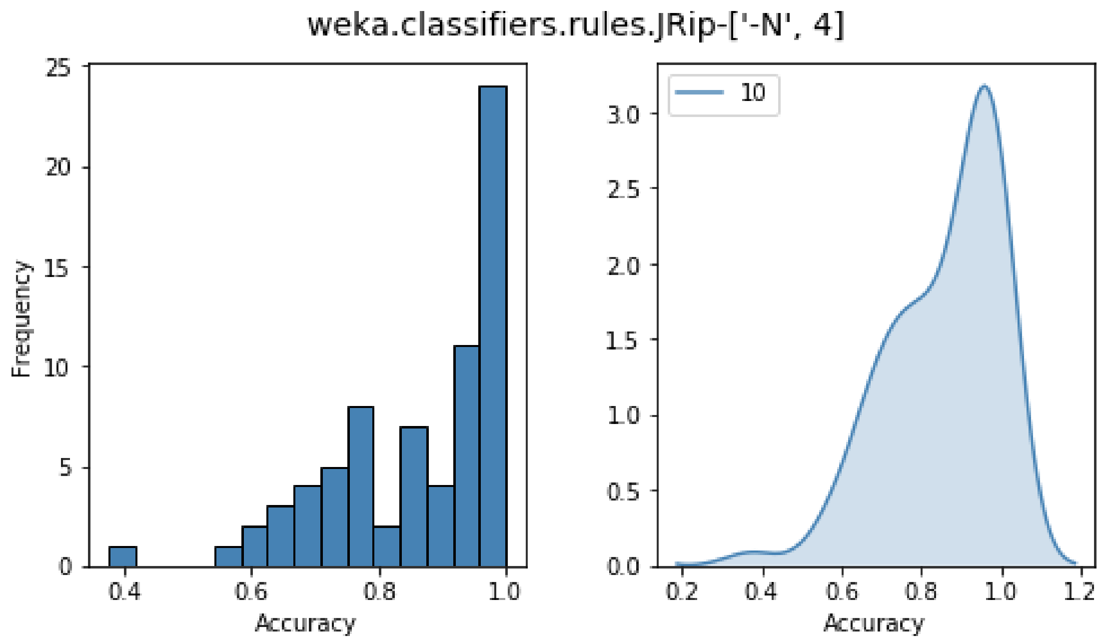


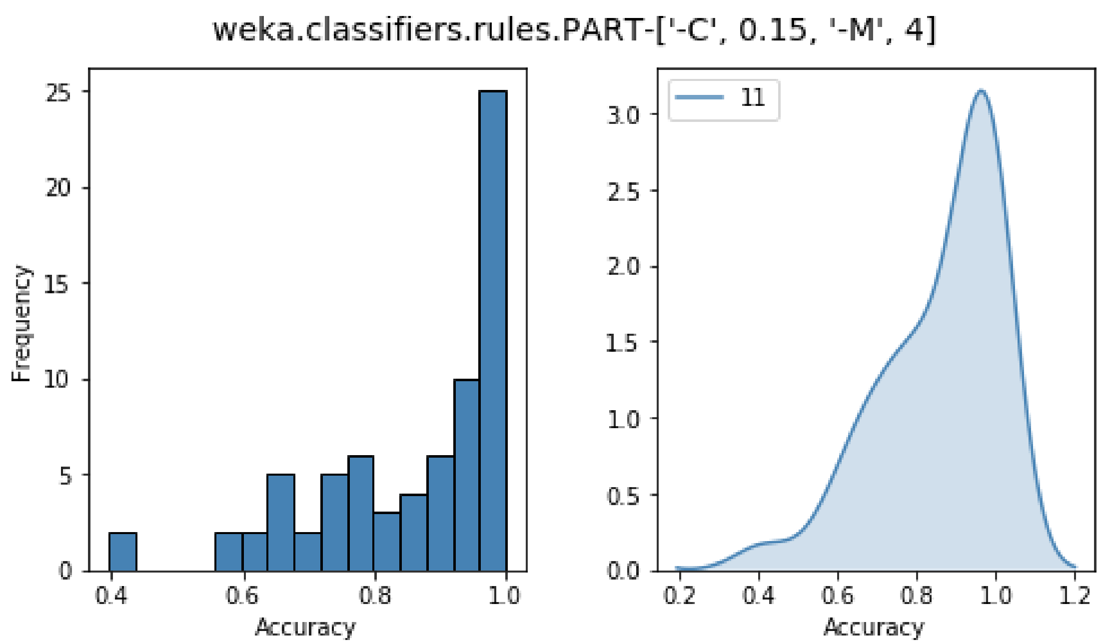
weka.classifiers.bayes.BayesNet-['-Q', 'weka.classifiers.bayes.net.search.local.LAGDHillClimber', '-E', 'weka.classifiers.bayes.net.estimate.BMAEstimator']

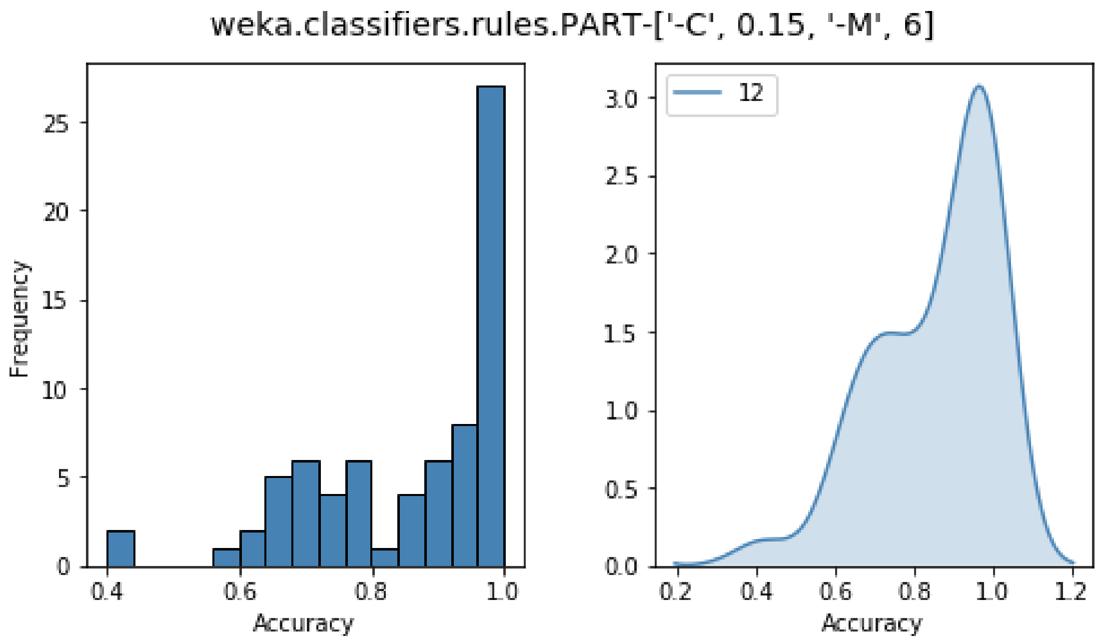


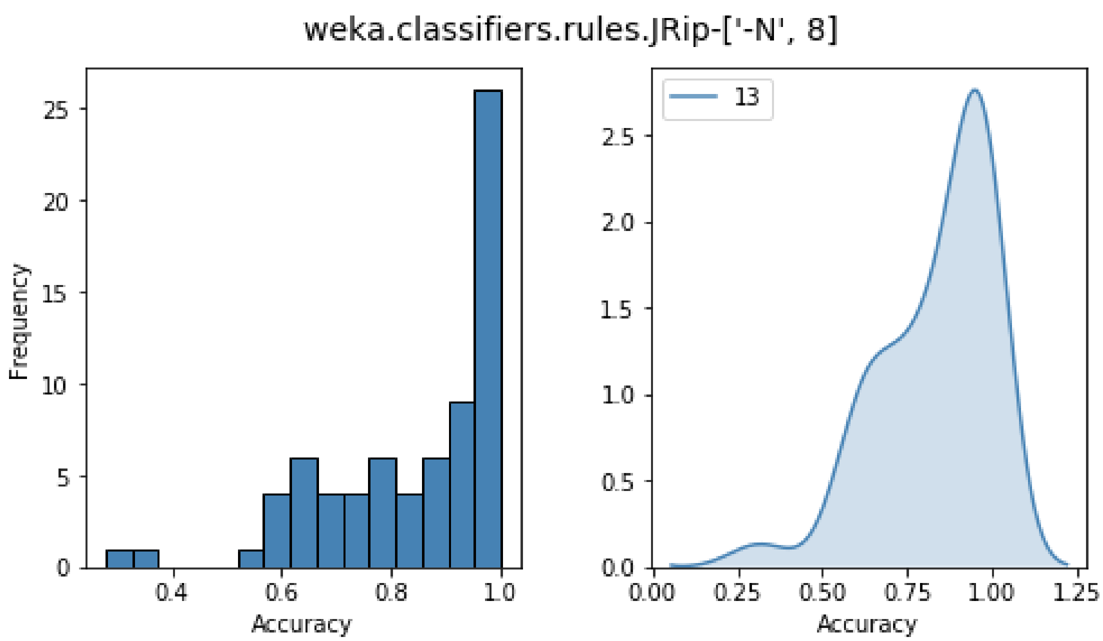
weka.classifiers.rules.PART-['-C', 0.25, '-M', 4]

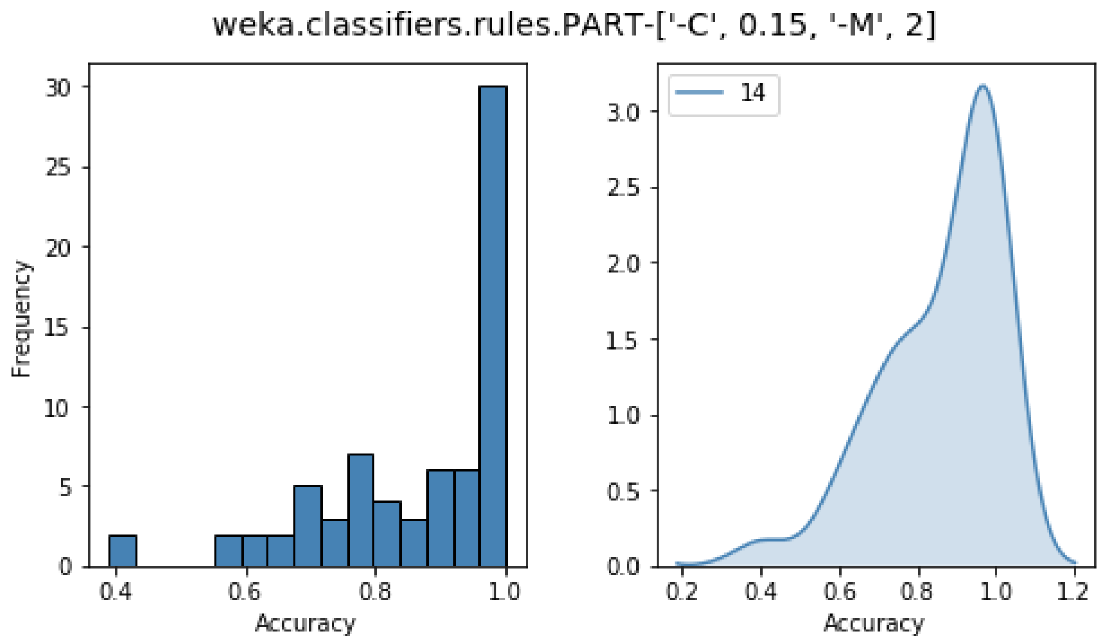


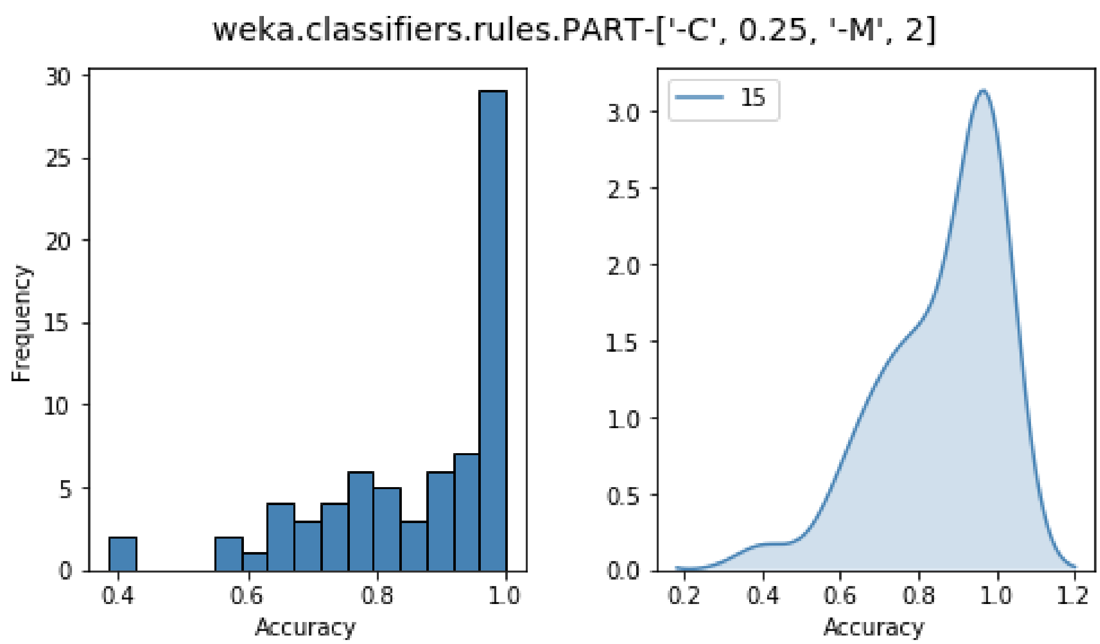

weka.classifiers.rules.JRip-['-N', 4]
Frequency
Accuracy
0
5
10
15
20
25
0.4
0.6
0.8
1.0
10
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.2
0.4
0.6
0.8
1.0
1.2
Accuracy

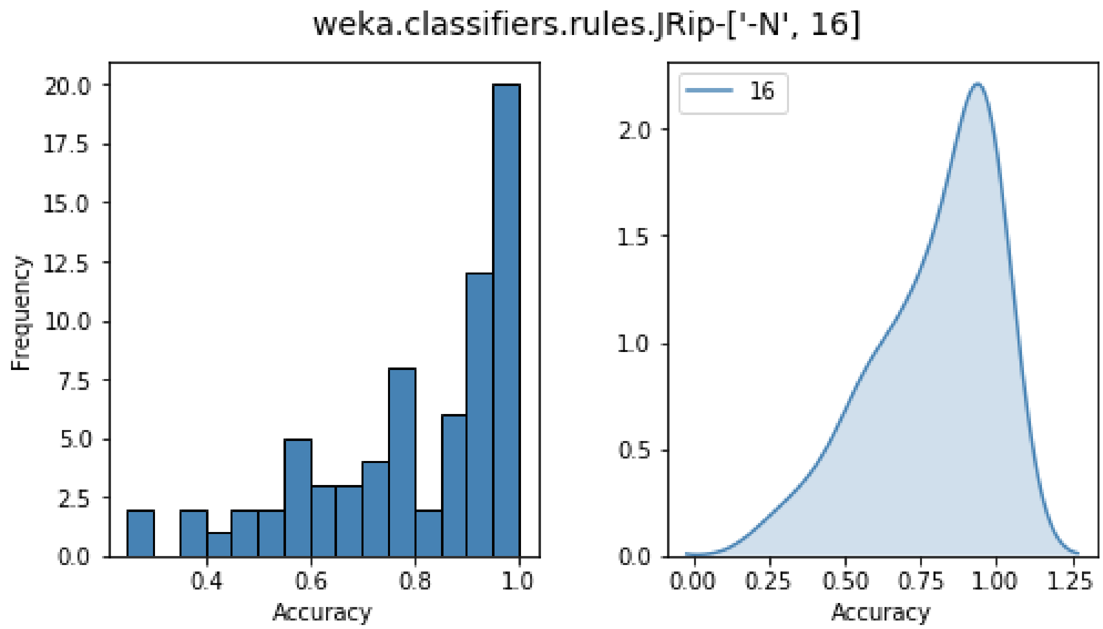

weka.classifiers.rules.PART-['-C', 0.15, '-M', 4]
Frequency
Accuracy
0
5
10
15
20
25
0.4
0.6
0.8
1.0
11
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.2
0.4
0.6
0.8
1.0
1.2
Accuracy

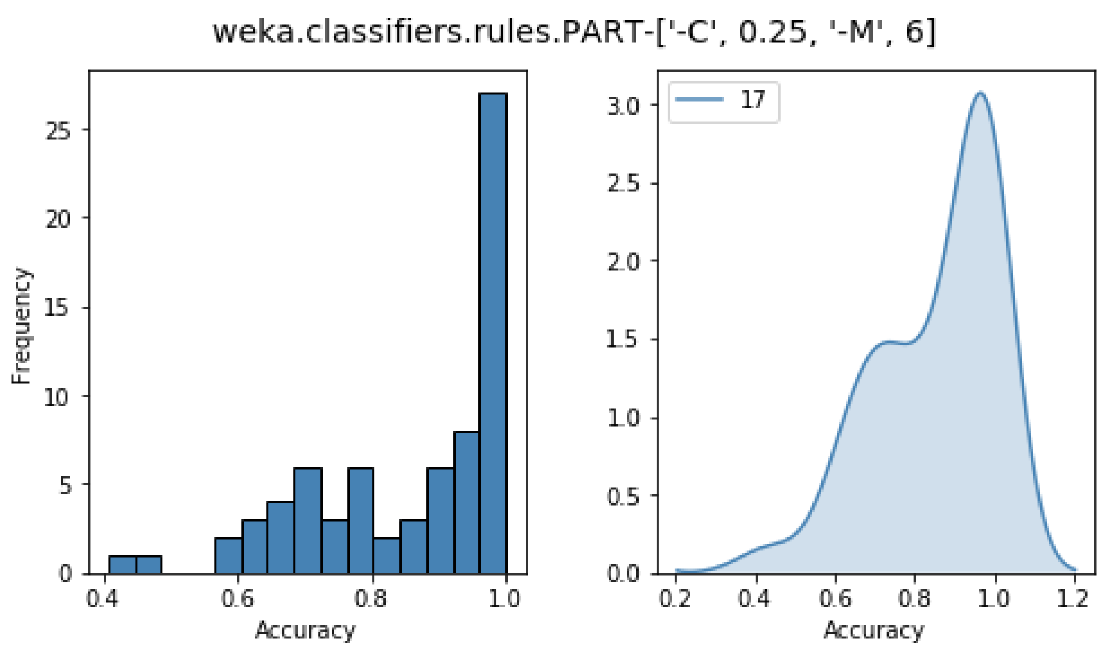

weka.classifiers.rules.PART-['-C', 0.15, '-M', 6]
Frequency
Accuracy
12
0
5
10
15
20
25
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.2
0.4
0.6
0.8
1.0
1.2


weka.classifiers.rules.JRip-['-N', 8]
Frequency
Accuracy
13
0
5
10
15
20
25
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
2.5
0.00
0.25
0.50
0.75
1.00
1.25

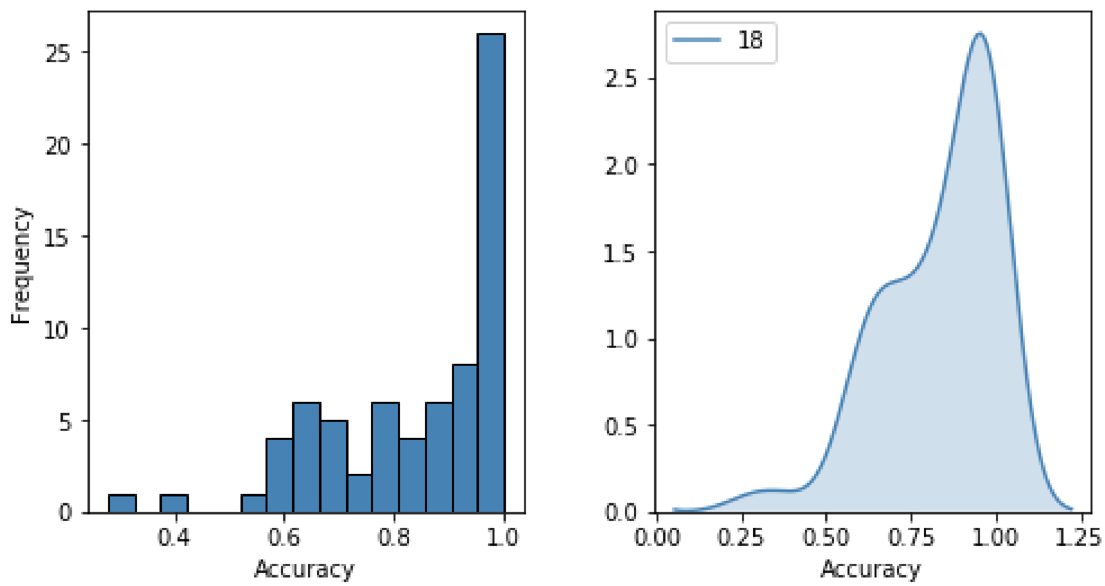

weka.classifiers.rules.PART-['-C', 0.15, '-M', 2]
Frequency
Accuracy
14
Accuracy


weka.classifiers.rules.PART-['-C', 0.25, '-M', 2]
Frequency
Accuracy
15
Accuracy

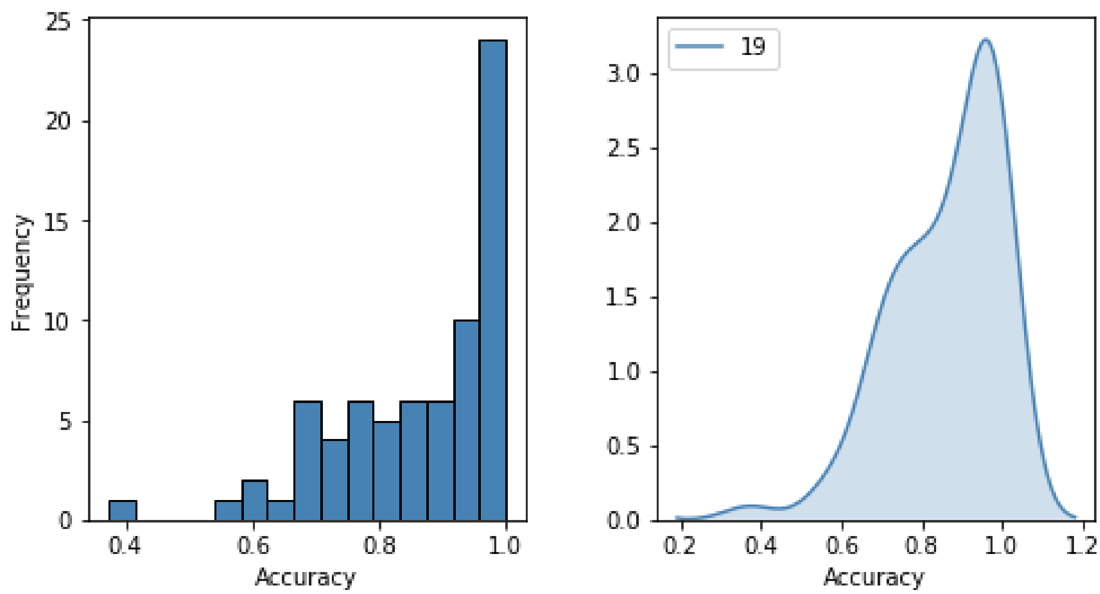

weka.classifiers.rules.JRip-['-N', 16]
Frequency
Accuracy
Accuracy
16

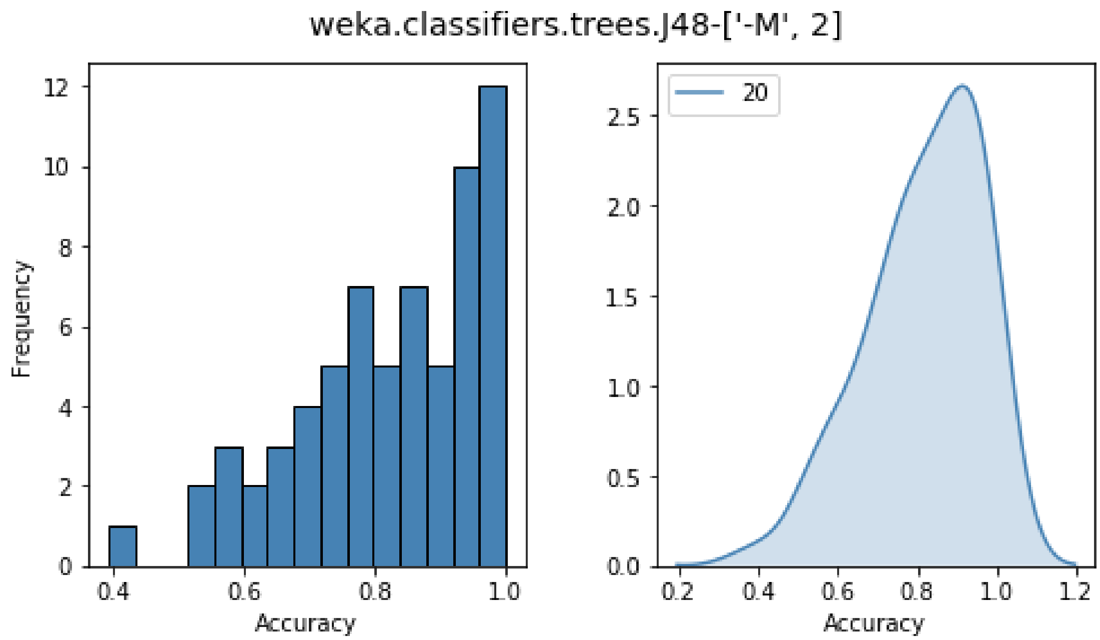

weka.classifiers.rules.PART-['-C', 0.25, '-M', 6]
Frequency
Accuracy
Accuracy
17

weka.classifiers.rules.JRip-['-N', 8, '-O', 4]

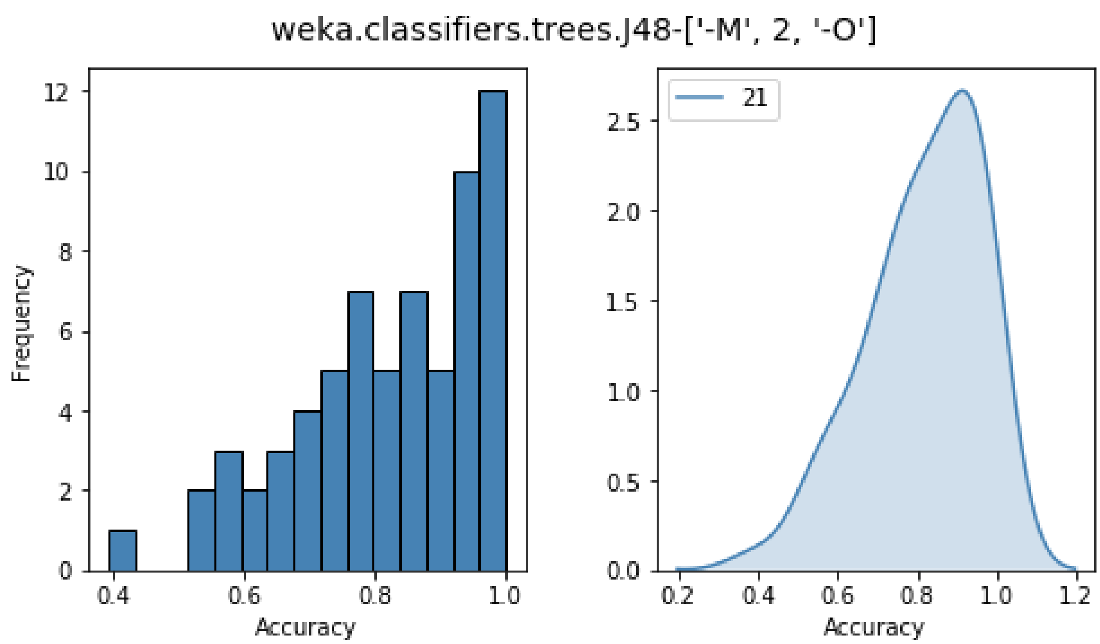


weka.classifiers.rules.JRip-['-N', 2]

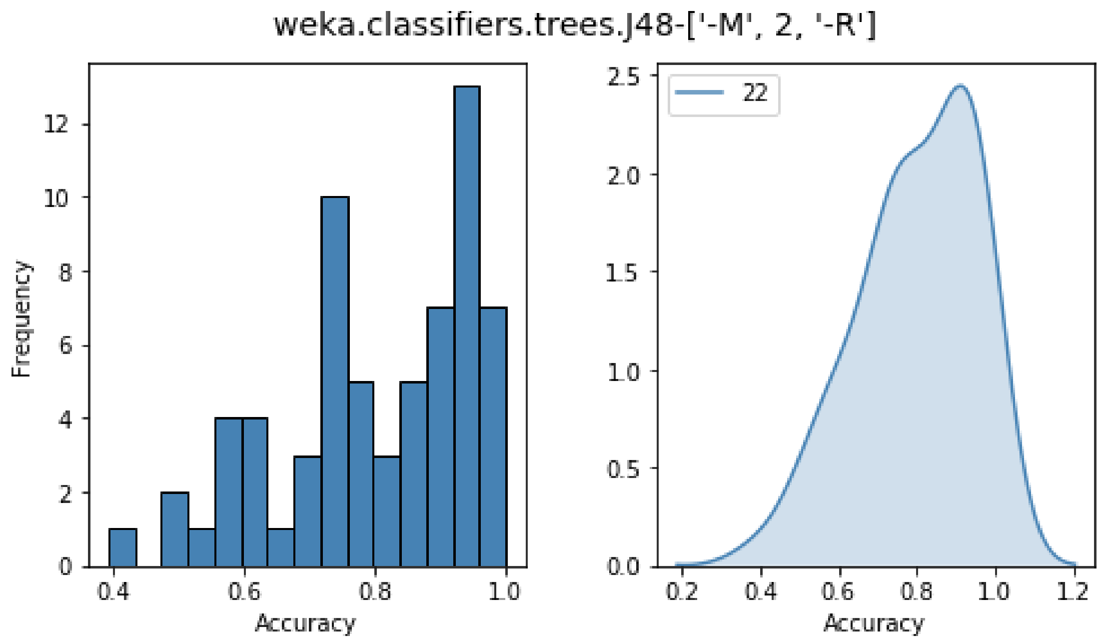


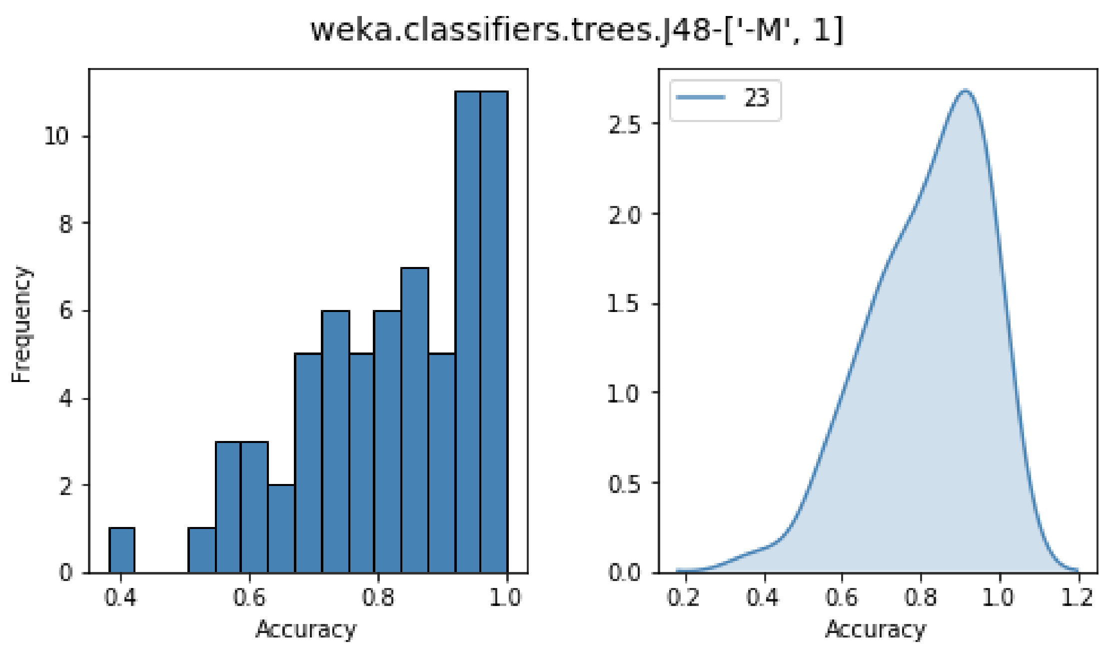


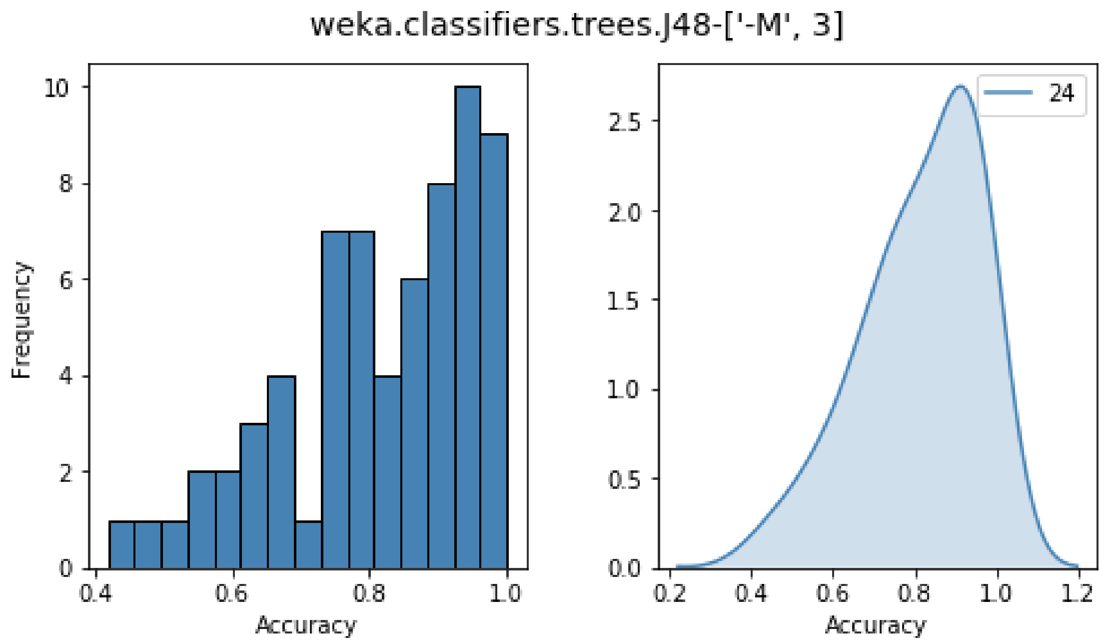
weka.classifiers.trees.J48-['-M', 2]
Frequency
Accuracy
20

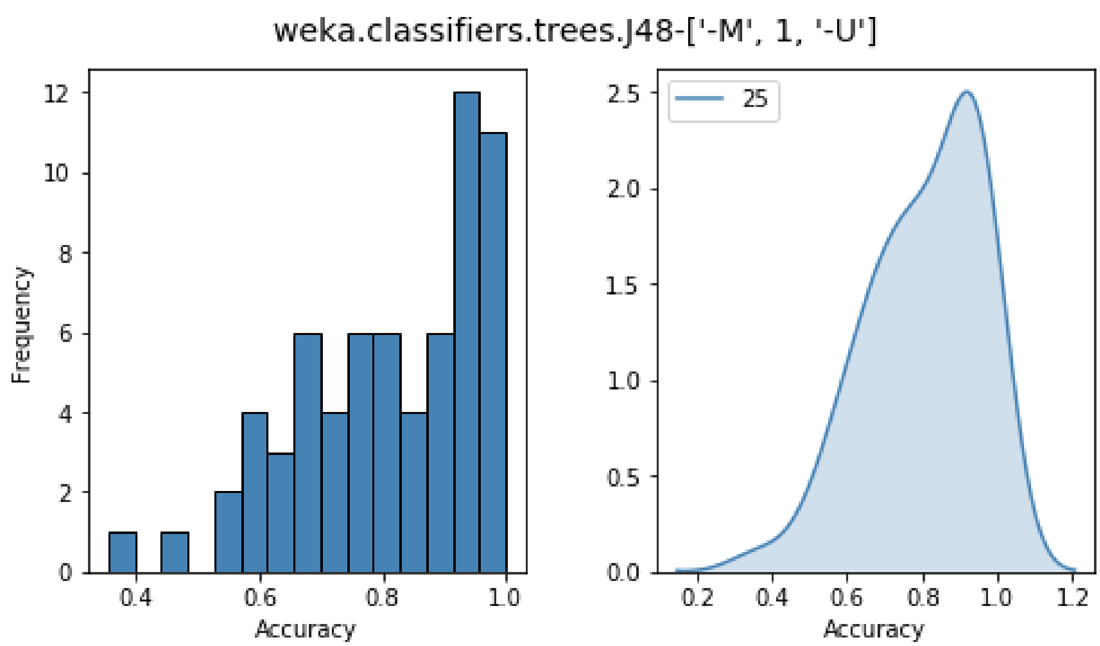


weka.classifiers.trees.J48-['-M', 2, '-O']
Frequency
Accuracy
21

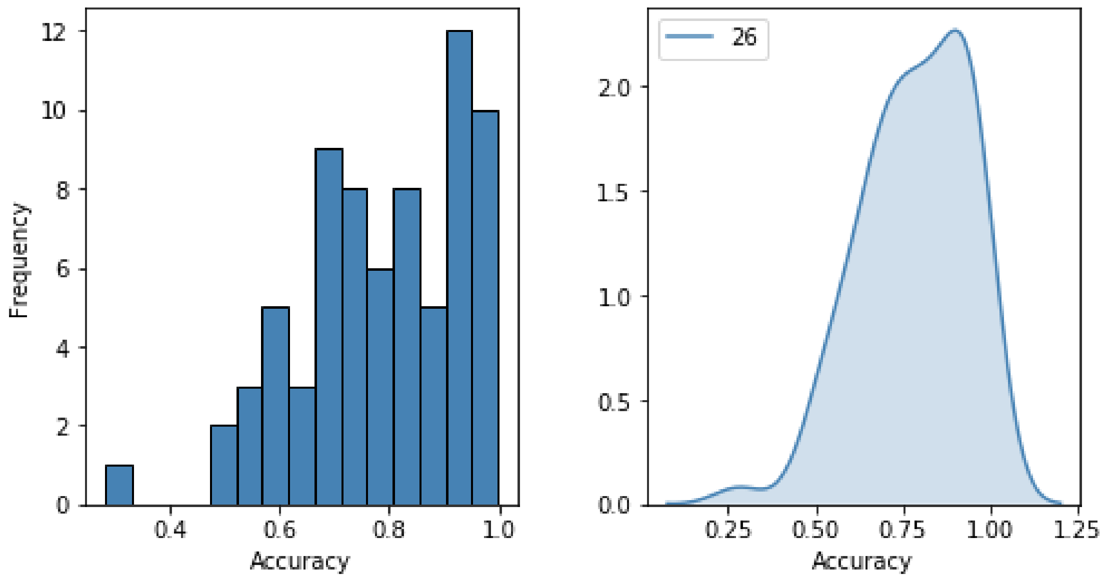

weka.classifiers.trees.J48-['-M', 2, '-R']
Frequency
Accuracy
22
0
2
4
6
8
10
12
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
2.5
0.2
1.2


weka.classifiers.trees.J48-['-M', 1]
Frequency
Accuracy
23
0
2
4
6
8
10
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
2.5
0.2
1.2

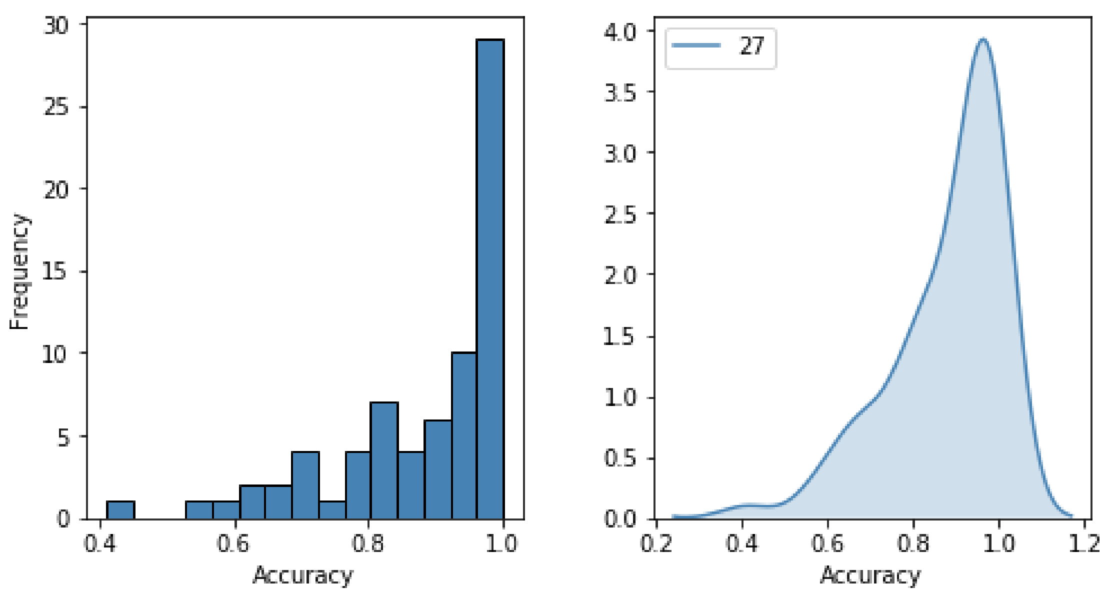

weka.classifiers.trees.J48-['-M', 3]
Frequency
Accuracy
Accuracy
24


weka.classifiers.trees.J48-['-M', 1, '-U']
Frequency
Accuracy
Accuracy
25

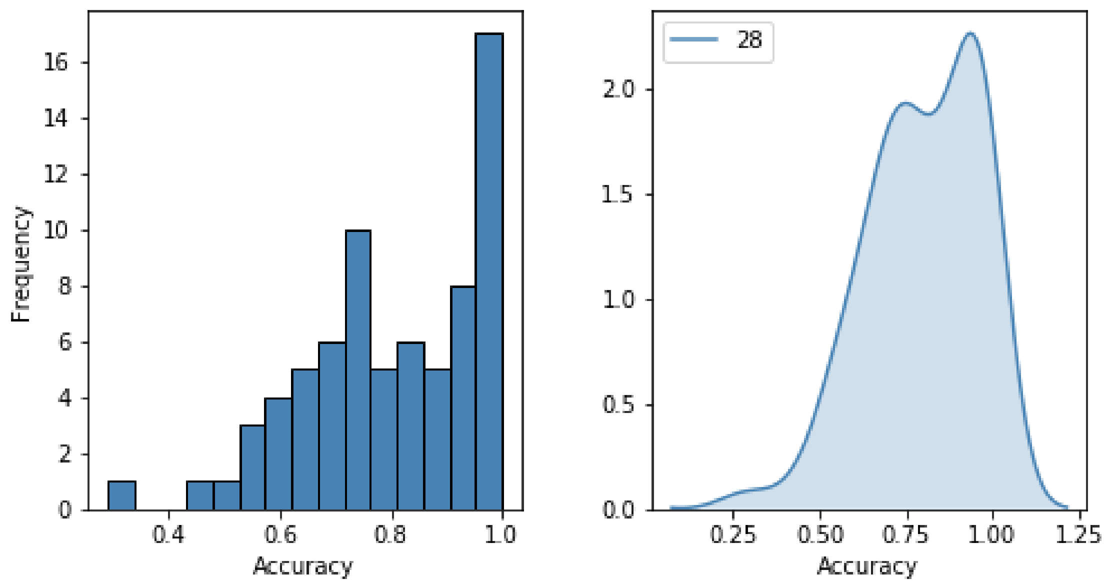
weka.classifiers.trees.RandomTree-['-K', 3]



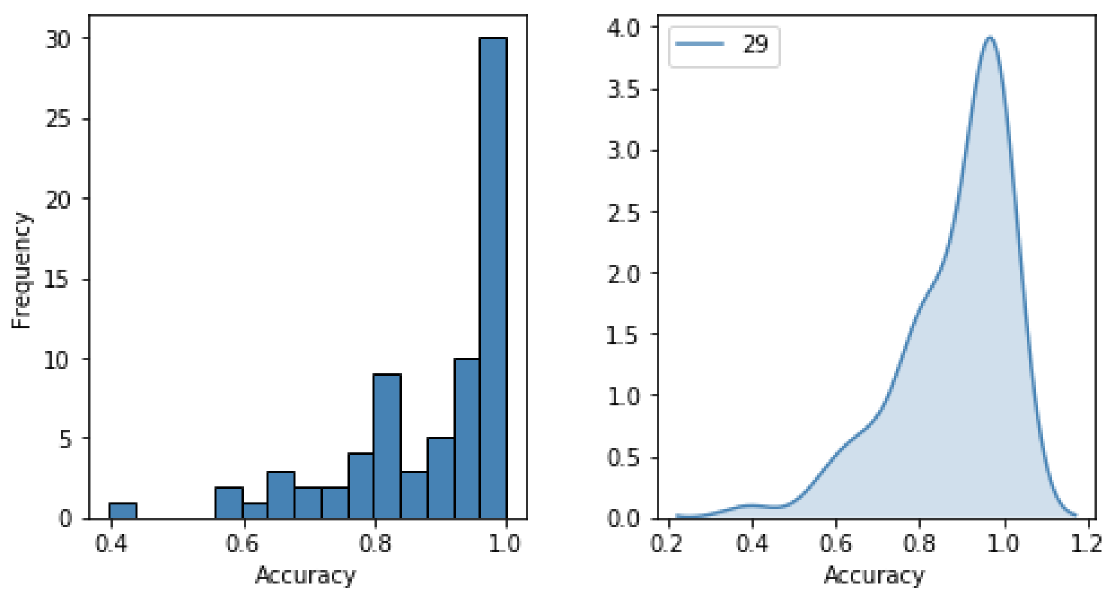
weka.classifiers.trees.RandomForest-['-K', 3]



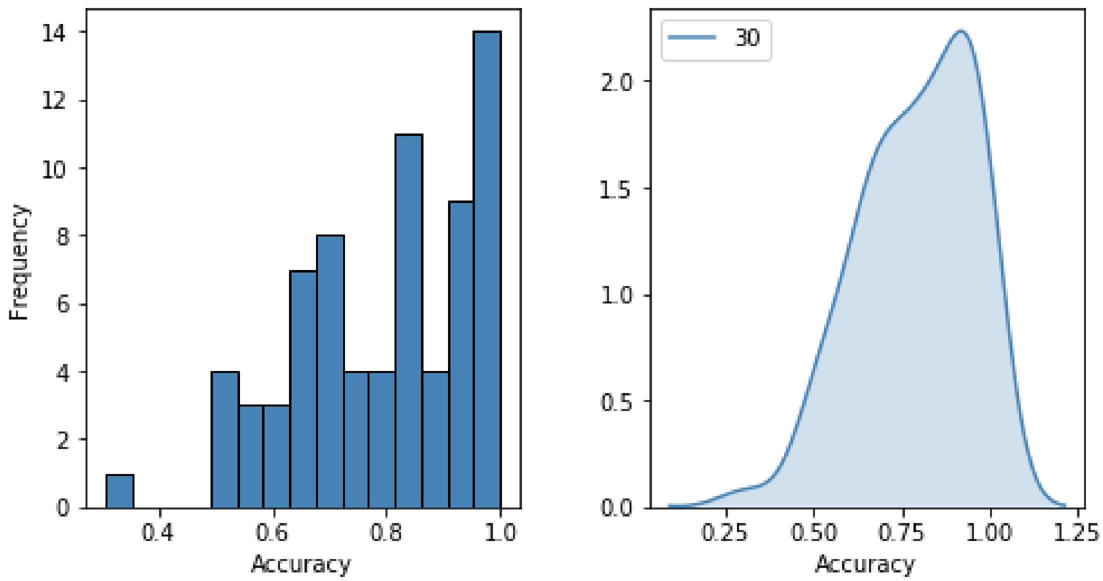
weka.classifiers.trees.RandomTree-['-K', 5]



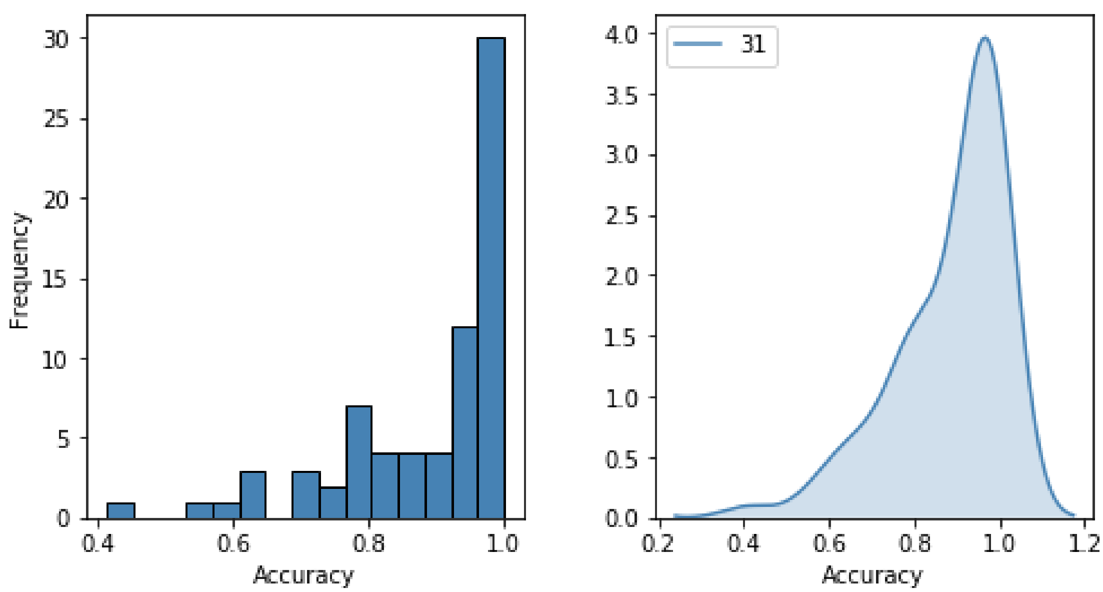
weka.classifiers.trees.RandomForest-['-K', 5]

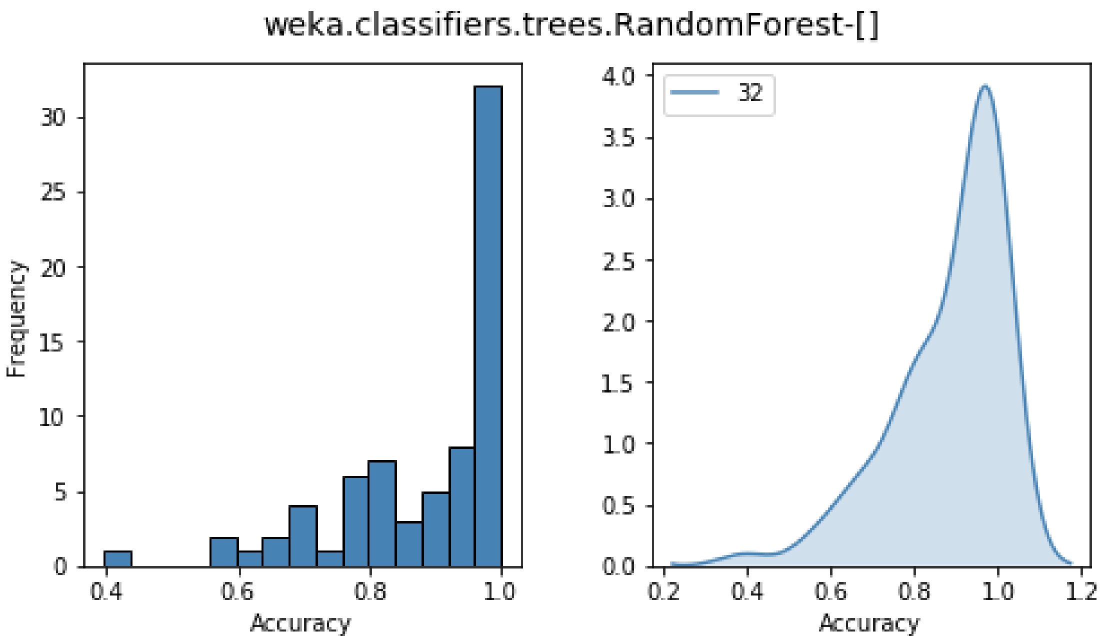


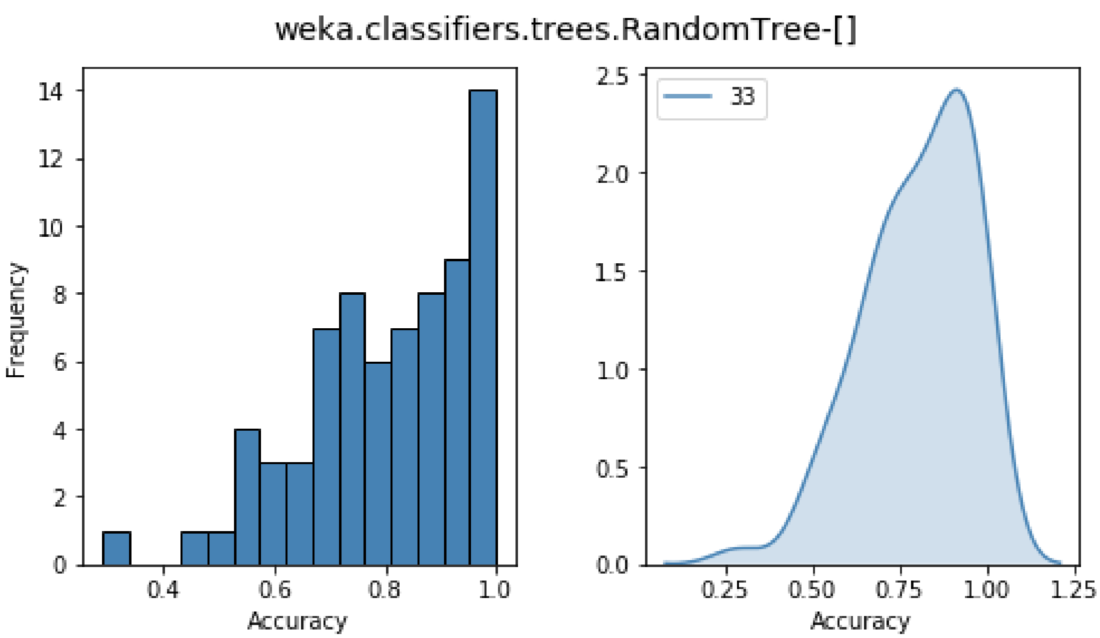
weka.classifiers.trees.RandomTree-['-K', 4]



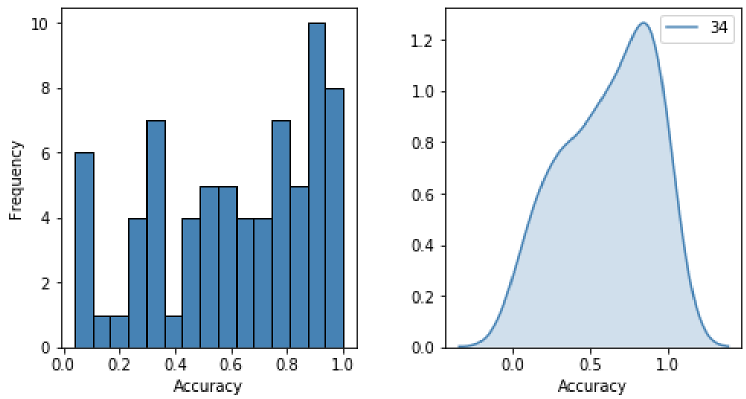
weka.classifiers.trees.RandomForest-['-K', 4]



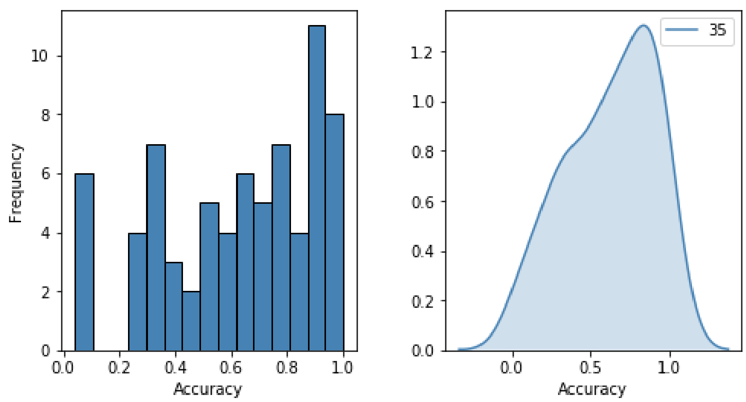

weka.classifiers.trees.RandomForest-[]
Frequency
Accuracy
32
Accuracy


weka.classifiers.trees.RandomTree-[]
Frequency
Accuracy
33
Accuracy

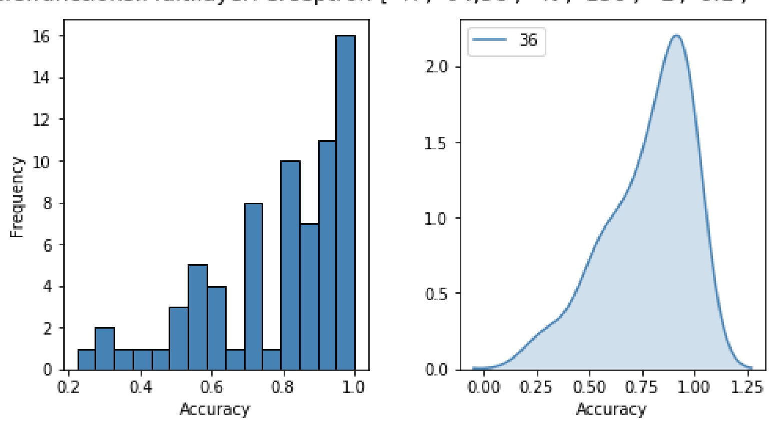
weka.classifiers.functions.MultilayerPerceptron-['-H', '24,24,12', '-N', '150', '-L', '0.1', '-V', '20', '-E', '10']



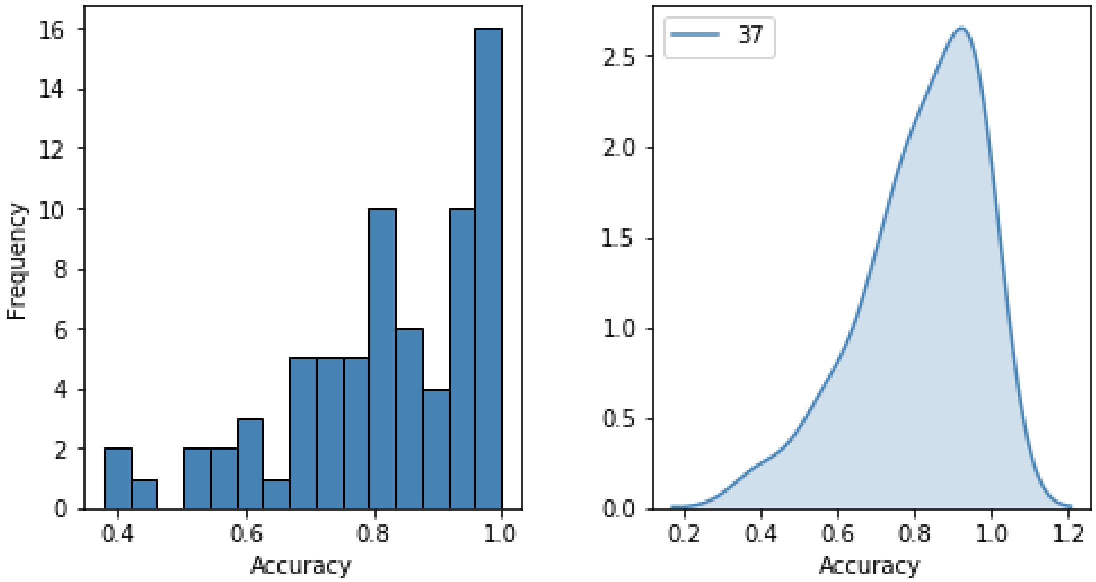
weka.classifiers.functions.MultilayerPerceptron-['-H', '24,12,12', '-N', '150', '-L', '0.1', '-V', '20', '-E', '10']



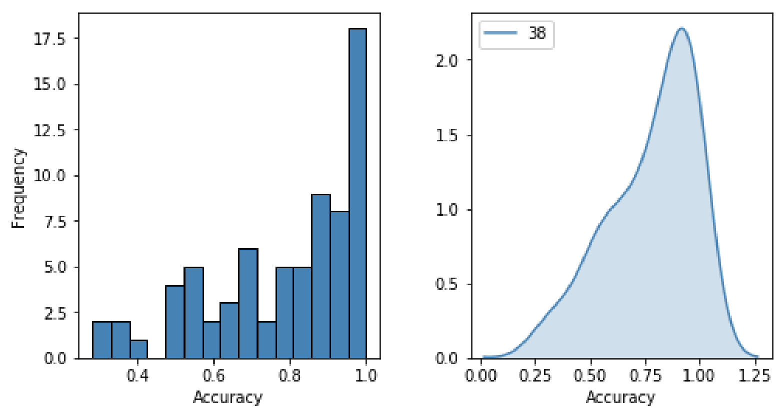
weka.classifiers.functions.MultilayerPerceptron-['-H', '64,36', '-N', '150', '-L', '0.1', '-V', '20', '-E', '10']



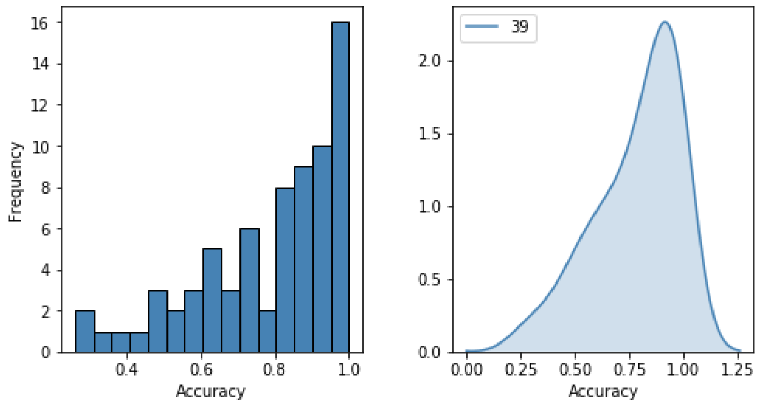
weka.classifiers.lazy.IBk-['-K', 3]



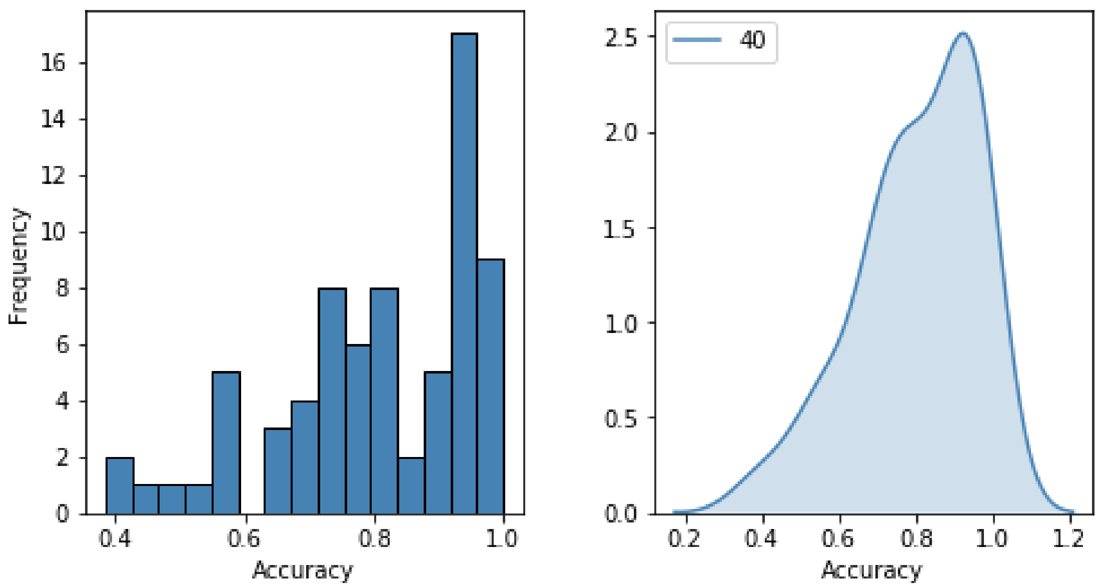
weka.classifiers.functions.MultilayerPerceptron-['-H', '72,24', '-N', '300', '-L', '0.05', '-V', '20', '-E', '10']



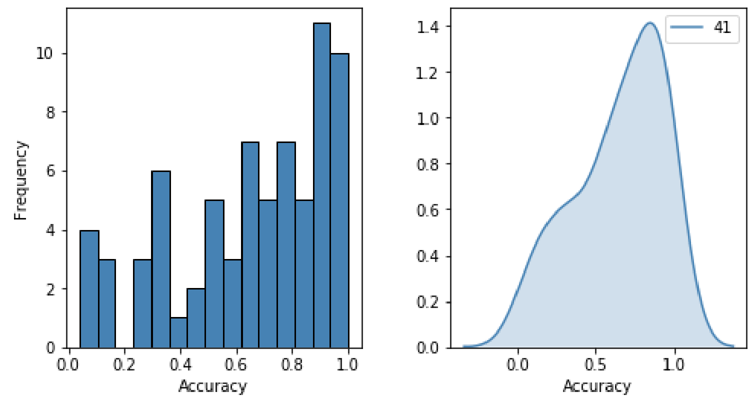
weka.classifiers.functions.MultilayerPerceptron-['-H', '100,50', '-N', '150', '-L', '0.1', '-V', '20', '-E', '10']



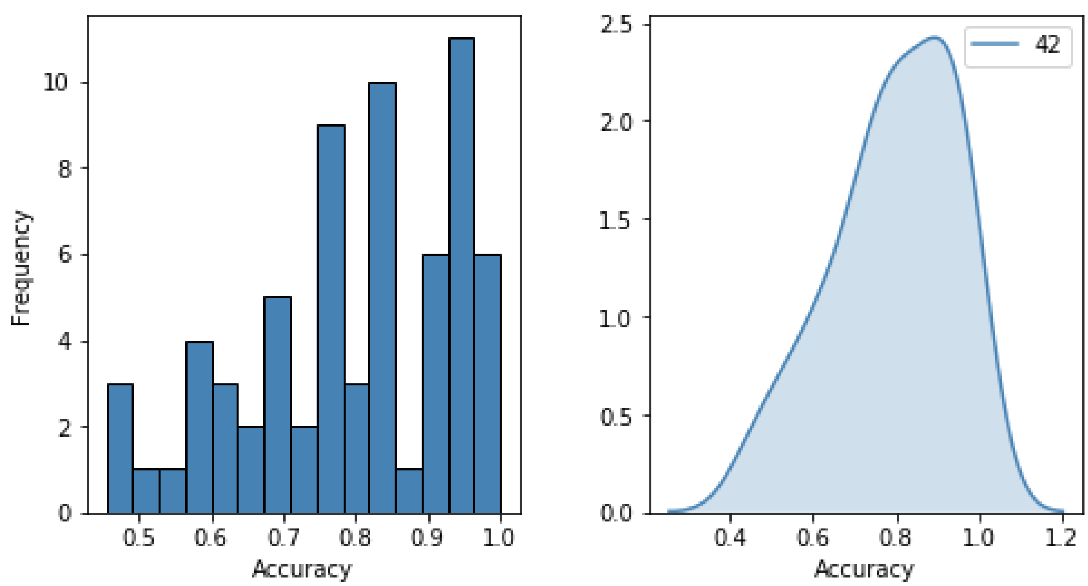
weka.classifiers.lazy.IBk-['-K', 2]



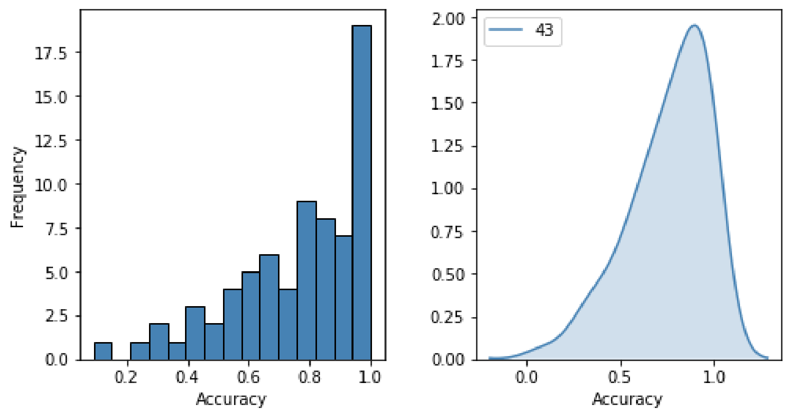
weka.classifiers.functions.MultilayerPerceptron-['-H', '24,24,24', '-N', '150', '-L', '0.1', '-V', '20', '-E', '10']



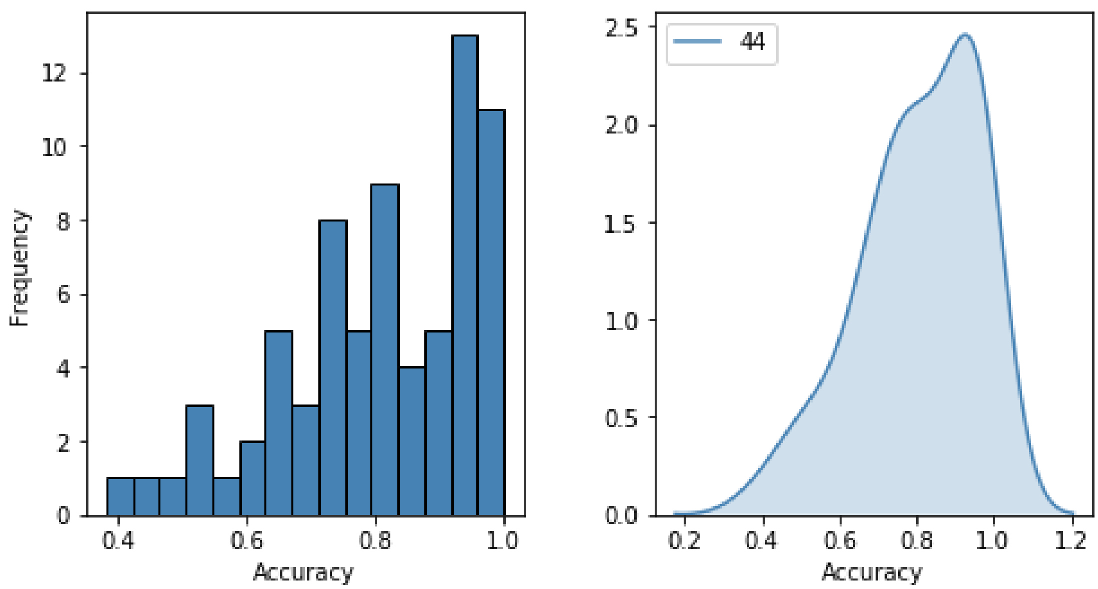
weka.classifiers.lazy.LWL-['-W', 'weka.classifiers.bayes.NaiveBayes']

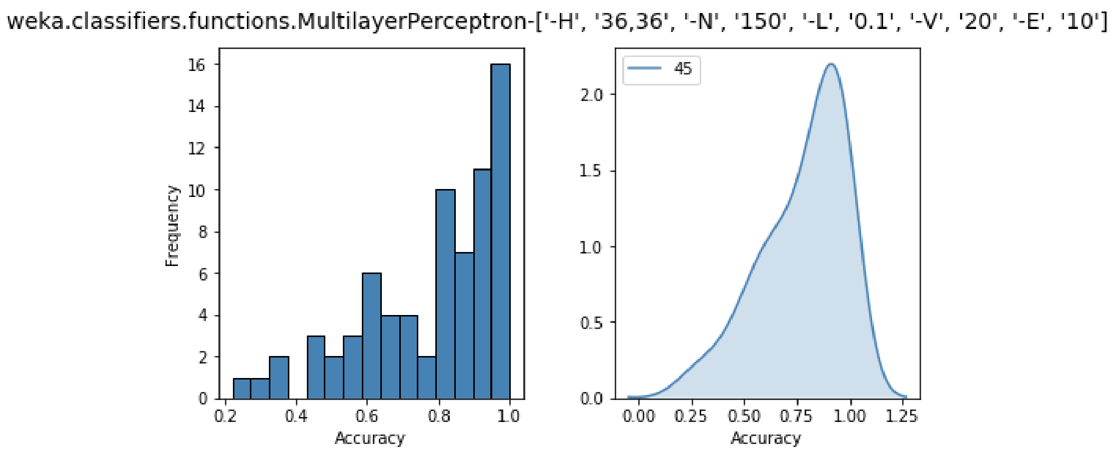


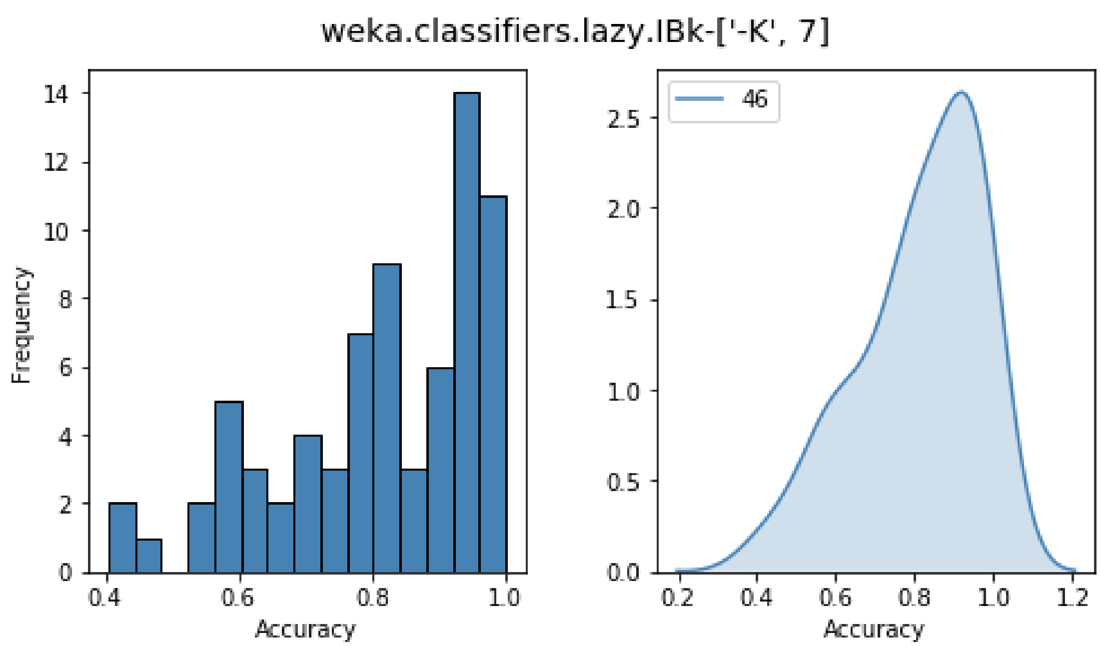
weka.classifiers.functions.MultilayerPerceptron-['-H', '24,24', '-N', '100', '-L', '0.1', '-V', '20', '-E', '10']

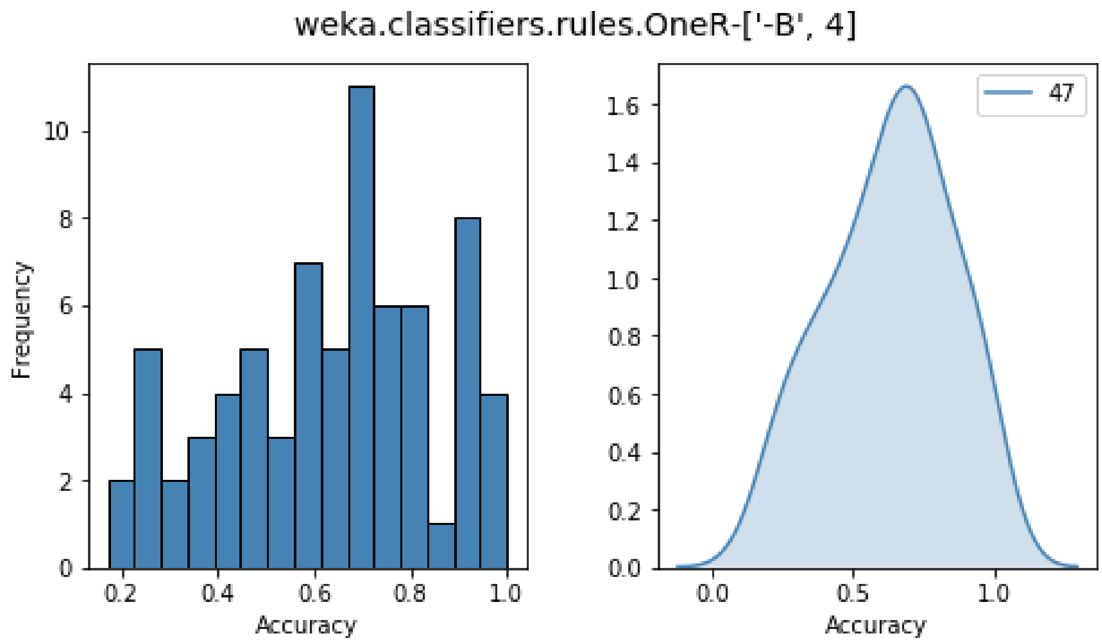


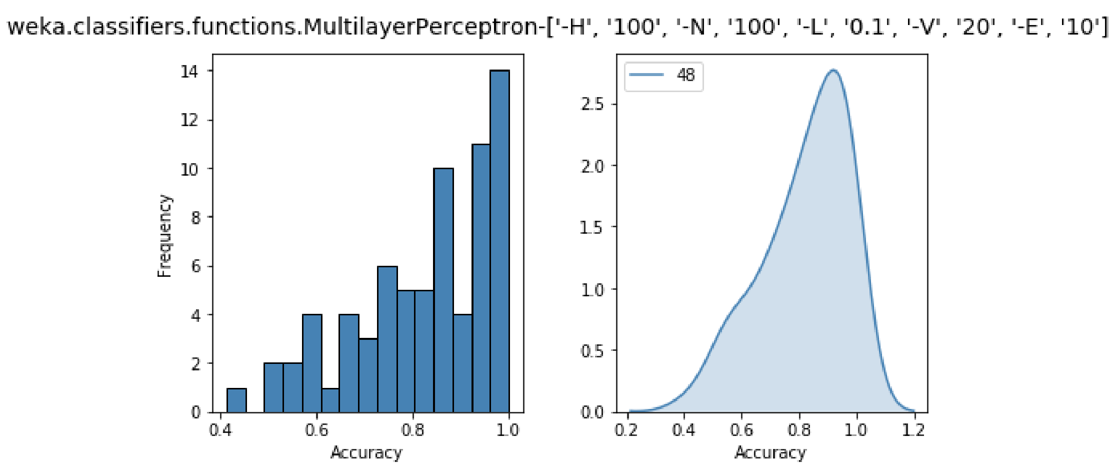
weka.classifiers.lazy.IBk-['-K', 1]

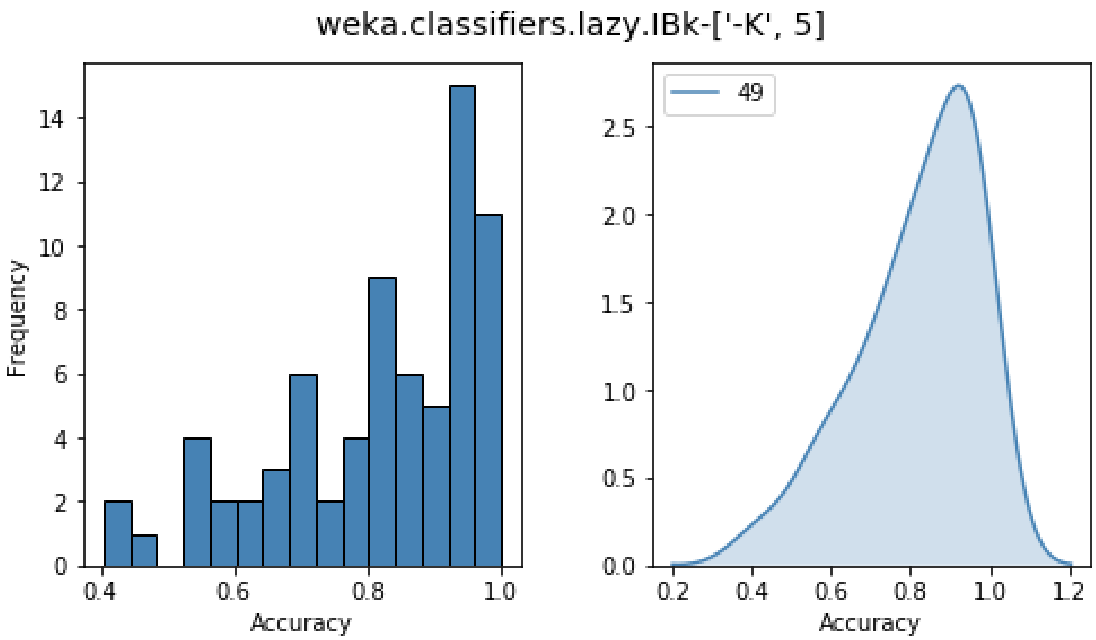


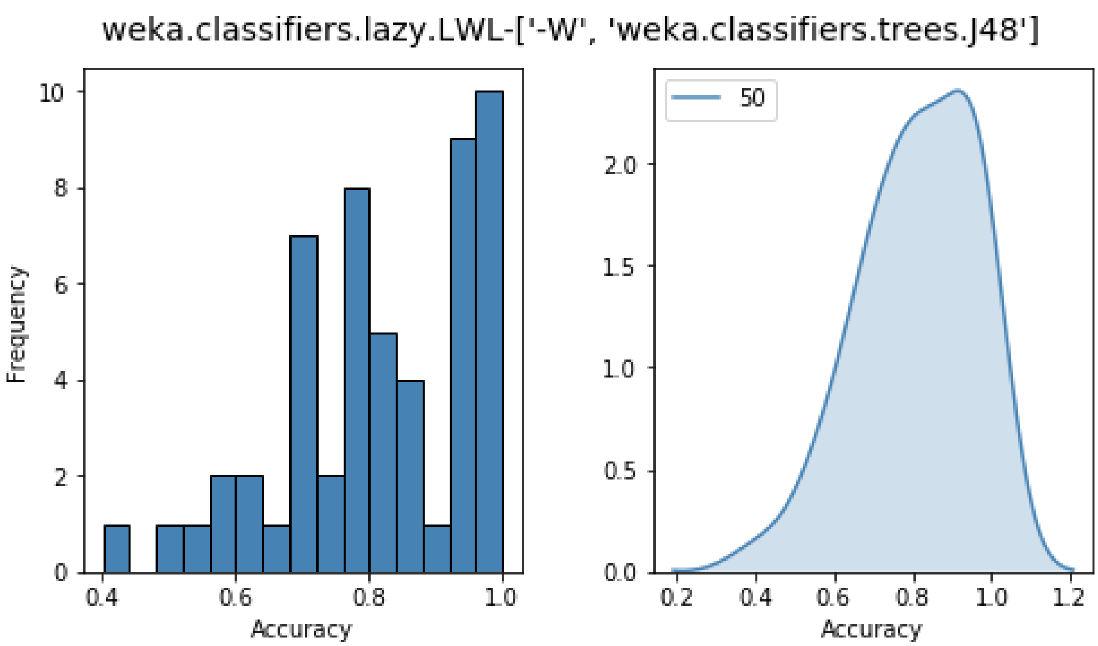

weka.classifiers.functions.MultilayerPerceptron-['-H', '36,36', '-N', '150', '-L', '0.1', '-V', '20', '-E', '10']
Frequency
Accuracy
45
Accuracy

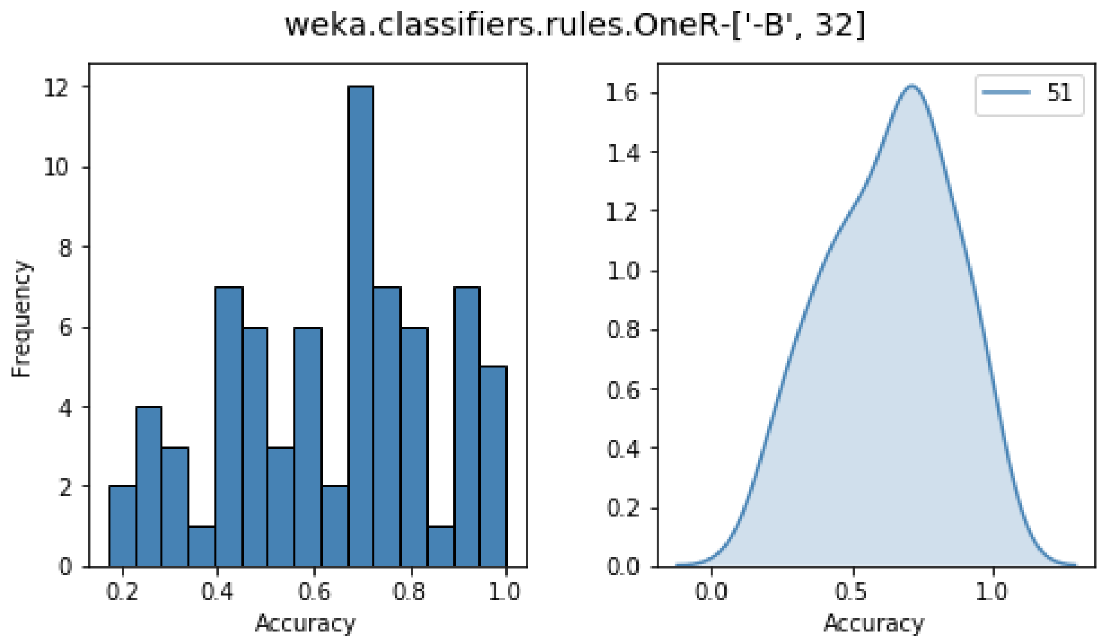

weka.classifiers.lazy.IBk-['-K', 7]
Frequency
Accuracy
46
Accuracy

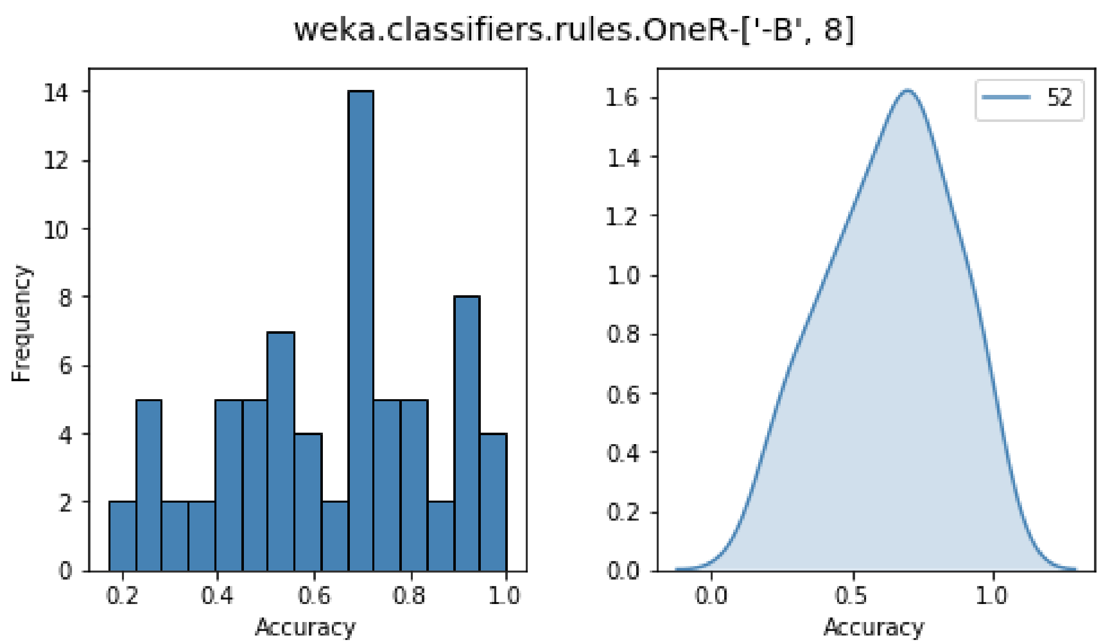

weka.classifiers.rules.OneR-['-B', 4]
Frequency
Accuracy
47
Accuracy

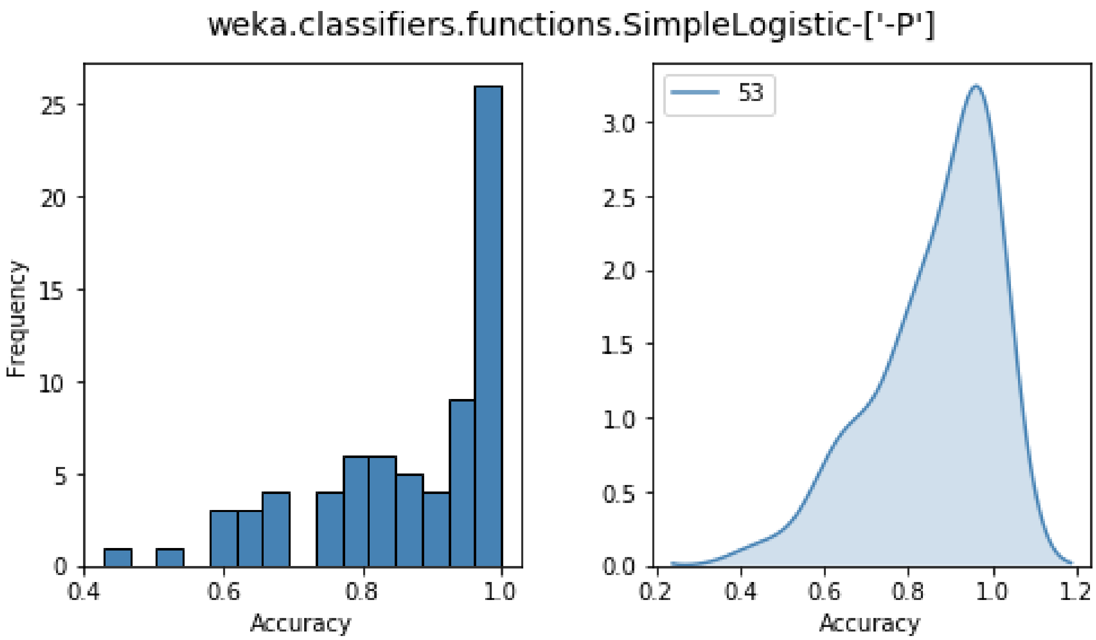

weka.classifiers.functions.MultilayerPerceptron-['-H', '100', '-N', '100', '-L', '0.1', '-V', '20', '-E', '10']
Frequency
Accuracy
48
Accuracy

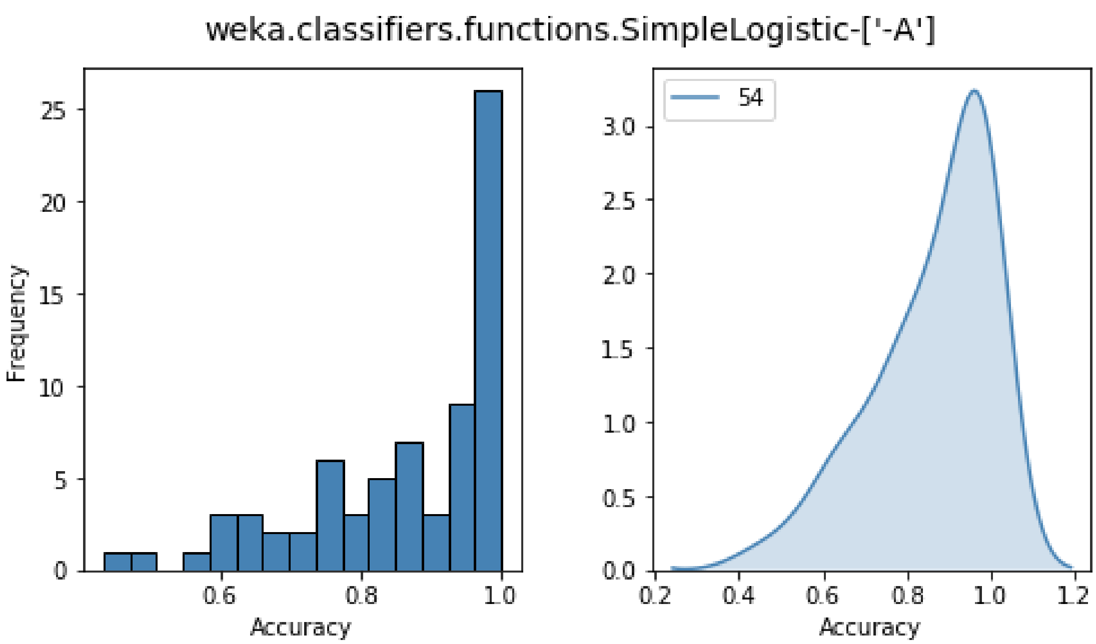

weka.classifiers.lazy.IBk-['-K', 5]
Frequency
Accuracy
49
Accuracy

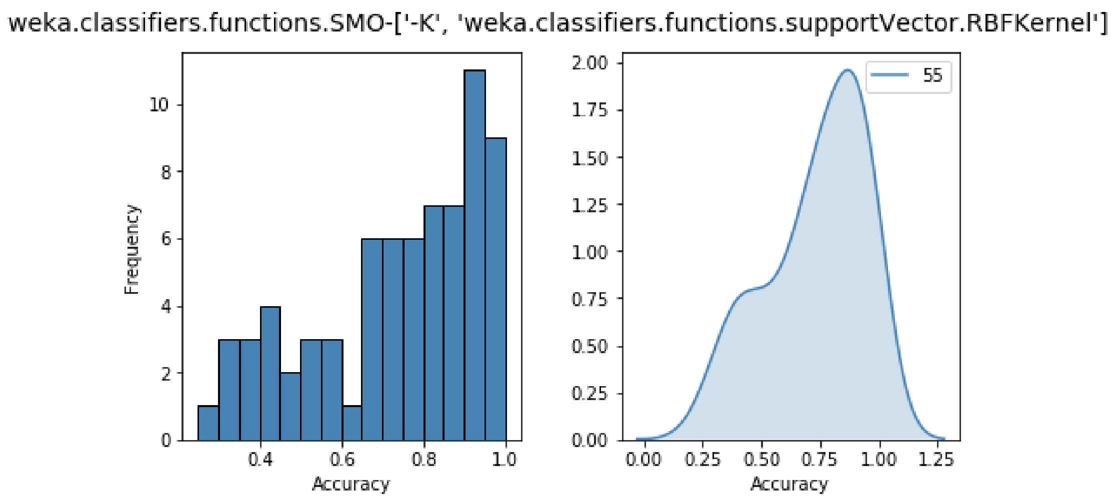

weka.classifiers.lazy.LWL-['-W', 'weka.classifiers.trees.J48']
Frequency
Accuracy
50
Accuracy

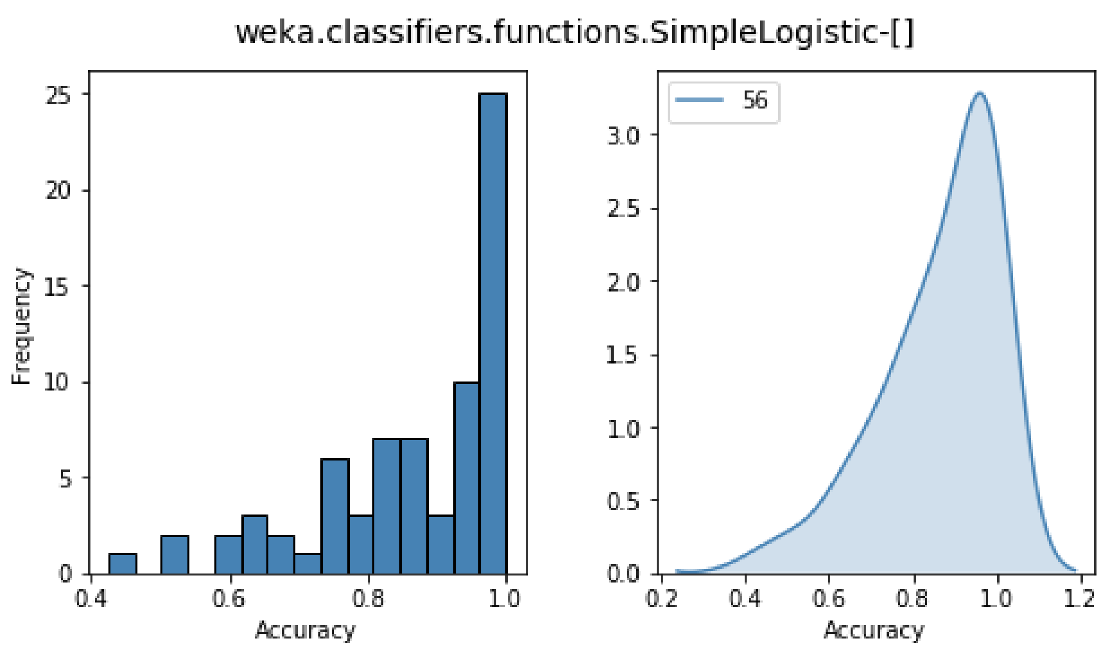

weka.classifiers.rules.OneR-['-B', 32]
Frequency
Accuracy
51
Accuracy


weka.classifiers.rules.OneR-['-B', 8]
Frequency
Accuracy
52
Accuracy

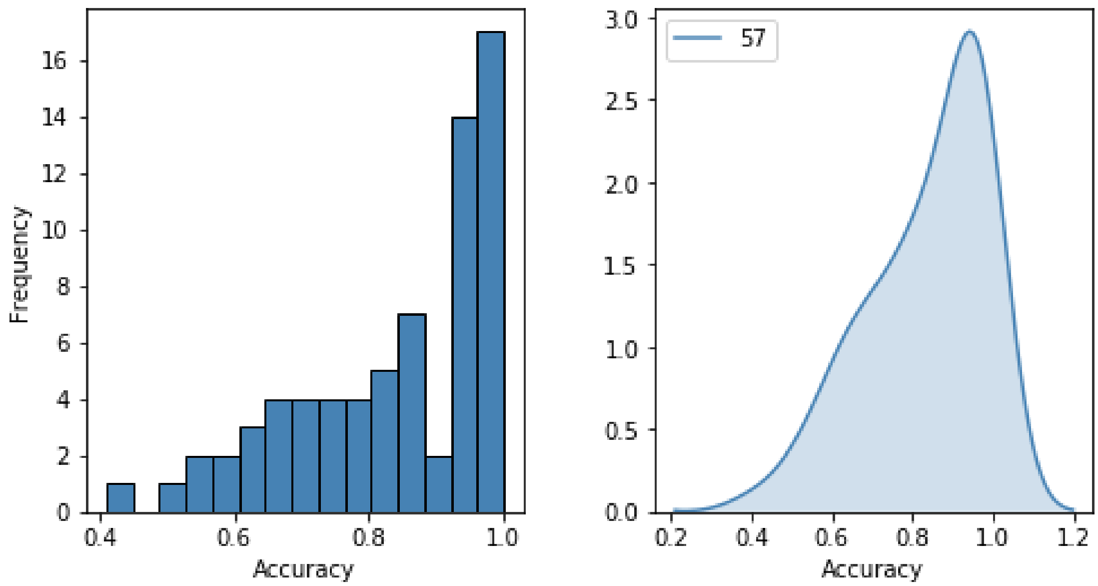

weka.classifiers.functions.SimpleLogistic-['-P']
Frequency
Accuracy
53
Accuracy


weka.classifiers.functions.SimpleLogistic-['-A']
Frequency
Accuracy
54
Accuracy

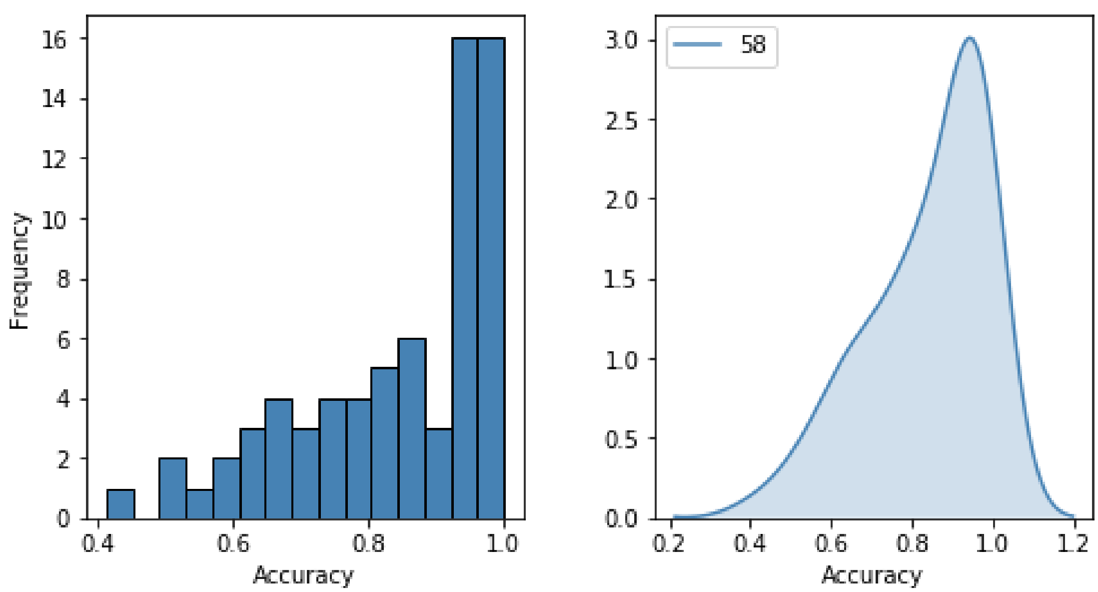

weka.classifiers.functions.SMO-['-K', 'weka.classifiers.functions.supportVector.RBFKernel']
Frequency
0
2
4
6
8
10
0.4
0.6
0.8
1.0
Accuracy
55
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0.00
0.25
0.50
0.75
1.00
1.25
Accuracy

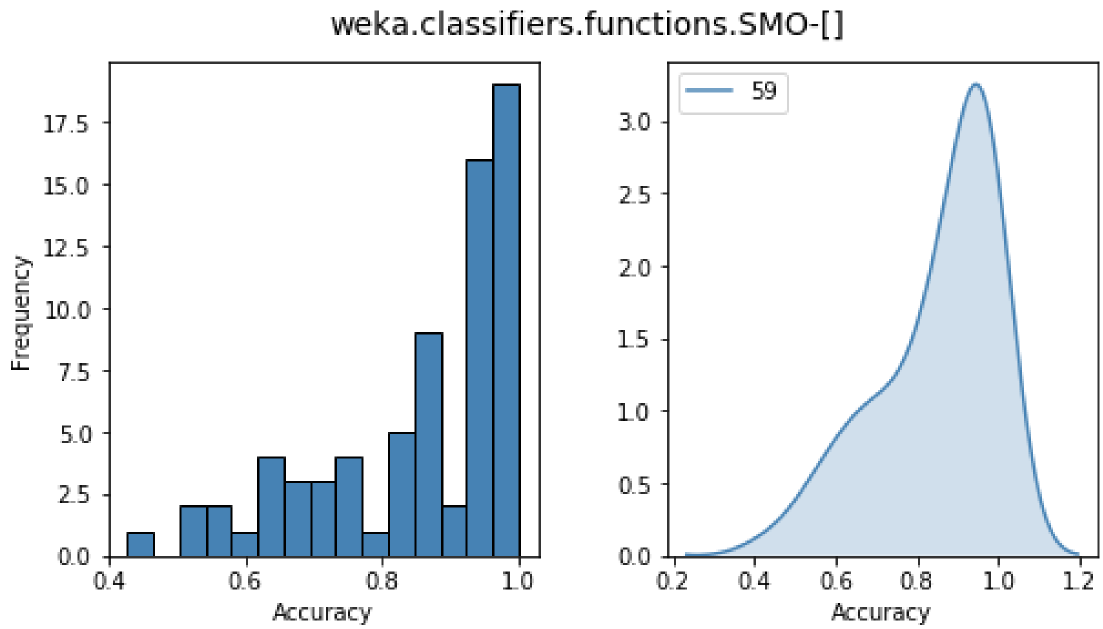

weka.classifiers.functions.SimpleLogistic-[]
Frequency
0
5
10
15
20
25
0.4
0.6
0.8
1.0
Accuracy
56
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.2
0.4
0.6
0.8
1.0
1.2
Accuracy

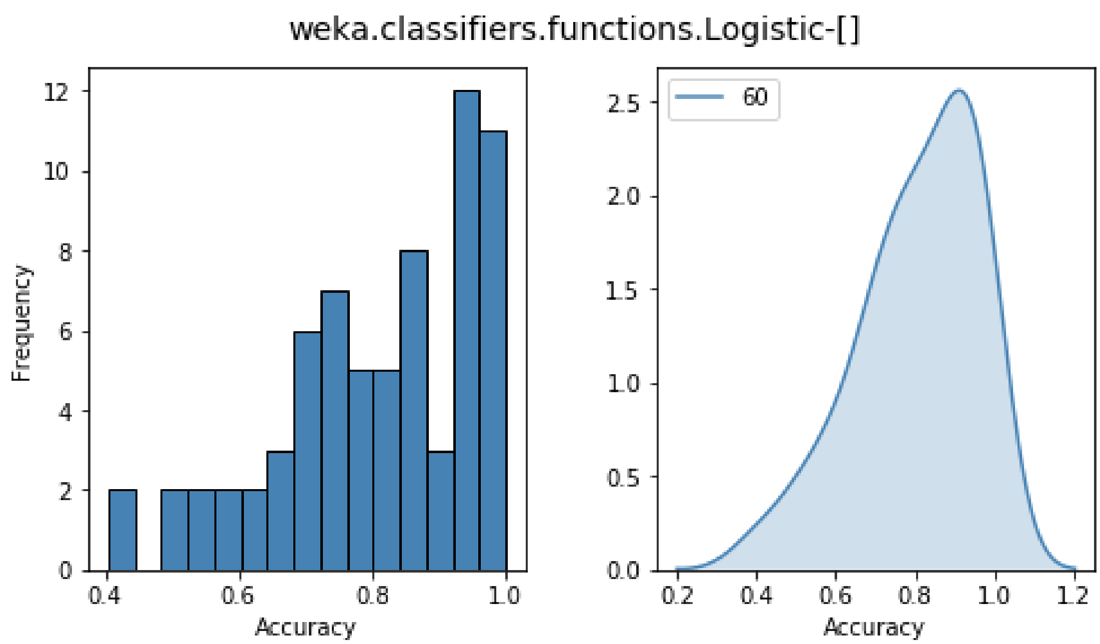
weka.classifiers.functions.Logistic-['-M', 100]

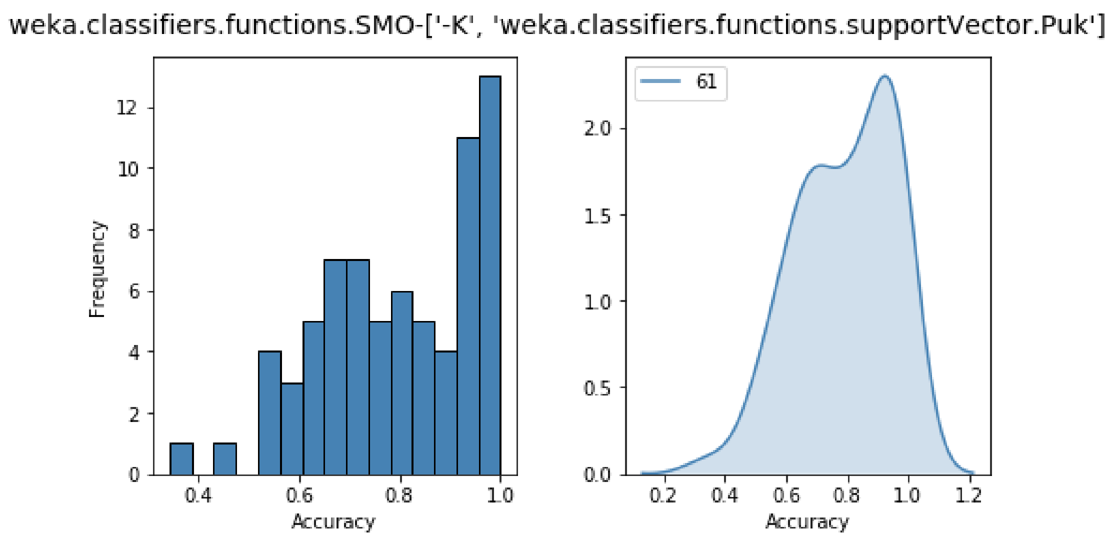


weka.classifiers.functions.Logistic-['-M', 300]




weka.classifiers.functions.SMO-[]
Frequency
Accuracy
59
Accuracy


weka.classifiers.functions.Logistic-[]
Frequency
Accuracy
60
Accuracy



4.0.1 Top 10 best algorithms

In [15]:
```
# add a new colum 'mean' in data_algo
data_algo['mean'] = data_algo.mean(axis=1).copy()
data_algo.sort_values(by='mean', ascending = False).head(10)
```

Out[15]:

	clf name & configuration	AP	MagicTelescope	\
31	weka.classifiers.trees.RandomForest-['-K', 4]	0.9402	0.9999	
32	weka.classifiers.trees.RandomForest-[]	0.9573	0.9999	
29	weka.classifiers.trees.RandomForest-['-K', 5]	0.9338	0.9999	
27	weka.classifiers.trees.RandomForest-['-K', 3]	0.9231	0.9999	
56	weka.classifiers.functions.SimpleLogistic-[]	0.9530	0.9999	
53	weka.classifiers.functions.SimpleLogistic-['-P']	0.9487	0.9999	
7	weka.classifiers.bayes.BayesNet-['-Q', 'weka.c...	NaN	NaN	
4	weka.classifiers.bayes.BayesNet-['-Q', 'weka.c...	NaN	NaN	
6	weka.classifiers.bayes.BayesNet-['-Q', 'weka.c...	NaN	0.9999	
14	weka.classifiers.rules.PART-['-C', 0.15, '-M', 2]	0.9380	0.9999	

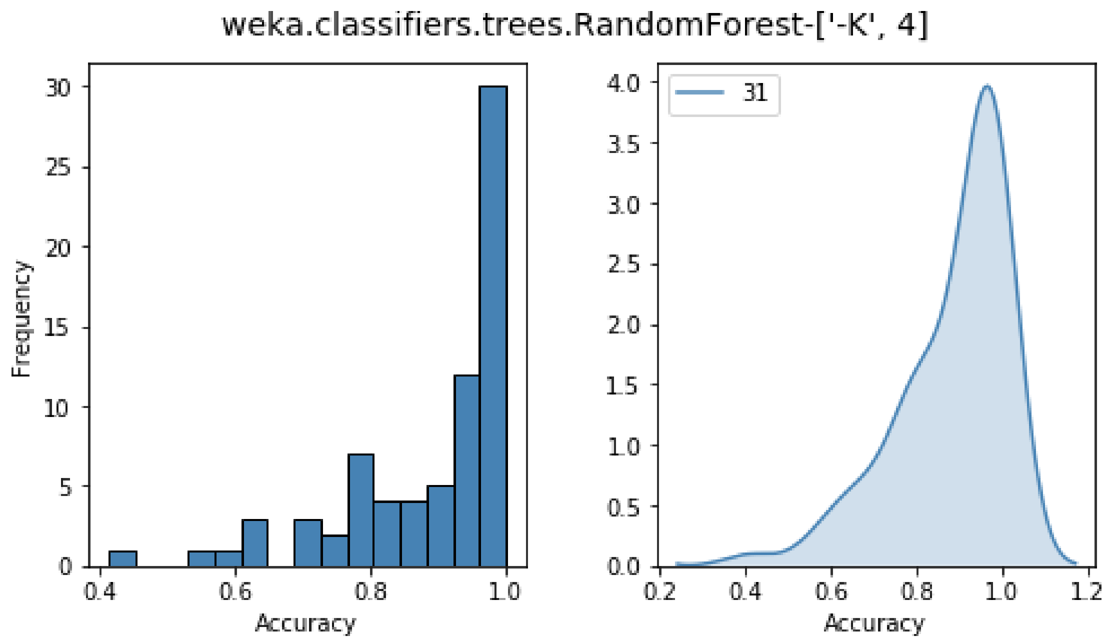
	abalone	anneal	ar1	arrhythmia	audiology	autos	badges2	...	\
31	0.6902	0.8886	0.9008	0.6460	0.7788	0.8634	1.0	...	
32	0.6902	0.9053	0.9008	0.6615	0.7920	0.8439	1.0	...	
29	0.6864	0.9053	0.9008	0.6527	0.7699	0.8439	1.0	...	
27	0.6895	0.8775	0.9008	0.6239	0.7965	0.8293	1.0	...	
56	0.6514	0.8797	0.9174	0.7434	0.8186	0.7366	1.0	...	
53	0.6533	0.8842	0.9091	0.6748	0.8274	0.7463	1.0	...	
7	0.6761	0.9432	0.9256	NaN	NaN	0.7707	1.0	...	
4	0.6775	0.9432	0.9256	NaN	NaN	0.7854	1.0	...	
6	0.6790	0.9265	0.9256	NaN	NaN	0.8293	1.0	...	
14	0.6378	0.9087	0.9008	0.6504	0.7965	0.8146	1.0	...	

```
    spambase  splice  teachingAssistant  tic-tac-toe    vote   vowel  \
31    0.9972  0.9868             0.5629        1.000  0.9632  0.9758
32    0.9993  0.9909             0.5629        1.000  0.9655  0.9758
29    0.9980  0.9931             0.5828        1.000  0.9655  0.9727
27    0.9950  0.9705             0.5629        1.000  0.9609  0.9798
56    0.9993  0.9987             0.5166        1.000  0.9678  0.8212
53    0.9991  0.9994             0.5960        1.000  0.9747  0.8404
7        NaN     NaN             0.9272        0.999  0.9563  0.7828
4        NaN     NaN             0.9205        0.999  0.9563  0.8303
6        NaN     NaN             0.8940        0.999  0.9517  0.7495
14    0.9996  0.9994             0.4172        0.999  0.9609  0.7576

    waveform-5000   yeast     zoo      mean
31         0.8482  0.6442  0.9406  0.885219
32         0.8500  0.6442  0.9208  0.884717
29         0.8510  0.6496  0.9208  0.884462
27         0.8476  0.6516  0.9406  0.880458
56         0.8688  0.5970  0.9208  0.865376
53         0.8662  0.5937  0.9109  0.865126
7             NaN  0.6024     NaN  0.865083
4             NaN  0.6024     NaN  0.864308
6             NaN  0.6004  0.9505  0.863352
14         0.7816  0.5748  0.9109  0.862190

[10 rows x 74 columns]
```

We try to review the algorithm id 31

In [16]:
```
algorithm_best = data_algo.sort_values(by='mean', ascending = False).head(1)
algorithm_best.reset_index(drop=True)

fig = plt.figure(figsize=(8, 4))
title = fig.suptitle(algorithm_best.iloc[0,0], fontsize=14)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = fig.add_subplot(1,2,1)
ax.set_xlabel('Accuracy')
ax.set_ylabel('Frequency')
freq, bins, patches = ax.hist(algorithm_best.iloc[0,1:].astype('float64'),
                              color='steelblue', bins=15,
                              edgecolor='black', linewidth=1 )
# Density Plot
fig.subplots_adjust(top=0.9, wspace=0.3)
ax1 = fig.add_subplot(1,2,2)
ax1.set_xlabel('Accuracy')
sns.kdeplot(algorithm_best.iloc[0,1:].astype('float64'),
            ax=ax1, shade=True, color='steelblue')
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8d3bae2588>
```



This algorithm clearly give quite high accuracy score results for multiple datasets. And we'd like to review what these datasets in below analysis.

In [17]:
```
algorithm_best.iloc[0,1:].astype('float64').sort_values(ascending=False).head(10)
```

Out[17]:
```
car-evaluation          1.0000
badges2                 1.0000
heart-h                 1.0000
tic-tac-toe             1.0000
mushroom                1.0000
MagicTelescope          0.9999
kropt                   0.9990
kr-vs-kp                0.9984
spambase                0.9972
mfeat-morphological     0.9960
Name: 31, dtype: float64
```

It includes 'car-evaluation', 'badges2', 'heart-h', 'tic-tac-toe', 'mushroom' . . .

4.1 Top 10 worst algorithm

In [18]:
```
algorithm_worst = data_algo.sort_values(by='mean', ascending = True)
algorithm_worst.reset_index(drop=True).head(10)
```

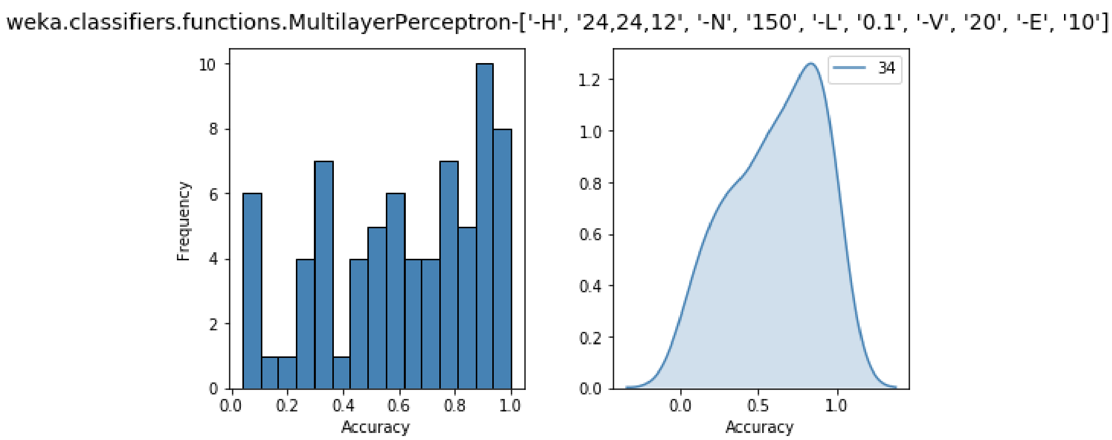
Out[18]:
```
                         clf name & configuration      AP  MagicTelescope  \
0  weka.classifiers.functions.MultilayerPerceptro...  0.9017          0.8644
1  weka.classifiers.functions.MultilayerPerceptro...  0.9017          0.8645
```

```
2              weka.classifiers.rules.OneR-['-B', 4]  0.9380          0.7011
3             weka.classifiers.rules.OneR-['-B', 32]  0.9081          0.7344
4              weka.classifiers.rules.OneR-['-B', 8]  0.9380          0.7160
5  weka.classifiers.functions.MultilayerPerceptro...  0.9124          0.8636
6  weka.classifiers.functions.SMO-['-K', 'weka.cl...  0.8932          0.7797
7  weka.classifiers.functions.MultilayerPerceptro...  0.9573          0.8623
8  weka.classifiers.functions.MultilayerPerceptro...  0.9530          0.8629
9  weka.classifiers.functions.MultilayerPerceptro...  0.9615          0.8631

   abalone  anneal     ar1  arrhythmia  audiology   autos  badges2  ...  \
0   0.6586  0.7617  0.9256      0.5420     0.2522  0.3268      1.0  ...
1   0.6565  0.7617  0.9256      0.5420     0.2522  0.3268      1.0  ...
2   0.5360  0.7962  0.9008      0.5774     0.4646  0.6537      1.0  ...
3   0.5942  0.7984  0.9008      0.5973     0.4646  0.5024      1.0  ...
4   0.5976  0.7984  0.9008      0.5774     0.4646  0.5463      1.0  ...
5   0.6591  0.7684  0.9256      0.5420     0.2522  0.3268      1.0  ...
6   0.5365  0.7617  0.9256      0.5420     0.4115  0.4341      1.0  ...
7   0.6526  0.7895  0.9256      0.5619     0.4469  0.4146      1.0  ...
8   0.6634  0.7984  0.9256      0.5597     0.5044  0.4780      1.0  ...
9   0.6596  0.8018  0.9256      0.5619     0.5221  0.4634      1.0  ...

   spambase  splice  teachingAssistant  tic-tac-toe    vote   vowel  \
0    0.8142  0.7172             0.3245       0.9144  0.8943  0.0909
1    0.8792  0.7028             0.3245       0.9165  0.8943  0.0909
2    0.7814  0.2436             0.4106       0.6994  0.9517  0.3242
3    0.7824  0.2436             0.4106       0.6994  0.9517  0.3121
4    0.7877  0.2436             0.4106       0.6994  0.9517  0.3172
5    0.8815  0.7129             0.3311       0.9154  0.8943  0.0909
6    0.7307  0.9611             0.3444       0.7296  0.9425  0.3394
7    0.8809  0.7796             0.3311       0.9843  0.9724  0.0909
8    0.8839  0.9097             0.3642       0.9875  0.9655  0.2212
9    0.8837  0.9414             0.3510       0.9791  0.9655  0.2232

   waveform-5000   yeast     zoo      mean
0         0.8600  0.3032  0.4059  0.611131
1         0.8614  0.3032  0.4059  0.623119
2         0.5132  0.3989  0.4257  0.631311
3         0.5522  0.3989  0.4257  0.632349
4         0.5446  0.4036  0.4257  0.633414
5         0.8598  0.3053  0.4059  0.647819
6         0.8506  0.3120  0.6733  0.733497
7         0.8620  0.4178  0.5743  0.758228
8         0.8634  0.4730  0.5941  0.778429
9         0.8564  0.5101  0.6139  0.779356

[10 rows x 74 columns]
```

```
In [19]: fig = plt.figure(figsize=(8, 4))
```

```
title = fig.suptitle(algorithm_worst.iloc[0,0], fontsize=14)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = fig.add_subplot(1,2,1)
ax.set_xlabel('Accuracy')
ax.set_ylabel('Frequency')
freq, bins, patches = ax.hist(algorithm_worst.iloc[0,1:].astype('float64'),
                              color='steelblue', bins=15,
                              edgecolor='black', linewidth=1 )
# Density Plot
fig.subplots_adjust(top=0.9, wspace=0.3)
ax1 = fig.add_subplot(1,2,2)
ax1.set_xlabel('Accuracy')
sns.kdeplot(algorithm_worst.iloc[0,1:].astype('float64'),
            ax=ax1, shade=True, color='steelblue')
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8d3ce7f320>



In [20]: `algorithm_worst.iloc[0,1:].astype('float64').sort_values(ascending=True).head(10)`

Out[20]:
```
letter                 0.0394
vowel                  0.0909
mfeat-zernike          0.1000
mfeat-fourier          0.1000
mfeat-morphological    0.1000
mfeat-karhunen         0.1000
mfeat-factors          0.1460
soybean                0.1947
primary-tumor          0.2478
audiology              0.2522
Name: 34, dtype: float64
```

The average accuracy result is about 0.6, the dataset 'letter' has too bad accuracy result (0.0394). Clearly, this is a bad algorithm.

5 III. Analyze each parameter for each algorithm

For each algorithm, we have the corresponding parameter. We'll analyze it and at the end of this part, we will summarize it.

5.1 1. Bayes

In [21]:
```
# Analysis for each algorithms with each parametre
# Example: weka.classifiers.bayes.BayesNet
BayesNet = data_algo[data_algo['clf name & configuration']
                    .str.contains('^weka.classifiers.bayes.BayesNet-*')].copy()
```

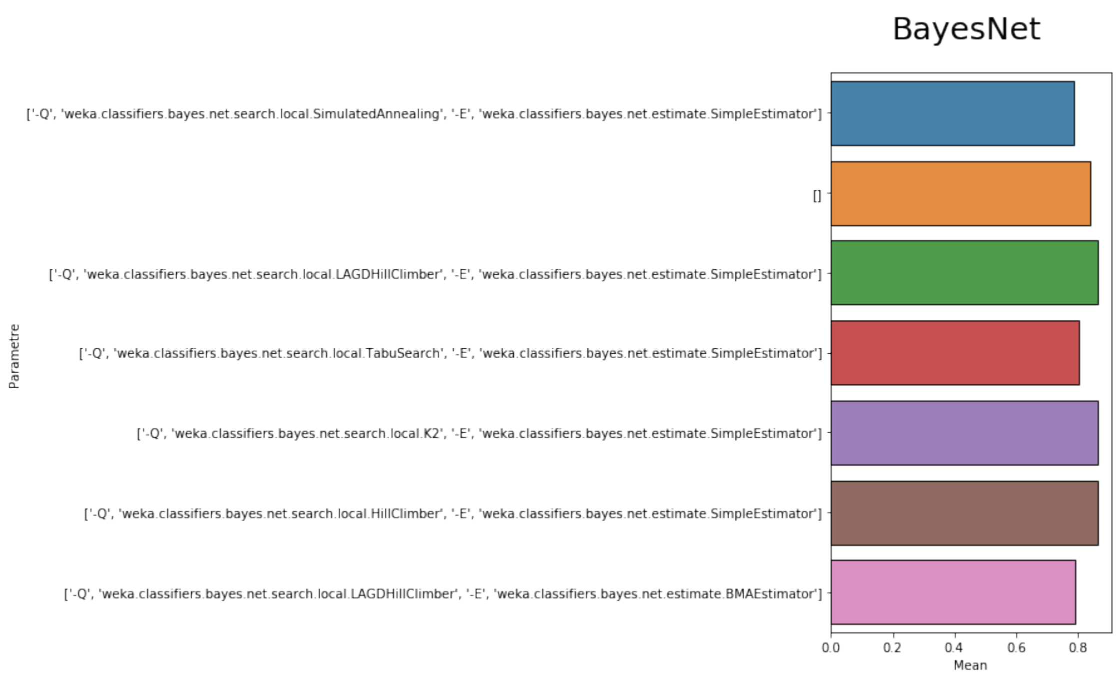
In [22]:
```
#reduce the name of algorith
BayesNet['clf name & configuration'] = BayesNet['clf name & configuration'].str.replac

BayesNet
```

Out[22]:
```
                                clf name & configuration  AP  MagicTelescope  \
1  ['-Q', 'weka.classifiers.bayes.net.search.loca...  NaN          0.8395
3                                                  []  NaN          0.9984
4  ['-Q', 'weka.classifiers.bayes.net.search.loca...  NaN             NaN
5  ['-Q', 'weka.classifiers.bayes.net.search.loca...  NaN          0.8363
6  ['-Q', 'weka.classifiers.bayes.net.search.loca...  NaN          0.9999
7  ['-Q', 'weka.classifiers.bayes.net.search.loca...  NaN             NaN
8  ['-Q', 'weka.classifiers.bayes.net.search.loca...  NaN             NaN

   abalone  anneal     ar1  arrhythmia  audiology   autos  badges2  ...  \
1   0.5688     NaN  0.9256         NaN        NaN     NaN      1.0  ...
3   0.6299  0.9131  0.9256      0.7168     0.7478  0.7073      1.0  ...
4   0.6775  0.9432  0.9256         NaN        NaN  0.7854      1.0  ...
5   0.6368  0.9232  0.9256      0.7102     0.7655  0.7854      1.0  ...
6   0.6790  0.9265  0.9256         NaN        NaN  0.8293      1.0  ...
7   0.6761  0.9432  0.9256         NaN        NaN  0.7707      1.0  ...
8      NaN     NaN  0.9256         NaN        NaN     NaN      NaN  ...

   spambase  splice  teachingAssistant  tic-tac-toe    vote   vowel  \
1       NaN     NaN             0.5166       0.9019  0.9655  0.7374
3       NaN     NaN             0.9073       0.9990  0.9011  0.6253
4       NaN     NaN             0.9205       0.9990  0.9563  0.8303
5       NaN     NaN             0.4172       0.7704  0.9517  0.7747
6       NaN     NaN             0.8940       0.9990  0.9517  0.7495
7       NaN     NaN             0.9272       0.9990  0.9563  0.7828
8       NaN     NaN                NaN          NaN     NaN     NaN

   waveform-5000   yeast     zoo      mean
1            NaN  0.5761  0.9505  0.789211
3            NaN  0.6004  0.9307  0.840755
4            NaN  0.6024     NaN  0.864308
```

```
5             NaN  0.5755  0.9406  0.803003
6             NaN  0.6004  0.9505  0.863352
7             NaN  0.6024     NaN  0.865083
8             NaN     NaN     NaN  0.789950

[7 rows x 74 columns]
```

In [23]:
```python
fig = plt.figure(figsize=(4,8))
title = fig.suptitle('BayesNet', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=BayesNet, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[23]:
```
Text(0, 0.5, 'Parametre')
```



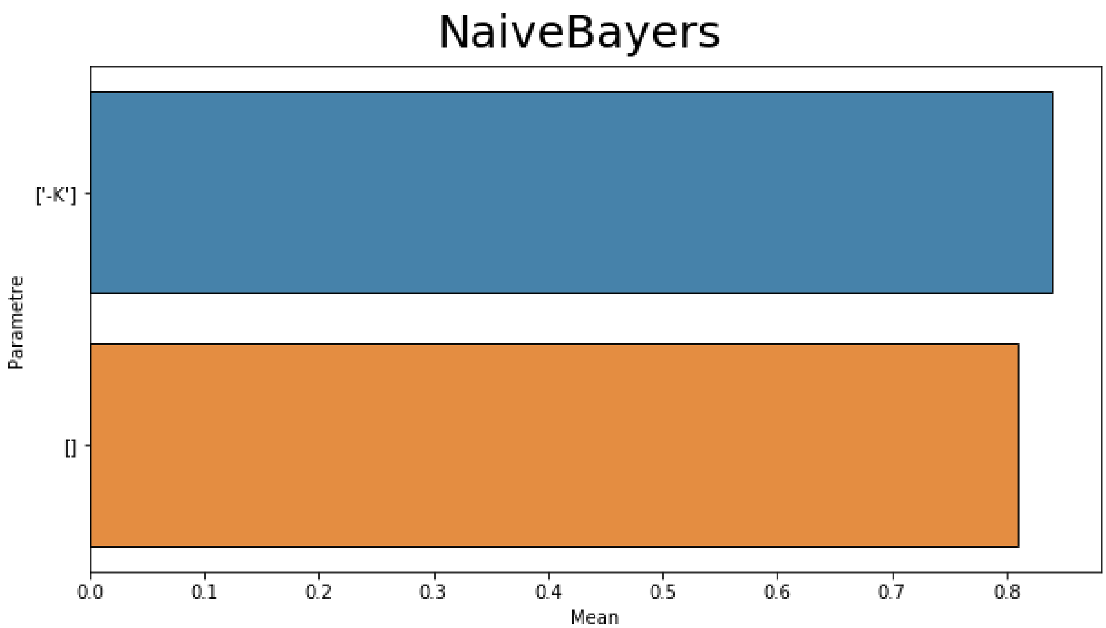
In [24]:
```python
BayesNet.mean(axis=1)
```

Out[24]:
```
1    0.789211
3    0.840755
4    0.864308
5    0.803003
6    0.863352
7    0.865083
8    0.789950
dtype: float64
```

```
In [25]: BayesNet.mean(axis=1).idxmax()

Out[25]: 7
```

5.2 2. Naive Bayers

```
In [26]: NaiveBayers = data_algo[data_algo['clf name & configuration']
                                  .str.contains('^weka.classifiers.bayes.NaiveBayes-*')].copy()

In [27]: NaiveBayers['clf name & configuration'] = NaiveBayers['clf name & configuration'].str

         NaiveBayers

Out[27]:   clf name & configuration      AP  MagicTelescope  abalone  anneal     ar1  \
         0                    ['-K']  0.9615          0.9967   0.6253  0.8608  0.8843
         2                        []  0.9594          0.8944   0.5808  0.6882  0.8595

            arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
         0      0.6504     0.7168  0.6780   0.9932  ...    0.9854  0.9991
         2      0.6173     0.7168  0.6098   0.9966  ...    0.8133  0.9925

            teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
         0             0.5497       0.9958  0.9011  0.6909         0.8012  0.6098
         2             0.5298       0.9916  0.9011  0.6303         0.7998  0.5856

               zoo      mean
         0  0.9604  0.840289
         2  0.9406  0.809447

         [2 rows x 74 columns]

In [28]: fig = plt.figure(figsize=(10,5))
         title = fig.suptitle('NaiveBayers', fontsize=25)
         fig.subplots_adjust(top=0.9, wspace=0.3)
         ax = sns.barplot(x='mean', y='clf name & configuration',
                          data=NaiveBayers, alpha=0.9, edgecolor='black')
         ax.set_xlabel('Mean')
         ax.set_ylabel('Parametre')

Out[28]: Text(0, 0.5, 'Parametre')
```



In [29]:
```
NaiveBayers.mean(axis=1)
```

Out[29]:
```
0    0.840289
2    0.809447
dtype: float64
```

In [30]:
```
NaiveBayers.mean(axis=1).idxmax()
```

Out[30]:
```
0
```

5.3 3. Rule Parts

In [31]:
```
RuleParts = data_algo[data_algo['clf name & configuration']
                      .str.contains('^weka.classifiers.rules.PART-*')].copy()
```

In [32]:
```
RuleParts['clf name & configuration'] = RuleParts['clf name & configuration'].str.repl
```

In [33]:
```
RuleParts
```

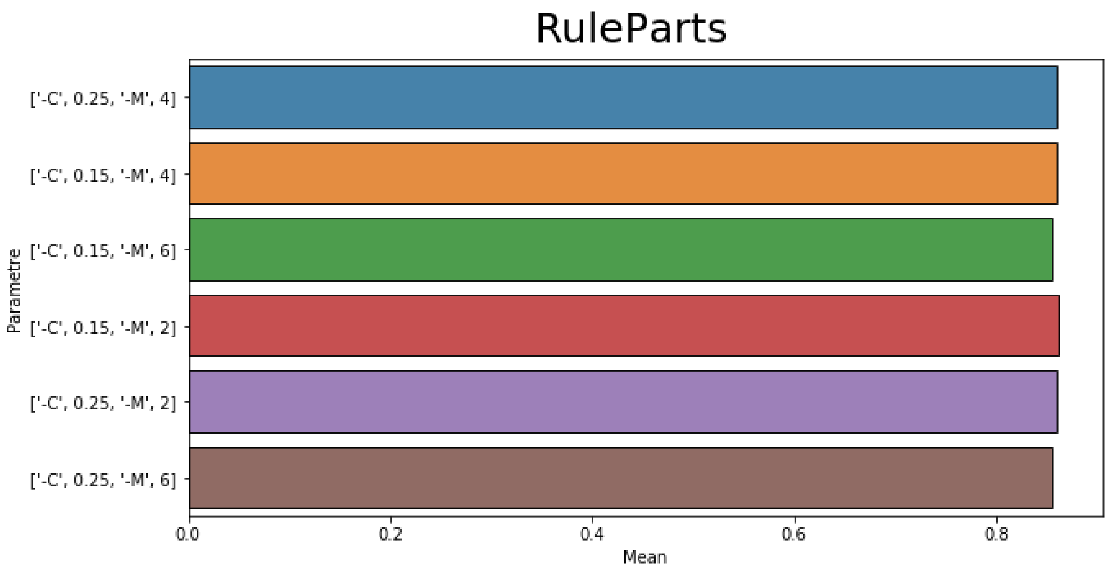
Out[33]:

	clf name & configuration	AP	MagicTelescope	abalone	anneal	ar1 \
9	['-C', 0.25, '-M', 4]	0.9338	0.9999	0.6445	0.9076	0.9256
11	['-C', 0.15, '-M', 4]	0.9338	0.9999	0.6519	0.9065	0.9339
12	['-C', 0.15, '-M', 6]	0.9316	0.9999	0.6459	0.8931	0.9174
14	['-C', 0.15, '-M', 2]	0.9380	0.9999	0.6378	0.9087	0.9008
15	['-C', 0.25, '-M', 2]	0.9380	0.9999	0.6325	0.9053	0.8843
17	['-C', 0.25, '-M', 6]	0.9316	0.9999	0.6457	0.8864	0.9174

```
    arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
9       0.6283     0.7611  0.6488      1.0  ...    0.9996  0.9994
11      0.6261     0.7522  0.6585      1.0  ...    0.9996  0.9994
12      0.6549     0.6814  0.6439      1.0  ...    0.9996  0.9994
14      0.6504     0.7965  0.8146      1.0  ...    0.9996  0.9994
15      0.6504     0.8009  0.8146      1.0  ...    0.9996  0.9994
17      0.6726     0.6814  0.6244      1.0  ...    0.9996  0.9994

    teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
9              0.4437        0.999  0.9563  0.7404         0.7812  0.5654
11             0.4305        0.999  0.9586  0.7444         0.7772  0.5654
12             0.4371        0.999  0.9632  0.6889         0.7812  0.5836
14             0.4172        0.999  0.9609  0.7576         0.7816  0.5748
15             0.4238        0.999  0.9609  0.7535         0.7816  0.5721
17             0.4570        0.999  0.9632  0.6838         0.7790  0.5809

       zoo      mean
9   0.8812  0.859849
11  0.8812  0.860604
12  0.9010  0.855542
14  0.9109  0.862190
15  0.9109  0.861097
17  0.9010  0.855272

[6 rows x 74 columns]
```

In [34]:
```
fig = plt.figure(figsize=(10,5))
title = fig.suptitle('RuleParts', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=RuleParts, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[34]:
```
Text(0, 0.5, 'Parametre')
```



In [35]:
```
RuleParts.mean(axis=1)
```

Out[35]:
```
9     0.859849
11    0.860604
12    0.855542
14    0.862190
15    0.861097
17    0.855272
dtype: float64
```

In [36]:
```
RuleParts.mean(axis=1).idxmax()
```

Out[36]:
```
14
```

5.4 4. Rules Jrip

In [37]:
```
RuleJrip = data_algo[data_algo['clf name & configuration']
                     .str.contains('^weka.classifiers.rules.JRip-*')].copy()
```

In [38]:
```
RuleJrip['clf name & configuration'] = RuleJrip['clf name & configuration'].str.replac
```

In [39]:
```
RuleJrip
```

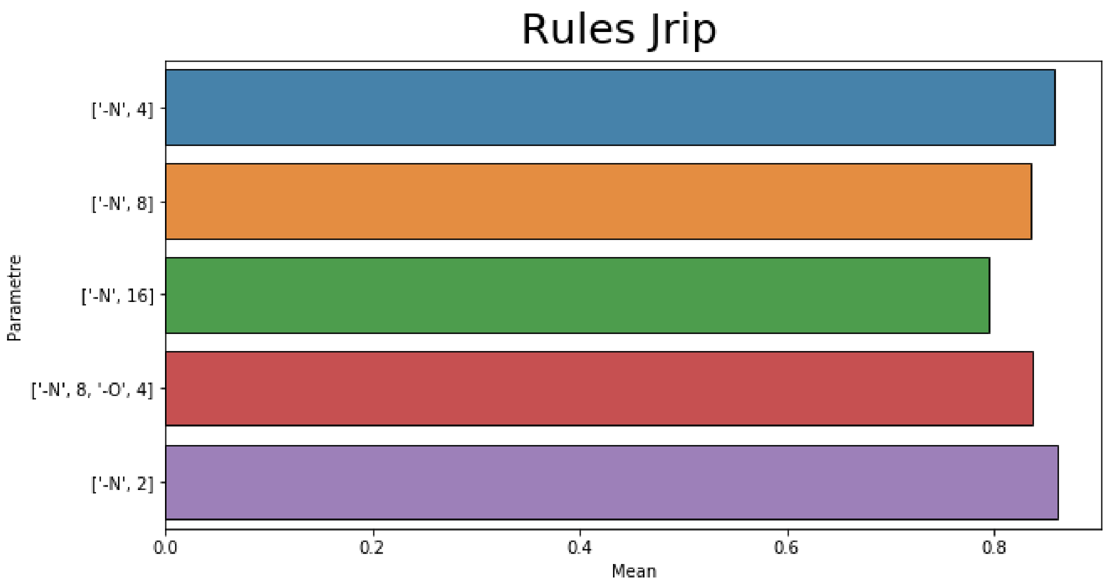
Out[39]:

	clf name & configuration	AP	MagicTelescope	abalone	anneal	ar1	\
10	['-N', 4]	0.9338	0.9999	0.6608	0.8909	0.9256	
13	['-N', 8]	0.9402	0.9999	0.6517	0.8831	0.9256	
16	['-N', 16]	0.9274	0.9999	0.6474	0.8207	0.9256	
18	['-N', 8, '-O', 4]	NaN	0.9999	0.6569	0.8964	0.9256	

```
19               ['-N', 2]  0.9209          0.9999   0.6608  0.8942  0.9008

    arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
10      0.7124     0.6726  0.6976      1.0  ...    0.9996  0.9991
13      0.6637     0.5973  0.6585      1.0  ...    0.9996  0.9991
16      0.5996     0.3938  0.4683      1.0  ...    0.9996  0.9991
18      0.6814     0.5708  0.6732      1.0  ...    0.9996  0.9991
19      0.7035     0.7301  0.6976      1.0  ...    0.9996  0.9991

    teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
10             0.7748        0.999  0.9540  0.6869         0.7894  0.6078
13             0.6291        0.999  0.9540  0.6232         0.7944  0.5863
16             0.3709        0.999  0.9517  0.4859         0.7954  0.5741
18             0.6424        0.999  0.9540  0.6404         0.8026  0.5930
19             0.8411        0.999  0.9517  0.6848         0.7894  0.6132

       zoo      mean
10  0.8713  0.857632
13  0.6238  0.836340
16  0.4059  0.795526
18  0.6238  0.837333
19  0.8713  0.861247

[5 rows x 74 columns]
```

In [40]:
```python
fig = plt.figure(figsize=(10,5))
title = fig.suptitle('Rules Jrip', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=RuleJrip, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[40]:
```
Text(0, 0.5, 'Parametre')
```




```
In [41]: RuleJrip.mean(axis=1)

Out[41]: 10    0.857632
         13    0.836340
         16    0.795526
         18    0.837333
         19    0.861247
         dtype: float64

In [42]: RuleJrip.mean(axis=1).idxmax()

Out[42]: 19
```

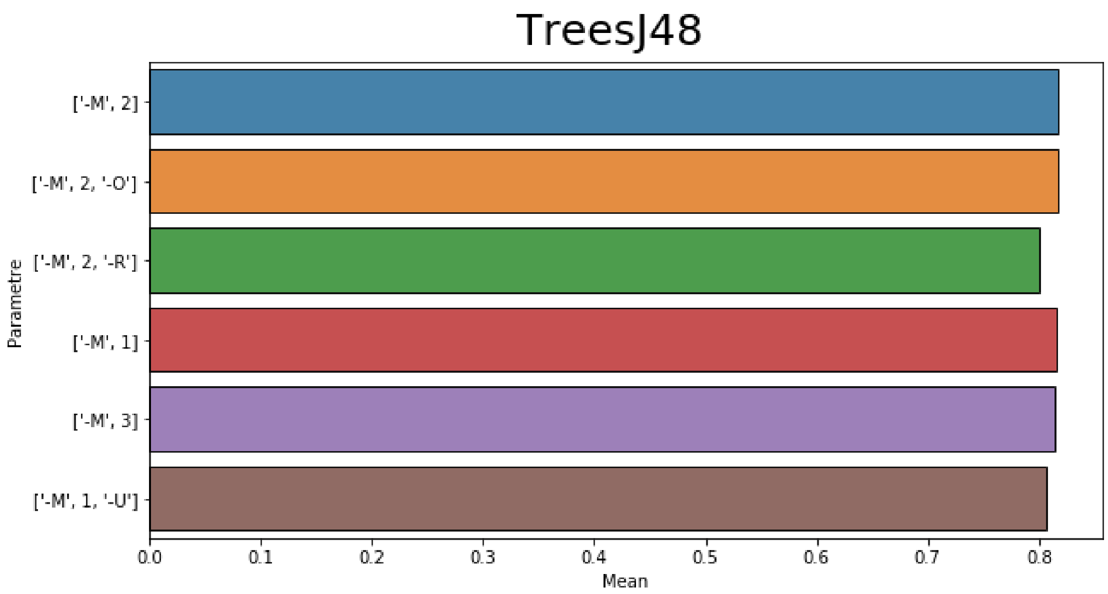
5.5 5. Trees J48

```
In [43]: TreesJ48 = data_algo[data_algo['clf name & configuration']
                                  .str.contains('^weka.classifiers.trees.J48-*')].copy()

In [44]: TreesJ48['clf name & configuration'] = TreesJ48['clf name & configuration'].str.repla

         TreesJ48

Out[44]:    clf name & configuration      AP  MagicTelescope  abalone  anneal     ar1  \
         20              ['-M', 2]  0.9338          0.8511   0.6090  0.9265  0.8843
         21         ['-M', 2, '-O']  0.9338          0.8511   0.6090  0.9265  0.8843
         22         ['-M', 2, '-R']  0.9252          0.8484   0.6335  0.9076  0.9256
         23              ['-M', 1]  0.9338          0.8513   0.6067  0.9243  0.8760
         24              ['-M', 3]  0.9316          0.8514   0.6122  0.9198  0.9008
```

```
25          ['-M', 1, '-U']  0.9338         0.8499   0.5959  0.9165  0.8843

    arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
20      0.6681     0.7876  0.8146      1.0  ...    0.9261  0.9420
21      0.6681     0.7876  0.8146      1.0  ...    0.9261  0.9420
22      0.6770     0.7301  0.6341      1.0  ...    0.9235  0.9348
23      0.6482     0.8274  0.8195      1.0  ...    0.9294  0.9364
24      0.6504     0.7832  0.7415      1.0  ...    0.9268  0.9423
25      0.6372     0.8186  0.8537      1.0  ...    0.9250  0.9160

    teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
20             0.5364       0.8424  0.9655  0.7758         0.7580  0.5546
21             0.5364       0.8424  0.9655  0.7758         0.7580  0.5546
22             0.4901       0.8372  0.9563  0.7263         0.7678  0.5714
23             0.5894       0.8591  0.9678  0.7919         0.7578  0.5512
24             0.4636       0.8330  0.9655  0.7556         0.7616  0.5465
25             0.6623       0.8737  0.9609  0.8283         0.7568  0.5357

       zoo      mean
20  0.9208  0.816474
21  0.9208  0.816474
22  0.8812  0.800814
23  0.9208  0.816345
24  0.9208  0.814794
25  0.9406  0.806527

[6 rows x 74 columns]
```

In [45]:
```
fig = plt.figure(figsize=(10,5))
title = fig.suptitle('TreesJ48', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=TreesJ48, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[45]:
```
Text(0, 0.5, 'Parametre')
```



In [46]:
```
TreesJ48.mean(axis=1)
```

Out[46]:
```
20    0.816474
21    0.816474
22    0.800814
23    0.816345
24    0.814794
25    0.806527
dtype: float64
```

In [47]:
```
TreesJ48.mean(axis=1).idxmax()
```

Out[47]:
```
20
```

5.6 6. Random Tree

In [48]:
```
RandomTree = data_algo[data_algo['clf name & configuration']
                          .str.contains('^weka.classifiers.trees.RandomTree-*')].copy()
```

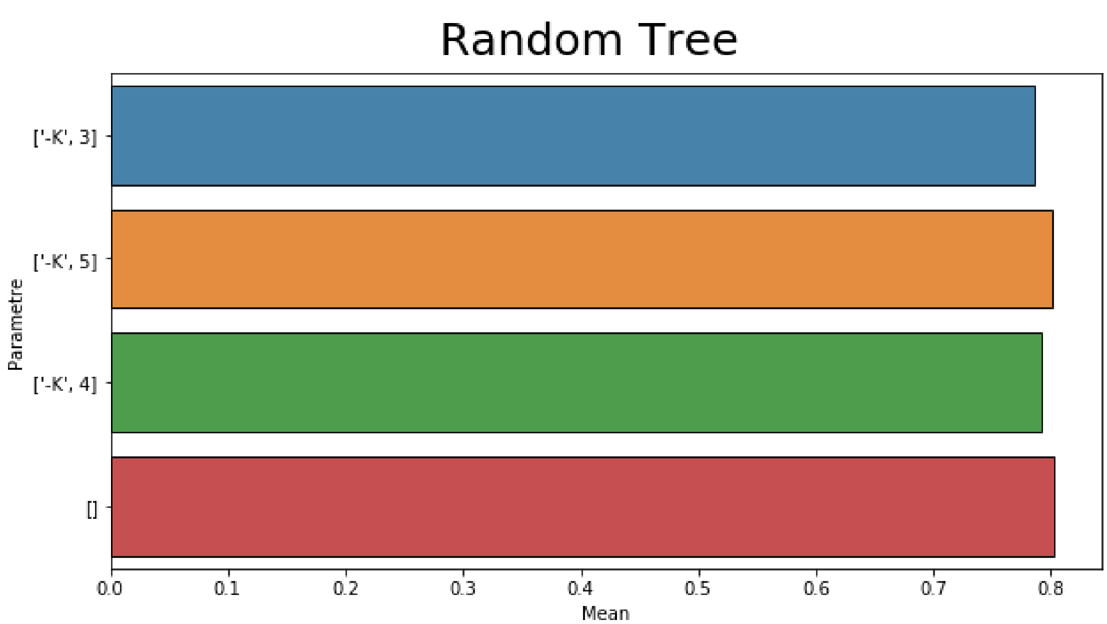
In [49]:
```
RandomTree['clf name & configuration'] = RandomTree['clf name & configuration'].str.r

RandomTree
```

Out[49]:

	clf name & configuration	AP	MagicTelescope	abalone	anneal	ar1	\
26	['-K', 3]	0.8013	0.9976	0.5901	0.7773	0.8760	
28	['-K', 5]	0.8077	0.9982	0.5961	0.8107	0.9008	
30	['-K', 4]	0.8226	0.9985	0.6016	0.8185	0.8595	
33	[]	0.8397	0.9985	0.6016	0.8374	0.9008	

```
    arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
26      0.4867     0.5929  0.7561   0.9694  ...    0.9591  0.6871
28      0.4403     0.5398  0.7268   0.9932  ...    0.9613  0.7420
30      0.5000     0.5088  0.7610   0.9932  ...    0.9672  0.6981
33      0.4779     0.5973  0.7268   0.9932  ...    0.9583  0.7859

    teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
26             0.5298       0.9342  0.9172  0.7929         0.6876  0.5290
28             0.5762       0.9948  0.9494  0.7970         0.7064  0.5256
30             0.5430       0.9885  0.9287  0.8000         0.7118  0.5007
33             0.5298       0.9885  0.9494  0.8000         0.7260  0.5007

       zoo      mean
26  0.7525  0.785368
28  0.6436  0.800100
30  0.6436  0.791612
33  0.6436  0.802317

[4 rows x 74 columns]
```

```
In [50]: fig = plt.figure(figsize=(10,5))
         title = fig.suptitle('Random Tree', fontsize=25)
         fig.subplots_adjust(top=0.9, wspace=0.3)
         ax = sns.barplot(x='mean', y='clf name & configuration',
                          data=RandomTree, alpha=0.9, edgecolor='black')
         ax.set_xlabel('Mean')
         ax.set_ylabel('Parametre')

Out[50]: Text(0, 0.5, 'Parametre')
```

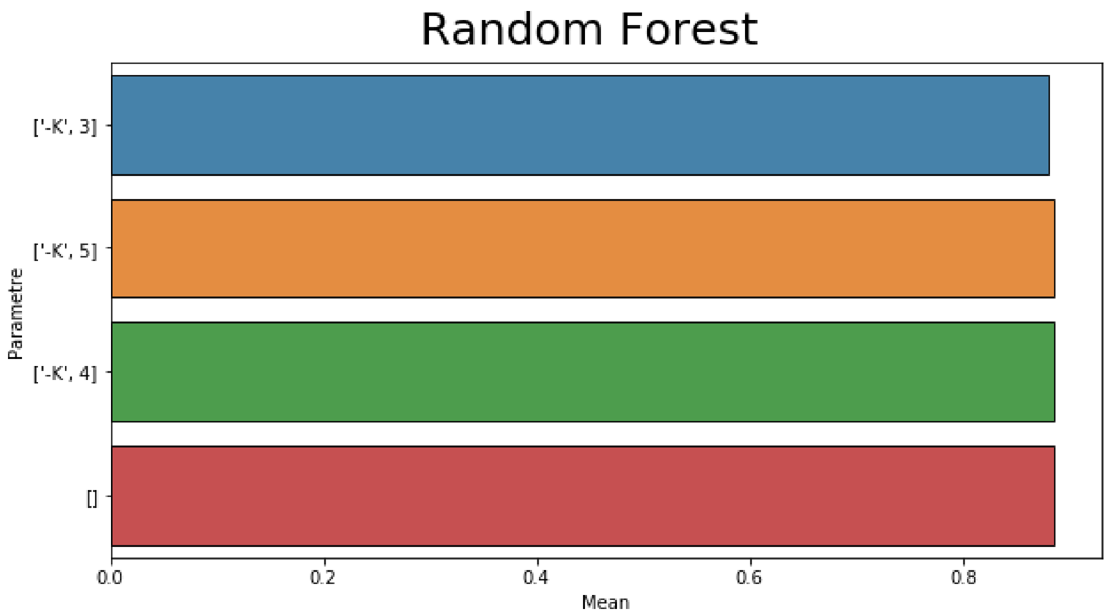


```
In [51]: RandomTree.mean(axis=1)

Out[51]: 26    0.785368
         28    0.800100
         30    0.791612
         33    0.802317
         dtype: float64

In [52]: RandomTree.mean(axis=1).idxmax()

Out[52]: 33
```

5.7 7. Random Forest

```
In [53]: RandomForest = data_algo[data_algo['clf name & configuration']
                                  .str.contains('^weka.classifiers.trees.RandomForest-*')].copy

In [54]: RandomForest['clf name & configuration'] = RandomForest['clf name & configuration'].st

         RandomForest

Out[54]:    clf name & configuration      AP  MagicTelescope  abalone  anneal     ar1  \
         27                  ['-K', 3]  0.9231          0.9999   0.6895  0.8775  0.9008
         29                  ['-K', 5]  0.9338          0.9999   0.6864  0.9053  0.9008
         31                  ['-K', 4]  0.9402          0.9999   0.6902  0.8886  0.9008
         32                         []  0.9573          0.9999   0.6902  0.9053  0.9008

             arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
         27      0.6239     0.7965  0.8293      1.0  ...    0.9950  0.9705
         29      0.6527     0.7699  0.8439      1.0  ...    0.9980  0.9931
         31      0.6460     0.7788  0.8634      1.0  ...    0.9972  0.9868
         32      0.6615     0.7920  0.8439      1.0  ...    0.9993  0.9909

             teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
         27             0.5629          1.0  0.9609  0.9798         0.8476  0.6516
         29             0.5828          1.0  0.9655  0.9727         0.8510  0.6496
         31             0.5629          1.0  0.9632  0.9758         0.8482  0.6442
         32             0.5629          1.0  0.9655  0.9758         0.8500  0.6442

                zoo      mean
         27  0.9406  0.880458
         29  0.9208  0.884462
         31  0.9406  0.885219
         32  0.9208  0.884717

         [4 rows x 74 columns]
```

```
In [55]: fig = plt.figure(figsize=(10,5))
         title = fig.suptitle('Random Forest', fontsize=25)
         fig.subplots_adjust(top=0.9, wspace=0.3)
         ax = sns.barplot(x='mean', y='clf name & configuration',
                          data=RandomForest, alpha=0.9, edgecolor='black')
         ax.set_xlabel('Mean')
         ax.set_ylabel('Parametre')

Out[55]: Text(0, 0.5, 'Parametre')
```




```
In [56]: RandomForest.mean(axis=1)

Out[56]: 27    0.880458
         29    0.884462
         31    0.885219
         32    0.884717
         dtype: float64

In [57]: RandomForest.mean(axis=1).idxmax()

Out[57]: 31
```

5.8 8. Multilayer Perceptron

```
In [58]: MultilayerPerceptron = data_algo[data_algo['clf name & configuration']
                                          .str.contains('^weka.classifiers.functions.Multilayer
```

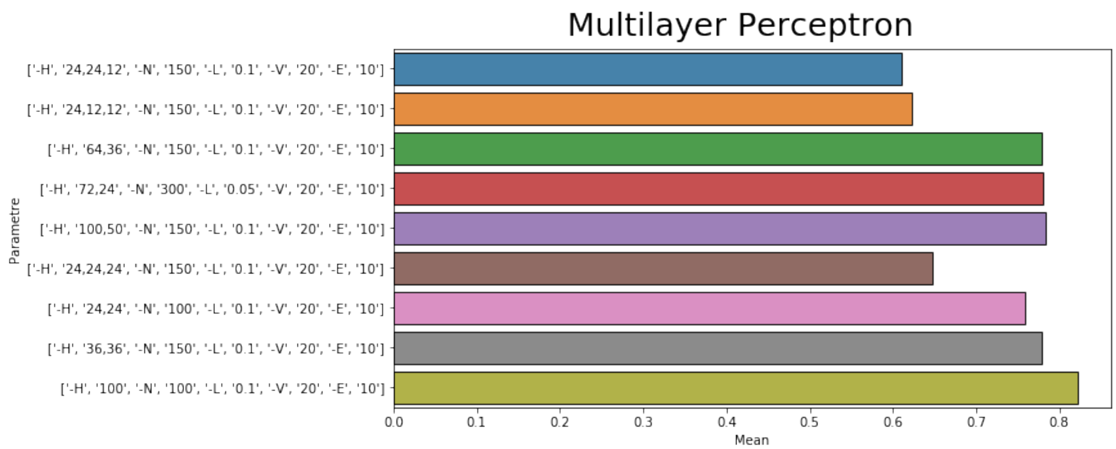
```
In [59]: MultilayerPerceptron['clf name & configuration'] = MultilayerPerceptron['clf name & co

         MultilayerPerceptron
```

```
Out[59]:                          clf name & configuration      AP  MagicTelescope  \
         34  ['-H', '24,24,12', '-N', '150', '-L', '0.1', '...  0.9017          0.8644
         35  ['-H', '24,12,12', '-N', '150', '-L', '0.1', '...  0.9017          0.8645
         36  ['-H', '64,36', '-N', '150', '-L', '0.1', '-V'...  0.9615          0.8631
         38  ['-H', '72,24', '-N', '300', '-L', '0.05', '-V...  0.9594          0.8664
         39  ['-H', '100,50', '-N', '150', '-L', '0.1', '-V...  0.9530          0.8644
         41  ['-H', '24,24,24', '-N', '150', '-L', '0.1', '...  0.9124          0.8636
         43  ['-H', '24,24', '-N', '100', '-L', '0.1', '-V'...  0.9573          0.8623
         45  ['-H', '36,36', '-N', '150', '-L', '0.1', '-V'...  0.9530          0.8629
         48  ['-H', '100', '-N', '100', '-L', '0.1', '-V', ...  0.9615          0.8631

             abalone  anneal     ar1  arrhythmia  audiology   autos  badges2  ...  \
         34   0.6586  0.7617  0.9256      0.5420     0.2522  0.3268      1.0  ...
         35   0.6565  0.7617  0.9256      0.5420     0.2522  0.3268      1.0  ...
         36   0.6596  0.8018  0.9256      0.5619     0.5221  0.4634      1.0  ...
         38   0.6655  0.7829  0.9256      0.5642     0.5088  0.4780      1.0  ...
         39   0.6615  0.8096  0.9256      0.5575     0.5088  0.4683      1.0  ...
         41   0.6591  0.7684  0.9256      0.5420     0.2522  0.3268      1.0  ...
         43   0.6526  0.7895  0.9256      0.5619     0.4469  0.4146      1.0  ...
         45   0.6634  0.7984  0.9256      0.5597     0.5044  0.4780      1.0  ...
         48   0.6572  0.8697  0.9256      0.6527     0.7522  0.6732      1.0  ...

             spambase  splice  teachingAssistant  tic-tac-toe    vote   vowel  \
         34    0.8142  0.7172             0.3245       0.9144  0.8943  0.0909
         35    0.8792  0.7028             0.3245       0.9165  0.8943  0.0909
         36    0.8837  0.9414             0.3510       0.9791  0.9655  0.2232
         38    0.8865  0.9495             0.3377       0.9781  0.9701  0.3646
         39    0.8835  0.9448             0.3576       0.9770  0.9678  0.2606
         41    0.8815  0.7129             0.3311       0.9154  0.8943  0.0909
         43    0.8809  0.7796             0.3311       0.9843  0.9724  0.0909
         45    0.8839  0.9097             0.3642       0.9875  0.9655  0.2212
         48    0.8648  0.9354             0.5099       0.9802  0.9678  0.7505

             waveform-5000   yeast     zoo      mean
         34         0.8600  0.3032  0.4059  0.611131
         35         0.8614  0.3032  0.4059  0.623119
         36         0.8564  0.5101  0.6139  0.779356
         38         0.8638  0.4926  0.5347  0.779685
         39         0.8592  0.4919  0.6238  0.783974
         41         0.8598  0.3053  0.4059  0.647819
         43         0.8620  0.4178  0.5743  0.758228
         45         0.8634  0.4730  0.5941  0.778429
         48         0.8646  0.5728  0.9109  0.821361
```

```
[9 rows x 74 columns]
```

In [60]:
```
fig = plt.figure(figsize=(10,5))
title = fig.suptitle('Multilayer Perceptron', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=MultilayerPerceptron, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[60]:
```
Text(0, 0.5, 'Parametre')
```



In [61]:
```
MultilayerPerceptron.mean(axis=1)
```

Out[61]:
```
34    0.611131
35    0.623119
36    0.779356
38    0.779685
39    0.783974
41    0.647819
43    0.758228
45    0.778429
48    0.821361
dtype: float64
```

In [62]:
```
MultilayerPerceptron.mean(axis=1).idxmax()
```

Out[62]:
```
48
```

5.9 9. IBk

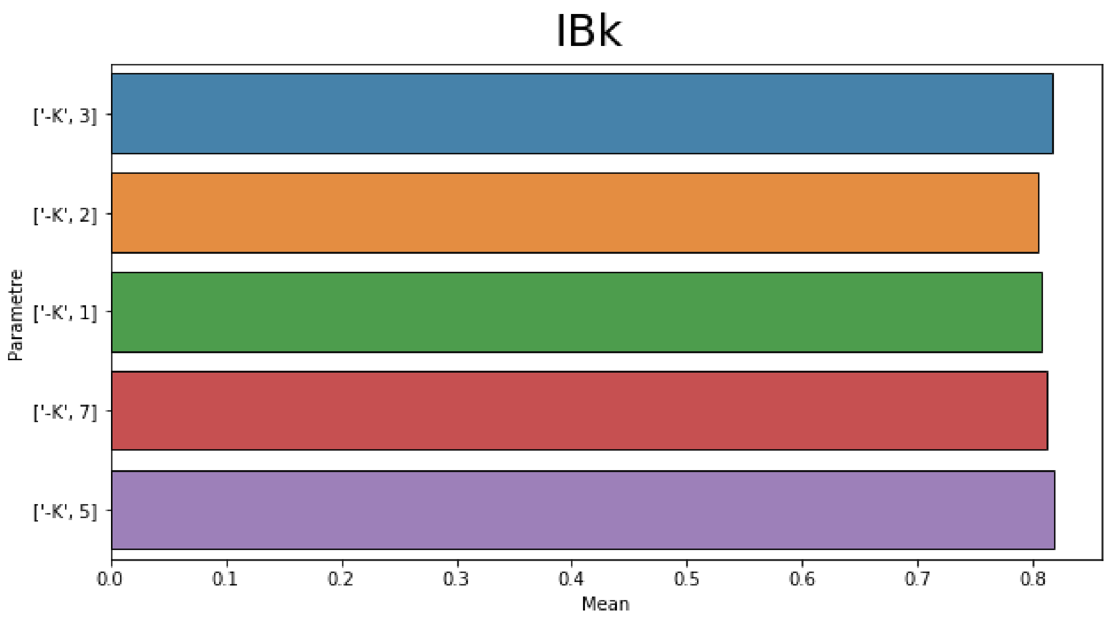
In [63]:
```
IBk = data_algo[data_algo['clf name & configuration']
                        .str.contains('^weka.classifiers.lazy.IBk-*')].copy()
```

In [64]:
```
IBk['clf name & configuration'] = IBk['clf name & configuration'].str.replace('^w.*IBk
                                                                               '', rege
IBk
```

Out[64]:
```
   clf name & configuration      AP  MagicTelescope  abalone  anneal     ar1  \
37             ['-K', 3]  0.9530          0.8299   0.5954  0.8118  0.9091
40             ['-K', 2]  0.9466          0.8126   0.5664  0.7673  0.9008
44             ['-K', 1]  0.9444          0.8084   0.5758  0.7795  0.9091
46             ['-K', 7]  0.9487          0.8377   0.6344  0.8096  0.9256
49             ['-K', 5]  0.9509          0.8324   0.6258  0.8129  0.9256

    arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
37      0.5863     0.6504  0.7024      1.0  ...    0.8992  0.7743
40      0.5796     0.6593  0.6878      1.0  ...    0.8892  0.7238
44      0.5265     0.7345  0.7366      1.0  ...    0.9020  0.7426
46      0.5796     0.6018  0.5707      1.0  ...    0.9018  0.8160
49      0.5907     0.6239  0.6000      1.0  ...    0.9042  0.7934

    teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
37             0.3775       0.9885  0.9402  0.9596         0.7748  0.5418
40             0.3907       0.9885  0.9448  0.9737         0.7202  0.5047
44             0.6291       0.9885  0.9448  0.9919         0.7394  0.5088
46             0.4371       0.9885  0.9287  0.7657         0.7978  0.5681
49             0.4040       0.9885  0.9379  0.8899         0.7856  0.5606

       zoo      mean
37  0.9109  0.816939
40  0.9208  0.803883
44  0.9406  0.806532
46  0.9109  0.811571
49  0.9406  0.817839

[5 rows x 74 columns]
```

In [65]:
```
fig = plt.figure(figsize=(10,5))
title = fig.suptitle('IBk', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=IBk, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[65]:
```
Text(0, 0.5, 'Parametre')
```



In [66]:
```
IBk.mean(axis=1)
```

Out[66]:
```
37     0.816939
40     0.803883
44     0.806532
46     0.811571
49     0.817839
dtype: float64
```

In [67]:
```
IBk.mean(axis=1).idxmax()
```

Out[67]:
```
49
```

5.10 10. OneR

In [68]:
```
OneR = data_algo[data_algo['clf name & configuration']
                  .str.contains('^weka.classifiers.rules.OneR-*')].copy()
```

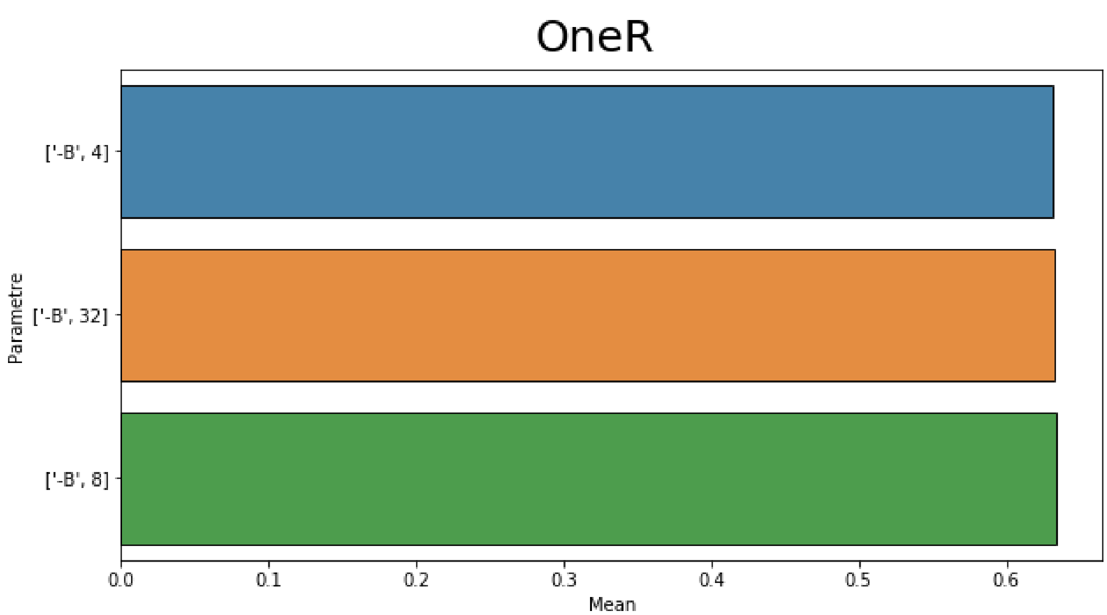
In [69]:
```
OneR['clf name & configuration'] = OneR['clf name & configuration'].str.replace('^w.*(
                                                                                  '', re
OneR
```

Out[69]:
```
   clf name & configuration      AP  MagicTelescope  abalone  anneal     ar1  \
47                 ['-B', 4]  0.9380          0.7011   0.5360  0.7962  0.9008
51                ['-B', 32]  0.9081          0.7344   0.5942  0.7984  0.9008
52                 ['-B', 8]  0.9380          0.7160   0.5976  0.7984  0.9008

    arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
```

```
47       0.5774      0.4646  0.6537       1.0  ...    0.7814  0.2436
51       0.5973      0.4646  0.5024       1.0  ...    0.7824  0.2436
52       0.5774      0.4646  0.5463       1.0  ...    0.7877  0.2436

    teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
47             0.4106       0.6994  0.9517  0.3242         0.5132  0.3989
51             0.4106       0.6994  0.9517  0.3121         0.5522  0.3989
52             0.4106       0.6994  0.9517  0.3172         0.5446  0.4036

       zoo      mean
47  0.4257  0.631311
51  0.4257  0.632349
52  0.4257  0.633414

[3 rows x 74 columns]
```

In [70]:
```
fig = plt.figure(figsize=(10,5))
title = fig.suptitle('OneR', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=OneR, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[70]:
```
Text(0, 0.5, 'Parametre')
```



In [71]:
```
OneR.mean(axis=1)
```

```
Out[71]: 47    0.631311
         51    0.632349
         52    0.633414
         dtype: float64
```

```
In [72]: OneR.mean(axis=1).idxmax()
```

```
Out[72]: 52
```

5.11 11. Simple Logistic

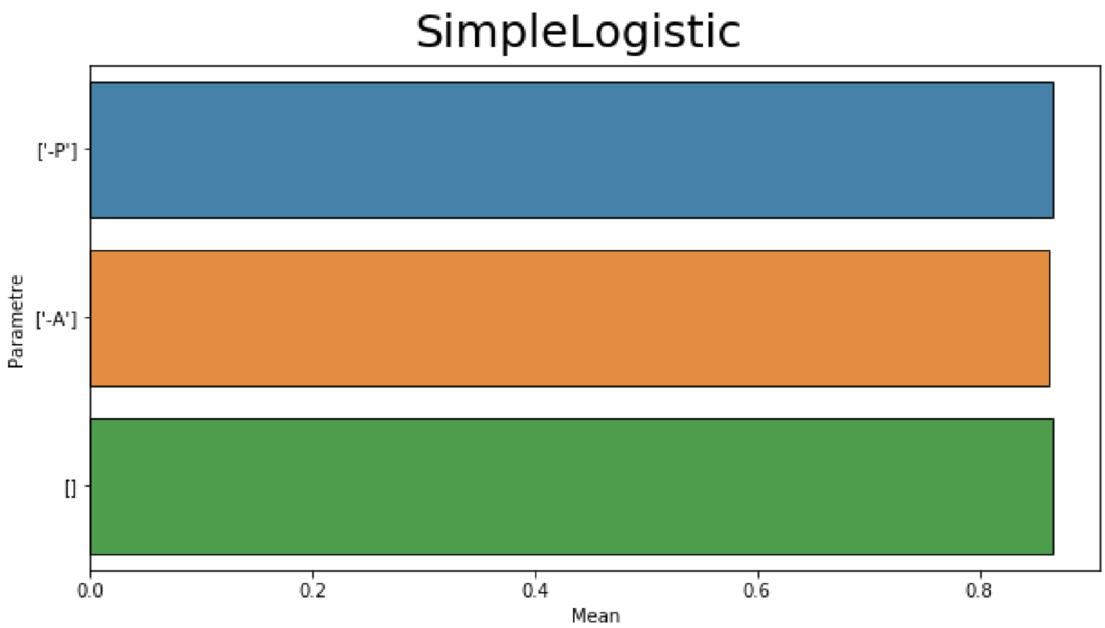
```
In [73]: SimpleLogistic = data_algo[data_algo['clf name & configuration']
                                    .str.contains('^weka.classifiers.functions.SimpleLogistic-
```

```
In [74]: SimpleLogistic['clf name & configuration'] = SimpleLogistic['clf name & configuration

         SimpleLogistic
```

```
Out[74]:    clf name & configuration      AP  MagicTelescope  abalone  anneal     ar1  \
         53                   ['-P']  0.9487          0.9999   0.6533  0.8842  0.9091
         54                   ['-A']  0.9530          1.0000   0.6483  0.8864  0.9174
         56                       []  0.9530          0.9999   0.6514  0.8797  0.9174

             arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
         53      0.6748     0.8274  0.7463      1.0  ...    0.9991  0.9994
         54      0.6836     0.8407  0.7512      1.0  ...    0.9996  0.9994
         56      0.7434     0.8186  0.7366      1.0  ...    0.9993  0.9987

             teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
         53             0.5960          1.0  0.9747  0.8404         0.8662  0.5937
         54             0.5497          1.0  0.9724  0.8071         0.8674  0.5896
         56             0.5166          1.0  0.9678  0.8212         0.8688  0.5970

                zoo      mean
         53  0.9109  0.865126
         54  0.9208  0.862056
         56  0.9208  0.865376

         [3 rows x 74 columns]
```

```
In [75]: fig = plt.figure(figsize=(10,5))
         title = fig.suptitle('SimpleLogistic', fontsize=25)
         fig.subplots_adjust(top=0.9, wspace=0.3)
         ax = sns.barplot(x='mean', y='clf name & configuration',
                          data=SimpleLogistic, alpha=0.9, edgecolor='black')
         ax.set_xlabel('Mean')
         ax.set_ylabel('Parametre')
```

```
Out[75]: Text(0, 0.5, 'Parametre')
```




```
In [76]: SimpleLogistic.mean(axis=1)

Out[76]: 53    0.865126
         54    0.862056
         56    0.865376
         dtype: float64

In [77]: SimpleLogistic.mean(axis=1).idxmax()

Out[77]: 56
```

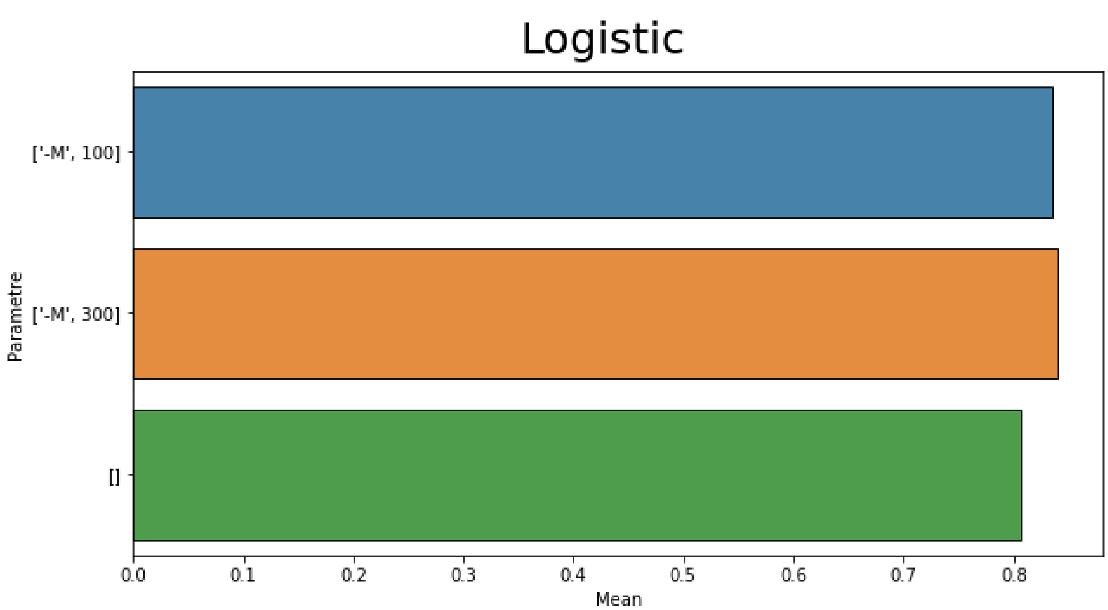
5.12 12. Logistic

```
In [78]: Logistic = data_algo[data_algo['clf name & configuration']
                             .str.contains('^weka.classifiers.functions.Logistic-*')].copy()

In [79]: Logistic['clf name & configuration'] = Logistic['clf name & configuration'].str.replac

         Logistic

Out[79]:    clf name & configuration  AP  MagicTelescope  abalone  anneal     ar1  \
         57              ['-M', 100] NaN          0.9997   0.6555  0.8686  0.8760
         58              ['-M', 300] NaN          0.9996   0.6555  0.8686  0.8843
         60                       [] NaN          0.7912   0.6555  0.8641  0.8760

             arrhythmia  audiology   autos  badges2  ...  spambase  splice  \
         57      0.5310     0.8009  0.6732   0.9966  ...    0.9909  0.9652
```

```
58       0.5177      0.7965  0.6780    0.9966  ...    0.9917  0.9382
60       0.5243      0.7832  0.7024    0.9966  ...    0.9257  0.9000

    teachingAssistant  tic-tac-toe    vote   vowel  waveform-5000   yeast  \
57              0.5960       1.0000  0.9632  0.8192         0.8662  0.5930
58              0.5960       1.0000  0.9632  0.8152         0.8662  0.5930
60              0.5497       0.9812  0.9678  0.8152         0.8664  0.5863

       zoo      mean
57  0.8515  0.835690
58  0.8515  0.839286
60  0.8812  0.806794

[3 rows x 74 columns]
```

In [80]:
```python
fig = plt.figure(figsize=(10,5))
title = fig.suptitle('Logistic', fontsize=25)
fig.subplots_adjust(top=0.9, wspace=0.3)
ax = sns.barplot(x='mean', y='clf name & configuration',
                 data=Logistic, alpha=0.9, edgecolor='black')
ax.set_xlabel('Mean')
ax.set_ylabel('Parametre')
```

Out[80]: Text(0, 0.5, 'Parametre')



In [81]:
```python
Logistic.mean(axis=1)
```

```
Out[81]: 57    0.835690
         58    0.839286
         60    0.806794
         dtype: float64
```

```
In [82]: Logistic.mean(axis=1).idxmax()
```

```
Out[82]: 58
```

5.13 13. SMO

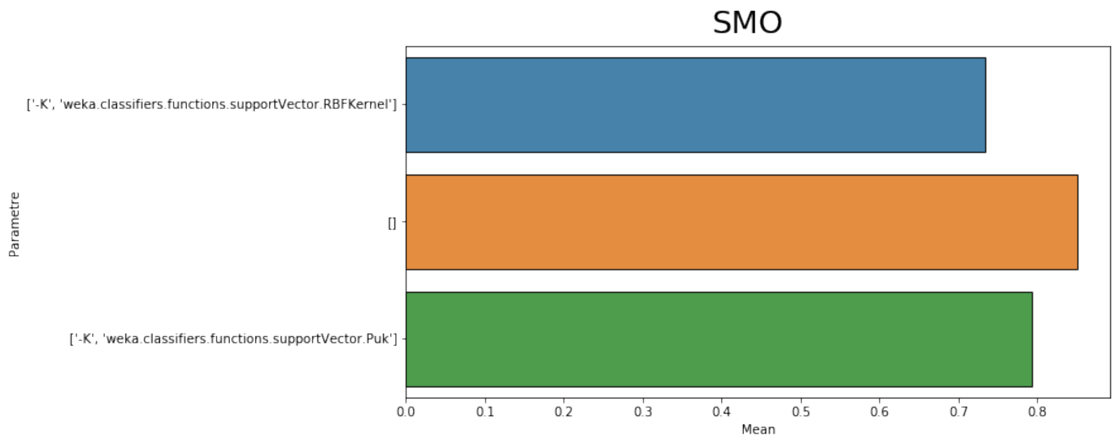
```
In [83]: SMO = data_algo[data_algo['clf name & configuration']
                         .str.contains('^weka.classifiers.functions.SMO-*')].copy()
```

```
In [84]: SMO['clf name & configuration'] = SMO['clf name & configuration'].str.replace('^w.*SMO
                                                                                       '', rege
         SMO
```

```
Out[84]:                              clf name & configuration      AP  MagicTelescope  \
         55  ['-K', 'weka.classifiers.functions.supportVect...  0.8932          0.7797
         59                                                 []  0.9530          0.9920
         61  ['-K', 'weka.classifiers.functions.supportVect...  0.7350          0.8618

             abalone  anneal     ar1  arrhythmia  audiology   autos  badges2  ...  \
         55   0.5365  0.7617  0.9256      0.5420     0.4115  0.4341      1.0  ...
         59   0.6284  0.8719  0.9174      0.6969     0.8142  0.6927      1.0  ...
         61   0.6500  0.7751  0.9008      0.5420     0.5354  0.6439      1.0  ...

             spambase  splice  teachingAssistant  tic-tac-toe    vote   vowel  \
         55    0.7307  0.9611             0.3444       0.7296  0.9425  0.3394
         59    0.9933  0.9602             0.5364       1.0000  0.9678  0.7010
         61    0.9304  0.5630             0.5298       0.7787  0.9517  0.9384

             waveform-5000   yeast     zoo      mean
         55         0.8506  0.3120  0.6733  0.733497
         59         0.8666  0.5694  0.9307  0.850218
         61         0.8634  0.6132  0.7723  0.792472

         [3 rows x 74 columns]
```

```
In [85]: fig = plt.figure(figsize=(10,5))
         title = fig.suptitle('SMO', fontsize=25)
         fig.subplots_adjust(top=0.9, wspace=0.3)
         ax = sns.barplot(x='mean', y='clf name & configuration',
                          data=SMO, alpha=0.9, edgecolor='black')
         ax.set_xlabel('Mean')
         ax.set_ylabel('Parametre')
```

```
Out[85]: Text(0, 0.5, 'Parametre')
```




```
In [86]: SMO.mean(axis=1)

Out[86]: 55    0.733497
         59    0.850218
         61    0.792472
         dtype: float64

In [87]: SMO.mean(axis=1).idxmax()

Out[87]: 59
```

5.14 13. Conclusion

Algorithm	Best Parameter
BayesNet	['-Q', 'weka.classifiers.bayes.net.search.local.HillClimber', '-E', 'weka.classifiers.bayes.net.estimate.SimpleEstimator']
Naive Bayers	['-K']
Rule Parts	['-C', 0.15, '-M', 2]
Rules Jrip	['-N', 2]
Trees J48	['-M', 2]
Random Tree	[]
Random Forest	['-K', 4]
Multilayer Perceptron	['-H', '100', '-N', '100', '-L', '0.1', '-V', '20', '-E', '10']
IBk	['-K', 5]
OneR	['-B', 8]
Simple Logistic	[]
Logistic	['-M', 300]
SMO	[]

```
In [ ]:
```