

2.1.Random-Forest-Feature-Selection

May 15, 2023

```
[262]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import time
from subprocess import check_output

from scipy import stats
plt.style.use("ggplot")
import warnings
warnings.filterwarnings("ignore")
from scipy import stats
```

```
[263]: data=pd.read_csv('wdbc.data',header=None)
```

```
data.head()
```

```
[264]: headers=['id','diagnosis','mean_radius','mean_texture','mean_perimeter','mean_area','mean_smoothness',
↳points','mean_symmetry','mean_fractal_dimension','SE_radius','SE_texture','SE_perimeter','SE_area','SE_smoothness','SE_compactness',
↳points','SE_symmetry','SE_fractal_dimension','worst_radius','worst_texture','worst_perimeter','worst_area','worst_smoothness',
↳points','worst_symmetry','worst_fractal_dimension']
```

```
[265]: data.to_csv('labeledData.csv',header=headers,index=False)
```

```
[266]: data=pd.read_csv('labeledData.csv')
data.head()
```

```
[266]:
```

	id	diagnosis	mean_radius	mean_texture	mean_perimeter	mean_area	
0	842302	M	17.99	10.38	122.80	1001.0	\
1	842517	M	20.57	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	M	11.42	20.38	77.58	386.1	
4	84358402	M	20.29	14.34	135.10	1297.0	

	mean_smoothness	mean_compactness	mean_concavity	mean_concave points	
0	0.11840	0.27760	0.3001	0.14710	\

1	0.08474	0.07864	0.0869	0.07017
2	0.10960	0.15990	0.1974	0.12790
3	0.14250	0.28390	0.2414	0.10520
4	0.10030	0.13280	0.1980	0.10430

	...	worst_radius	worst_texture	worst_perimeter	worst_area	
0	...	25.38	17.33	184.60	2019.0	\
1	...	24.99	23.41	158.80	1956.0	
2	...	23.57	25.53	152.50	1709.0	
3	...	14.91	26.50	98.87	567.7	
4	...	22.54	16.67	152.20	1575.0	

		worst_smoothness	worst_compactness	worst_concavity	worst_concave points	
0		0.1622	0.6656	0.7119	0.2654	\
1		0.1238	0.1866	0.2416	0.1860	
2		0.1444	0.4245	0.4504	0.2430	
3		0.2098	0.8663	0.6869	0.2575	
4		0.1374	0.2050	0.4000	0.1625	

		worst_symmetry	worst_fractal dimension
0		0.4601	0.11890
1		0.2750	0.08902
2		0.3613	0.08758
3		0.6638	0.17300
4		0.2364	0.07678

[5 rows x 32 columns]

```
[267]: data.shape
```

```
[267]: (569, 32)
```

```
[268]: data.isna().sum()
```

```
[268]: id          0
diagnosis      0
mean_radius    0
mean_texture   0
mean_perimeter 0
mean_area      0
mean_smoothness 0
mean_compactness 0
mean_concavity 0
mean_concave points 0
mean_symmetry  0
mean_fractal dimension 0
SE_radius      0
```

```

SE_texture          0
SE_perimeter        0
SE_area             0
SE_smoothness       0
SE_compactness      0
SE_concavity        0
SE_concave points   0
SE_symmetry         0
SE_fractal dimension 0
worst_radius        0
worst_texture       0
worst_perimeter     0
worst_area          0
worst_smoothness    0
worst_compactness   0
worst_concavity     0
worst_concave points 0
worst_symmetry      0
worst_fractal dimension 0
dtype: int64

```

```
[269]: data['diagnosis'].value_counts()
```

```

[269]: diagnosis
B      357
M      212
Name: count, dtype: int64

```

```
[270]: data.dtypes
```

```

[270]: id          int64
diagnosis         object
mean_radius       float64
mean_texture      float64
mean_perimeter    float64
mean_area         float64
mean_smoothness   float64
mean_compactness  float64
mean_concavity    float64
mean_concave points float64
mean_symmetry     float64
mean_fractal dimension float64
SE_radius         float64
SE_texture        float64
SE_perimeter      float64
SE_area           float64
SE_smoothness     float64

```

```

SE_compactness      float64
SE_concavity         float64
SE_concave points   float64
SE_symmetry          float64
SE_fractal dimension float64
worst_radius         float64
worst_texture        float64
worst_perimeter      float64
worst_area           float64
worst_smoothness     float64
worst_compactness    float64
worst_concavity      float64
worst_concave points float64
worst_symmetry       float64
worst_fractal dimension float64
dtype: object

```

```

[271]: list=['id','diagnosis']
y=data.diagnosis
x=data.drop(list,axis=1)
x.head()

```

```

[271]:   mean_radius  mean_texture  mean_perimeter  mean_area  mean_smoothness
0         17.99         10.38         122.80        1001.0         0.11840 \
1         20.57         17.77         132.90        1326.0         0.08474
2         19.69         21.25         130.00        1203.0         0.10960
3         11.42         20.38          77.58         386.1         0.14250
4         20.29         14.34         135.10        1297.0         0.10030

      mean_compactness  mean_concavity  mean_concave points  mean_symmetry
0           0.27760         0.3001         0.14710         0.2419 \
1           0.07864         0.0869         0.07017         0.1812
2           0.15990         0.1974         0.12790         0.2069
3           0.28390         0.2414         0.10520         0.2597
4           0.13280         0.1980         0.10430         0.1809

      mean_fractal dimension  ...  worst_radius  worst_texture  worst_perimeter
0           0.07871  ...         25.38         17.33         184.60 \
1           0.05667  ...         24.99         23.41         158.80
2           0.05999  ...         23.57         25.53         152.50
3           0.09744  ...         14.91         26.50          98.87
4           0.05883  ...         22.54         16.67         152.20

      worst_area  worst_smoothness  worst_compactness  worst_concavity
0         2019.0         0.1622         0.6656         0.7119 \
1         1956.0         0.1238         0.1866         0.2416
2         1709.0         0.1444         0.4245         0.4504

```

3	567.7	0.2098	0.8663	0.6869
4	1575.0	0.1374	0.2050	0.4000

	worst_concave points	worst_symmetry	worst_fractal dimension
0	0.2654	0.4601	0.11890
1	0.1860	0.2750	0.08902
2	0.2430	0.3613	0.08758
3	0.2575	0.6638	0.17300
4	0.1625	0.2364	0.07678

[5 rows x 30 columns]

[272]: x.describe()

```
[272]:
```

	mean_radius	mean_texture	mean_perimeter	mean_area
count	569.000000	569.000000	569.000000	569.000000 \
mean	14.127292	19.289649	91.969033	654.889104
std	3.524049	4.301036	24.298981	351.914129
min	6.981000	9.710000	43.790000	143.500000
25%	11.700000	16.170000	75.170000	420.300000
50%	13.370000	18.840000	86.240000	551.100000
75%	15.780000	21.800000	104.100000	782.700000
max	28.110000	39.280000	188.500000	2501.000000

	mean_smoothness	mean_compactness	mean_concavity	mean_concave points
count	569.000000	569.000000	569.000000	569.000000 \
mean	0.096360	0.104341	0.088799	0.048919
std	0.014064	0.052813	0.079720	0.038803
min	0.052630	0.019380	0.000000	0.000000
25%	0.086370	0.064920	0.029560	0.020310
50%	0.095870	0.092630	0.061540	0.033500
75%	0.105300	0.130400	0.130700	0.074000
max	0.163400	0.345400	0.426800	0.201200

	mean_symmetry	mean_fractal dimension	...	worst_radius
count	569.000000	569.000000	...	569.000000 \
mean	0.181162	0.062798	...	16.269190
std	0.027414	0.007060	...	4.833242
min	0.106000	0.049960	...	7.930000
25%	0.161900	0.057700	...	13.010000
50%	0.179200	0.061540	...	14.970000
75%	0.195700	0.066120	...	18.790000
max	0.304000	0.097440	...	36.040000

	worst_texture	worst_perimeter	worst_area	worst_smoothness
count	569.000000	569.000000	569.000000	569.000000 \
mean	25.677223	107.261213	880.583128	0.132369

std	6.146258	33.602542	569.356993	0.022832
min	12.020000	50.410000	185.200000	0.071170
25%	21.080000	84.110000	515.300000	0.116600
50%	25.410000	97.660000	686.500000	0.131300
75%	29.720000	125.400000	1084.000000	0.146000
max	49.540000	251.200000	4254.000000	0.222600

	worst_compactness	worst_concavity	worst_concave points	
count	569.000000	569.000000	569.000000	\
mean	0.254265	0.272188	0.114606	
std	0.157336	0.208624	0.065732	
min	0.027290	0.000000	0.000000	
25%	0.147200	0.114500	0.064930	
50%	0.211900	0.226700	0.099930	
75%	0.339100	0.382900	0.161400	
max	1.058000	1.252000	0.291000	

	worst_symmetry	worst_fractal dimension
count	569.000000	569.000000
mean	0.290076	0.083946
std	0.061867	0.018061
min	0.156500	0.055040
25%	0.250400	0.071460
50%	0.282200	0.080040
75%	0.317900	0.092080
max	0.663800	0.207500

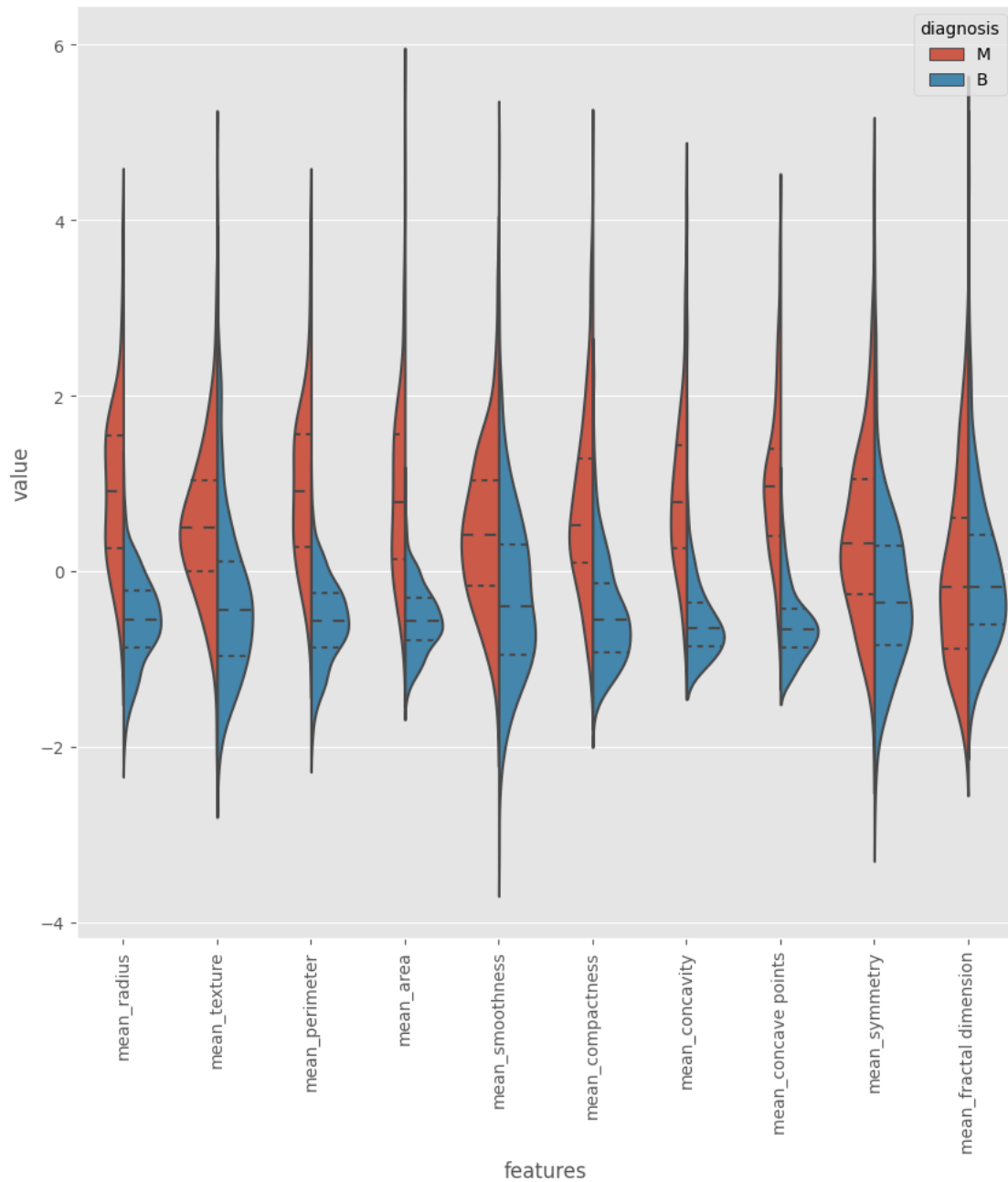
[8 rows x 30 columns]

```
[273]: diag=y
data=x
data_std=(data-data.mean())/(data.std())
```

```
[274]: data=pd.concat([y,data_std.iloc[:,0:10]],axis=1)
data=pd.melt(data,id_vars='diagnosis',var_name='features',value_name='value')
plt.figure(figsize=(10,10))
sns.
    ↪violinplot(x='features',y='value',hue='diagnosis',data=data,split=True,inner='quart')
plt.xticks(rotation=90)
```

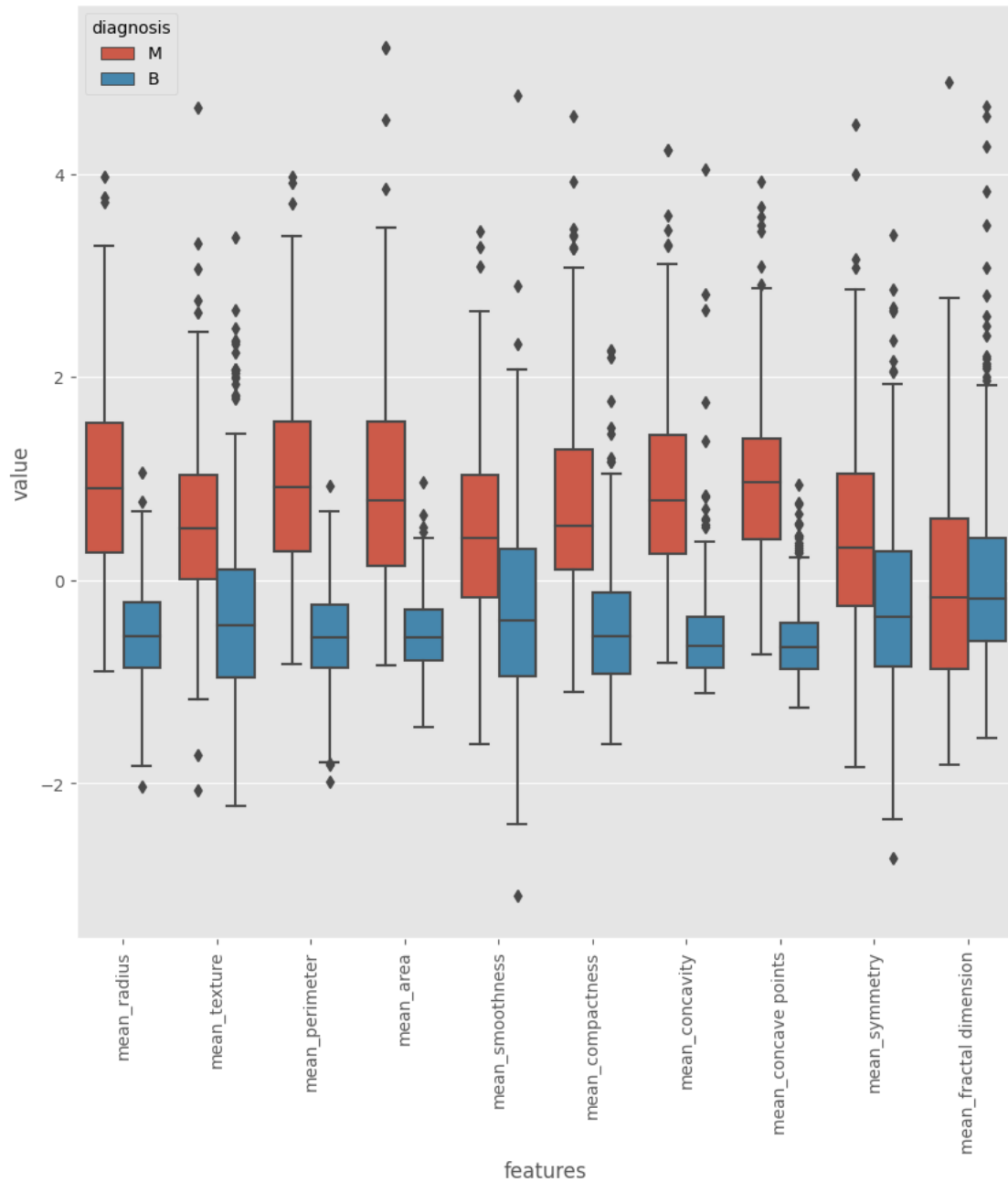
```
[274]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
[Text(0, 0, 'mean_radius'),
Text(1, 0, 'mean_texture'),
Text(2, 0, 'mean_perimeter'),
Text(3, 0, 'mean_area'),
Text(4, 0, 'mean_smoothness'),
Text(5, 0, 'mean_compactness'),
```

```
Text(6, 0, 'mean_concavity'),
Text(7, 0, 'mean_concave points'),
Text(8, 0, 'mean_symmetry'),
Text(9, 0, 'mean_fractal dimension']])
```



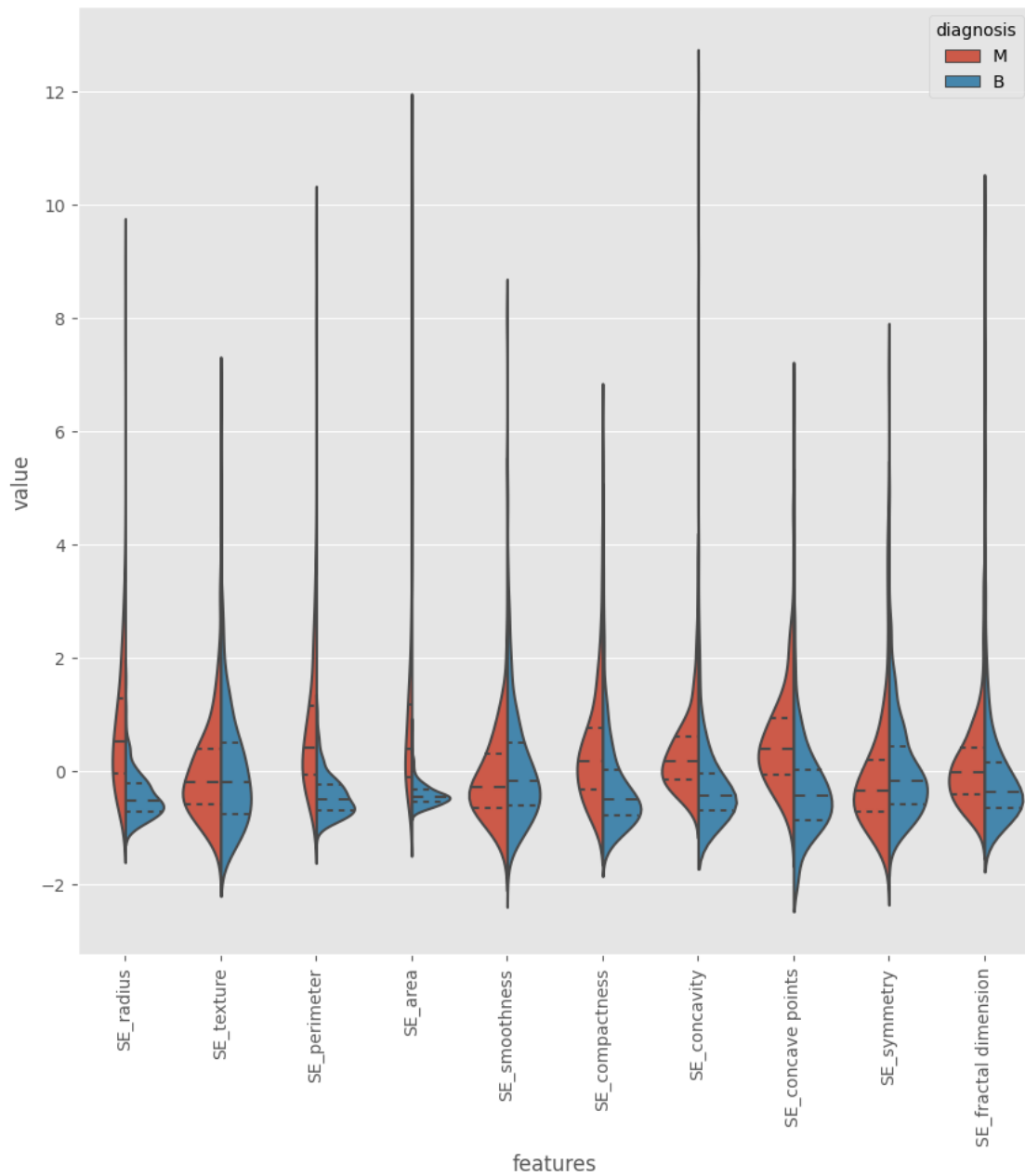
```
[275]: plt.figure(figsize=(10,10))
sns.boxplot(x="features",y="value",hue='diagnosis',data=data)
plt.xticks(rotation=90)
```

```
[275]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
      [Text(0, 0, 'mean_radius'),
       Text(1, 0, 'mean_texture'),
       Text(2, 0, 'mean_perimeter'),
       Text(3, 0, 'mean_area'),
       Text(4, 0, 'mean_smoothness'),
       Text(5, 0, 'mean_compactness'),
       Text(6, 0, 'mean_concavity'),
       Text(7, 0, 'mean_concave points'),
       Text(8, 0, 'mean_symmetry'),
       Text(9, 0, 'mean_fractal dimension')])
```

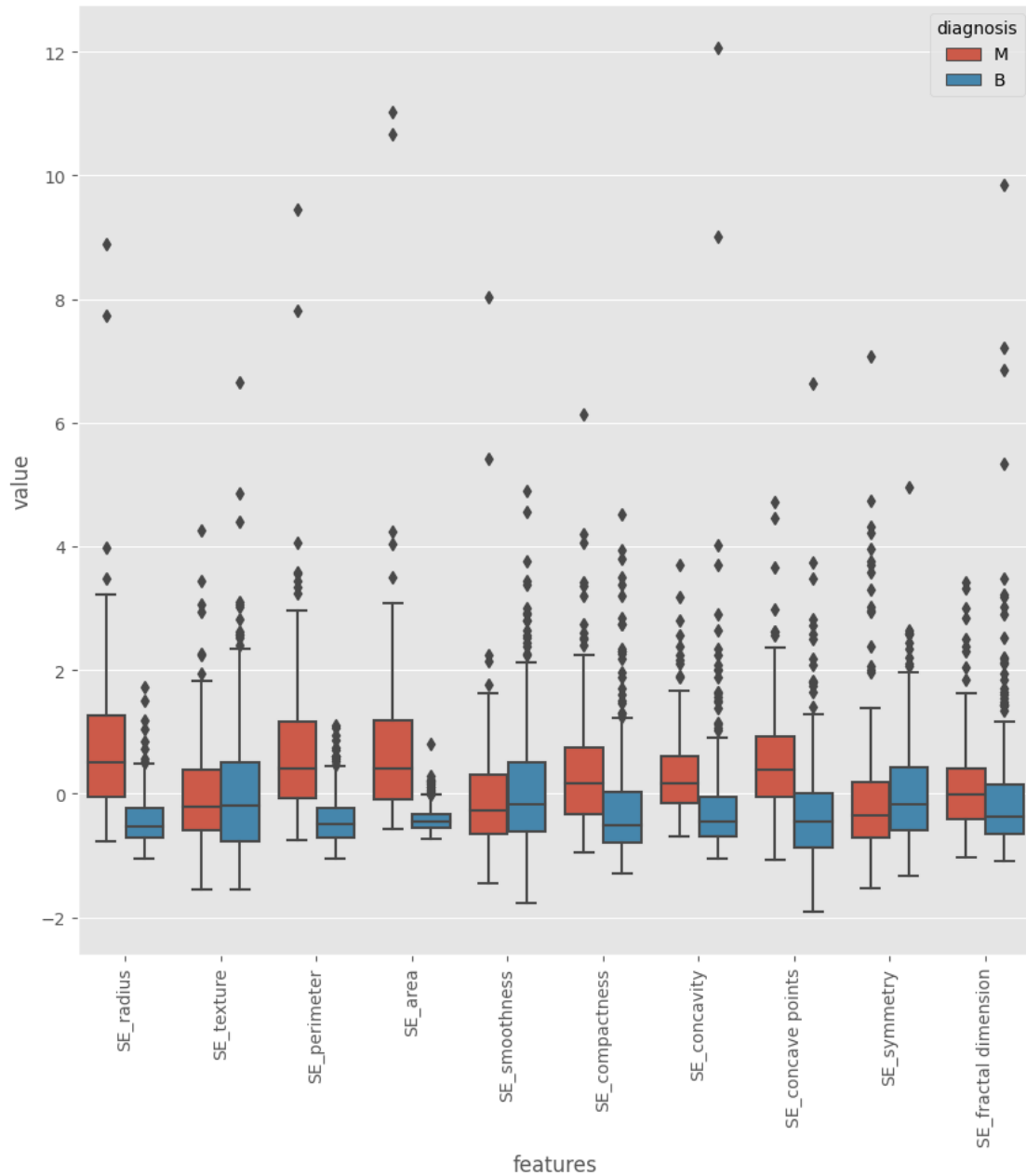
```
[276]: data = pd.concat([y,data_std.iloc[:,10:20]],axis=1)
data = pd.melt(data,id_vars="diagnosis",
               var_name="features",
               value_name='value')
plt.figure(figsize=(10,10))
sns.violinplot(x="features", y="value", hue="diagnosis", data=data,split=True,
               inner="quart")
plt.xticks(rotation=90)
```

```
[276]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
      [Text(0, 0, 'SE_radius'),
       Text(1, 0, 'SE_texture'),
       Text(2, 0, 'SE_perimeter'),
       Text(3, 0, 'SE_area'),
       Text(4, 0, 'SE_smoothness'),
       Text(5, 0, 'SE_compactness'),
       Text(6, 0, 'SE_concavity'),
       Text(7, 0, 'SE_concave points'),
       Text(8, 0, 'SE_symmetry'),
       Text(9, 0, 'SE_fractal dimension')])
```



```
[277]: plt.figure(figsize=(10,10))
sns.boxplot(x="features",y="value",hue='diagnosis',data=data)
plt.xticks(rotation=90)
```

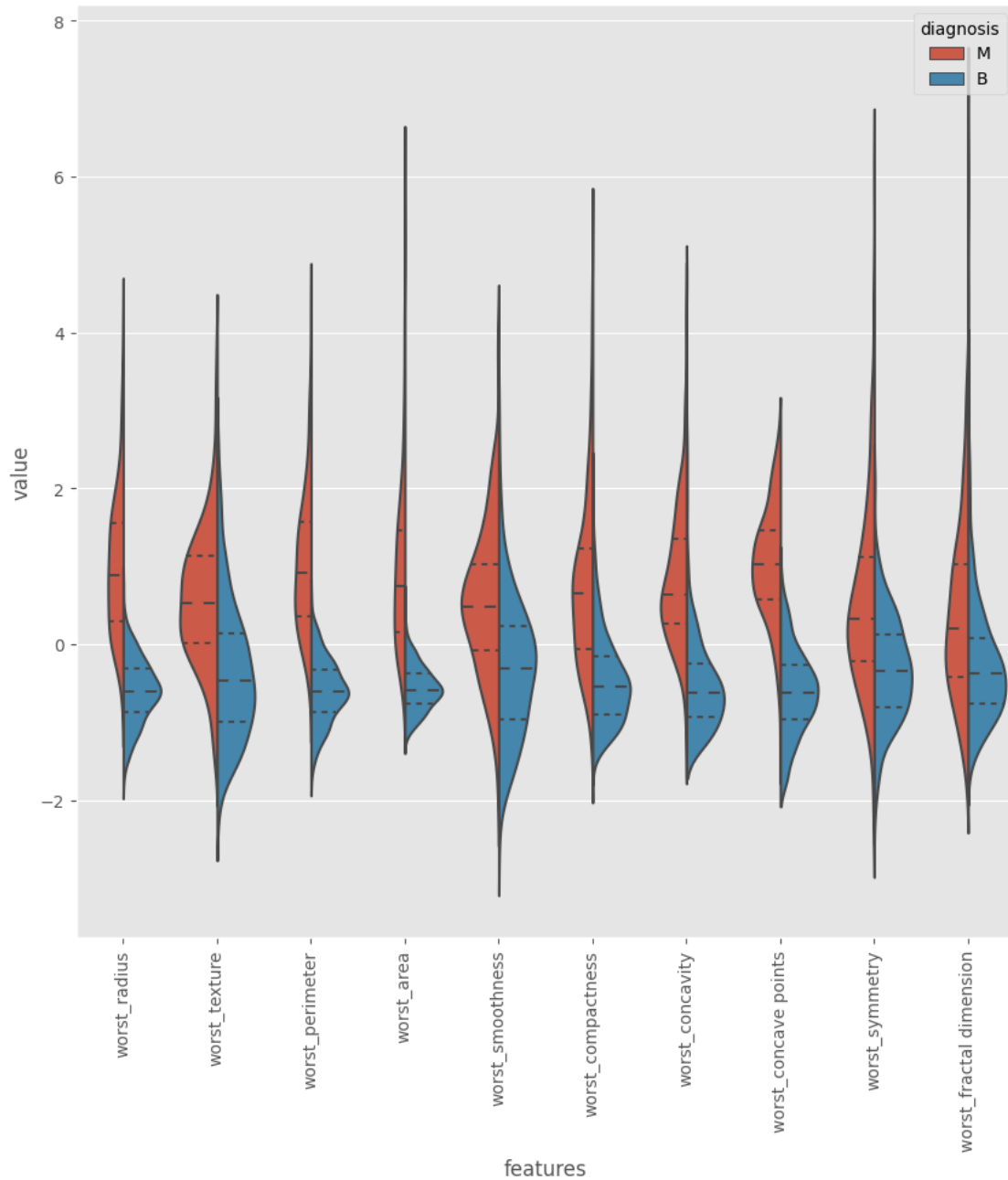
```
[277]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
[Text(0, 0, 'SE_radius'),
Text(1, 0, 'SE_texture'),
Text(2, 0, 'SE_perimeter'),
Text(3, 0, 'SE_area'),
Text(4, 0, 'SE_smoothness'),
Text(5, 0, 'SE_compactness'),
Text(6, 0, 'SE_concavity'),
Text(7, 0, 'SE_concave points'),
Text(8, 0, 'SE_symmetry'),
Text(9, 0, 'SE_fractal dimension')])
```



```
[278]: data = pd.concat([y,data_std.iloc[:,20:31]],axis=1)
data = pd.melt(data,id_vars="diagnosis",
               var_name="features",
               value_name='value')

plt.figure(figsize=(10,10))
sns.violinplot(x="features", y="value", hue="diagnosis", data=data,split=True,
               inner="quart")
plt.xticks(rotation=90)
```

```
[278]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
      [Text(0, 0, 'worst_radius'),
       Text(1, 0, 'worst_texture'),
       Text(2, 0, 'worst_perimeter'),
       Text(3, 0, 'worst_area'),
       Text(4, 0, 'worst_smoothness'),
       Text(5, 0, 'worst_compactness'),
       Text(6, 0, 'worst_concavity'),
       Text(7, 0, 'worst_concave points'),
       Text(8, 0, 'worst_symmetry'),
       Text(9, 0, 'worst_fractal dimension')])
```



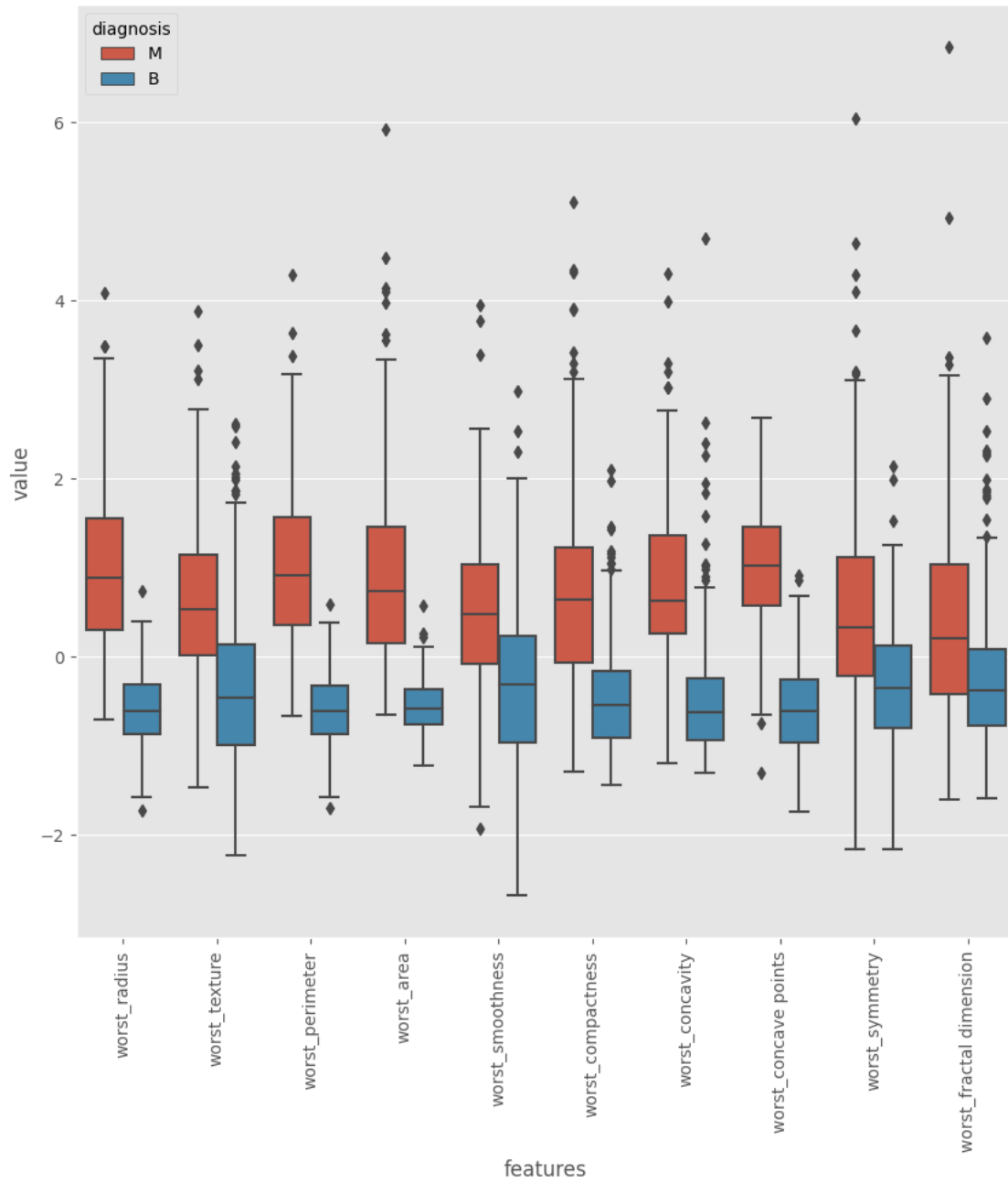
```
[279]: plt.figure(figsize=(10,10))
sns.boxplot(x="features",y="value",hue='diagnosis',data=data)
plt.xticks(rotation=90)
```

```
[279]: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
[Text(0, 0, 'worst_radius'),
Text(1, 0, 'worst_texture'),
Text(2, 0, 'worst_perimeter'),
```

```

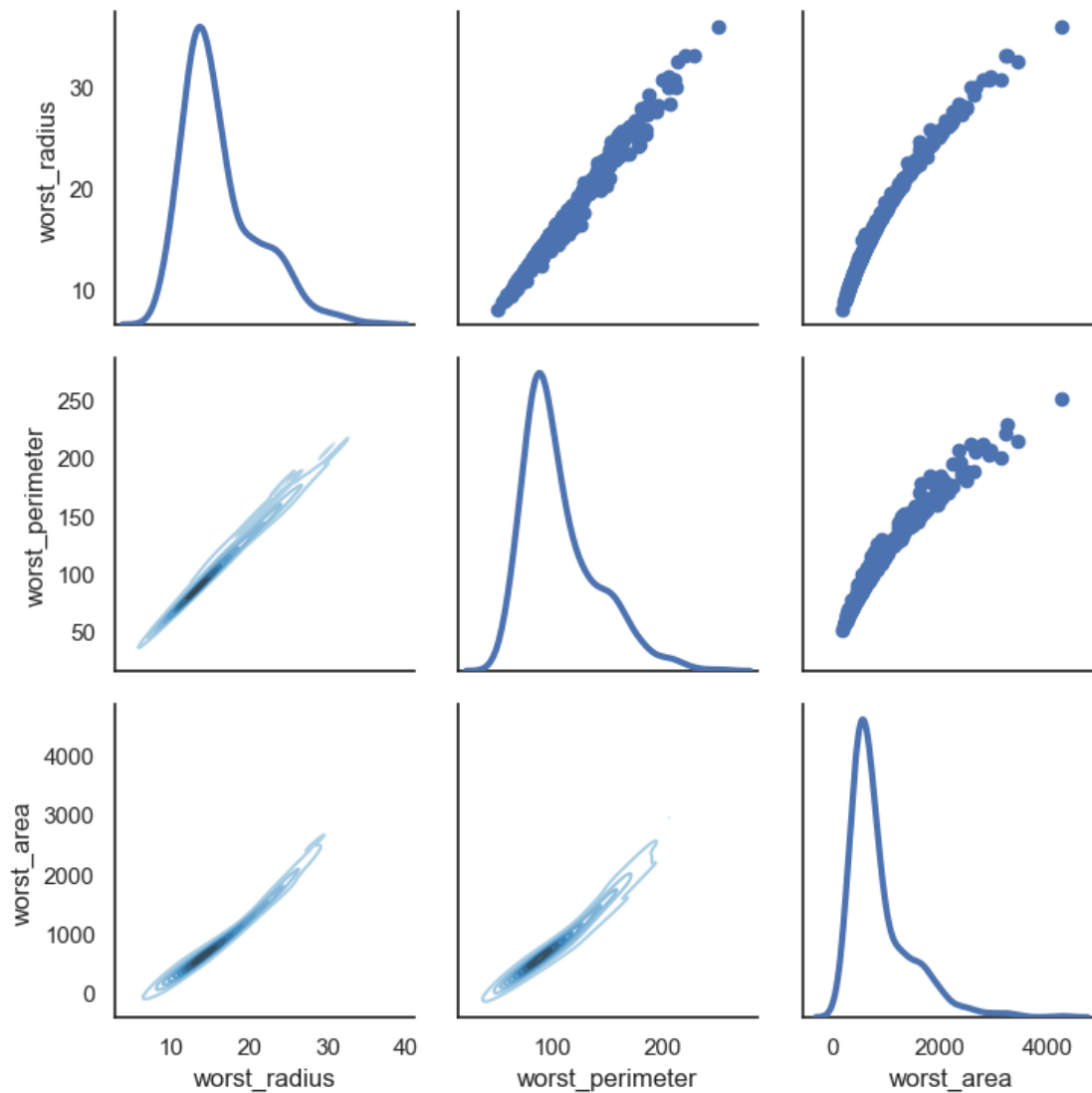
Text(3, 0, 'worst_area'),
Text(4, 0, 'worst_smoothness'),
Text(5, 0, 'worst_compactness'),
Text(6, 0, 'worst_concavity'),
Text(7, 0, 'worst_concave points'),
Text(8, 0, 'worst_symmetry'),
Text(9, 0, 'worst_fractal dimension')]]

```



```
[280]: sns.set(style='white')
df=x.loc[:,['worst_radius','worst_perimeter','worst_area']]
g=sns.PairGrid(df,diag_sharey=False)
g.map_lower(sns.kdeplot,cmap='Blues_d')
g.map_upper(plt.scatter)
g.map_diag(sns.kdeplot,lw=3)
```

```
[280]: <seaborn.axisgrid.PairGrid at 0x25871c93b50>
```



```
[281]: sns.set(style='whitegrid',palette='muted')
diag=y
data=x
data_n=(data-data.mean())/(data.std())
```



```

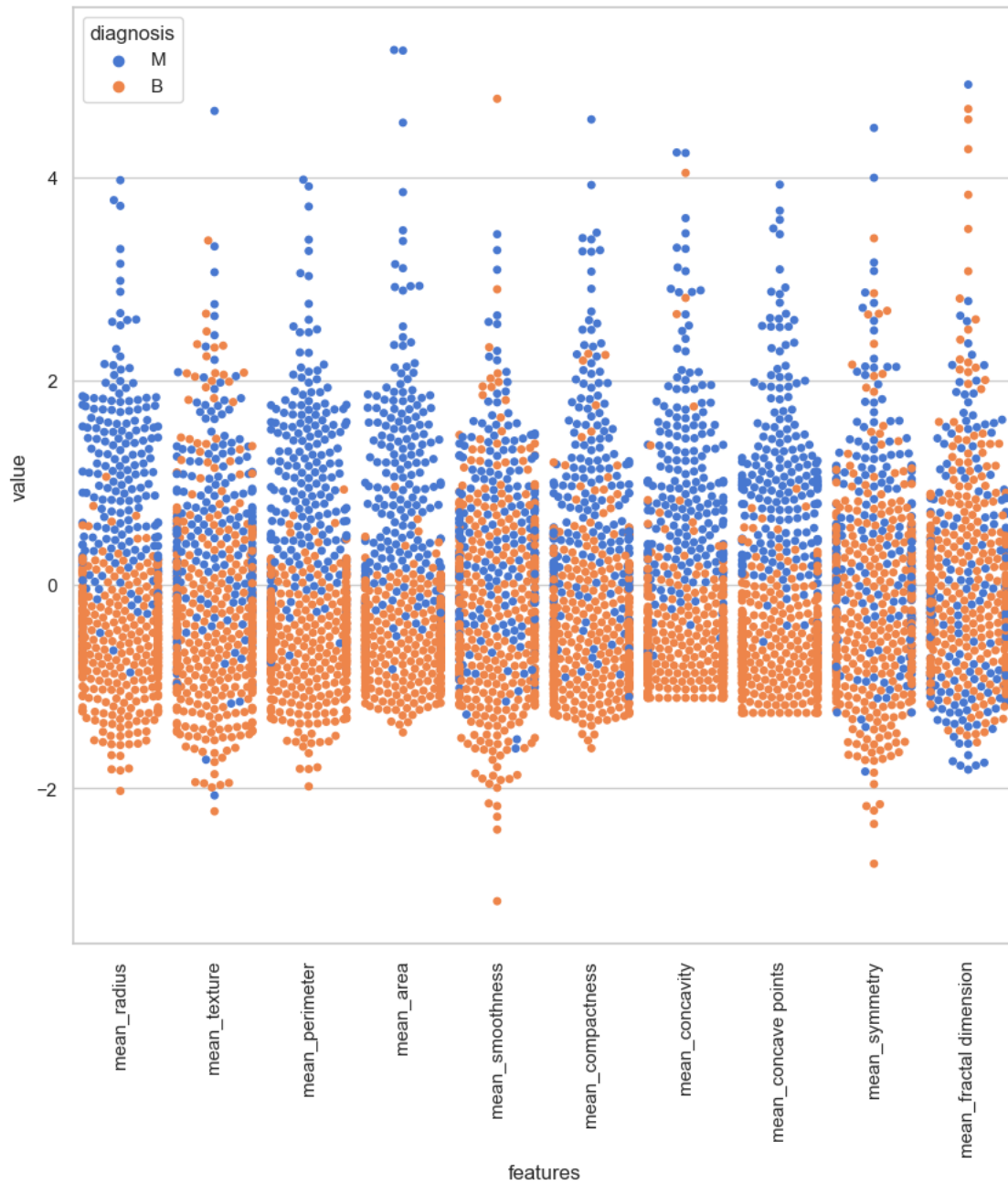
data=pd.concat([y,data_n.iloc[:,0:10]],axis=1)
data=pd.melt(data,id_vars='diagnosis',var_name='features',value_name='value')
plt.figure(figsize=(10,10))
tic=time.time()
sns.swarmplot(x='features',y='value',hue='diagnosis',data=data)
plt.xticks(rotation=90)

```

```

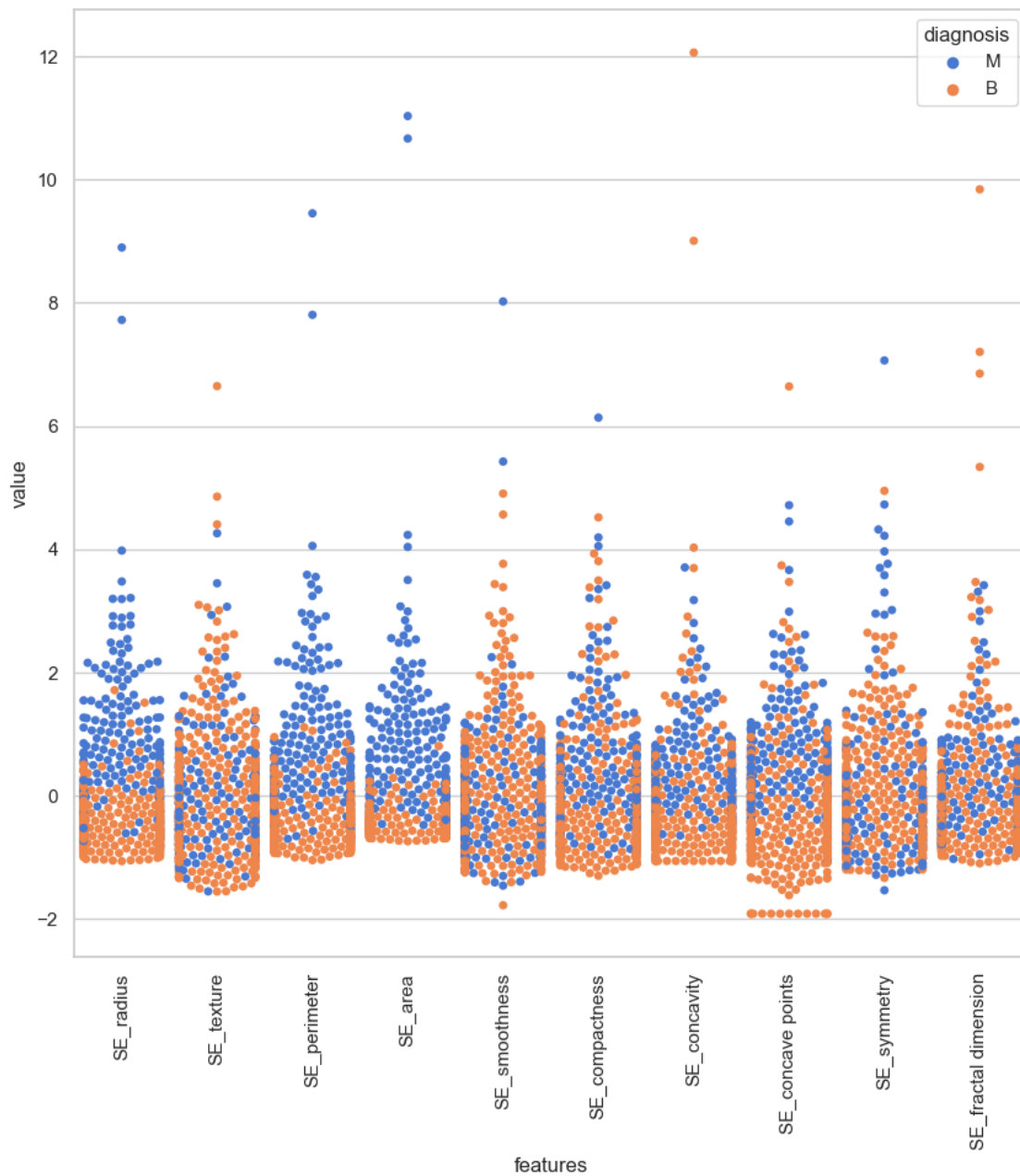
[281]: ([0, 1, 2, 3, 4, 5, 6, 7, 8, 9],
       [Text(0, 0, 'mean_radius'),
        Text(1, 0, 'mean_texture'),
        Text(2, 0, 'mean_perimeter'),
        Text(3, 0, 'mean_area'),
        Text(4, 0, 'mean_smoothness'),
        Text(5, 0, 'mean_compactness'),
        Text(6, 0, 'mean_concavity'),
        Text(7, 0, 'mean_concave points'),
        Text(8, 0, 'mean_symmetry'),
        Text(9, 0, 'mean_fractal dimension')])

```



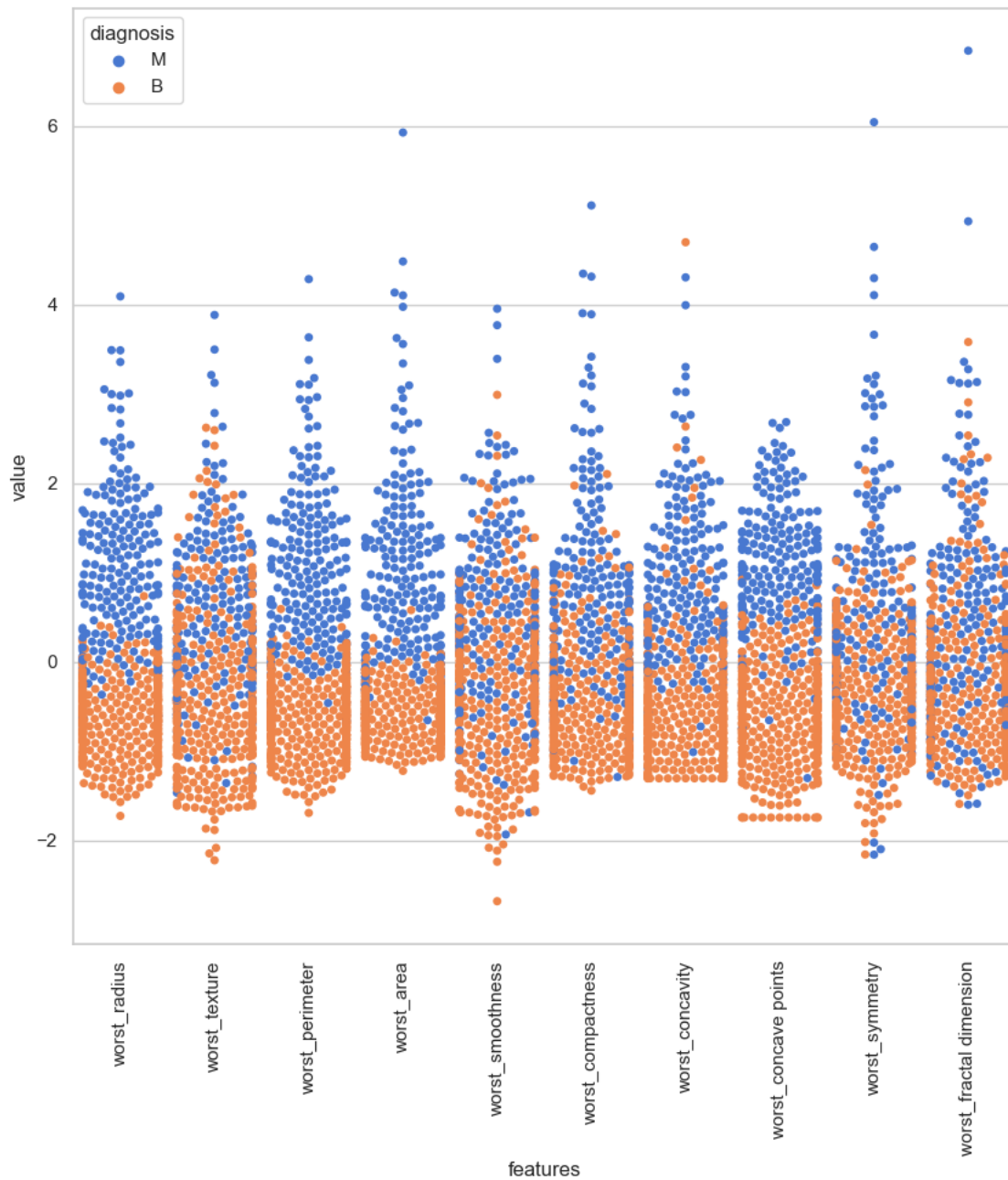
```
[282]: data=pd.concat([y,data_n.iloc[:,10:20]],axis=1)
data=pd.melt(data,id_vars='diagnosis',var_name='features',value_name='value')
plt.figure(figsize=(10,10))
tic=time.time()
sns.swarmplot(x='features',y='value',hue='diagnosis',data=data)
plt.xticks(rotation=90)
```

```
[282]: ([0, 1, 2, 3, 4, 5, 6, 7, 8, 9],
        [Text(0, 0, 'SE_radius'),
         Text(1, 0, 'SE_texture'),
         Text(2, 0, 'SE_perimeter'),
         Text(3, 0, 'SE_area'),
         Text(4, 0, 'SE_smoothness'),
         Text(5, 0, 'SE_compactness'),
         Text(6, 0, 'SE_concavity'),
         Text(7, 0, 'SE_concave points'),
         Text(8, 0, 'SE_symmetry'),
         Text(9, 0, 'SE_fractal dimension')])
```



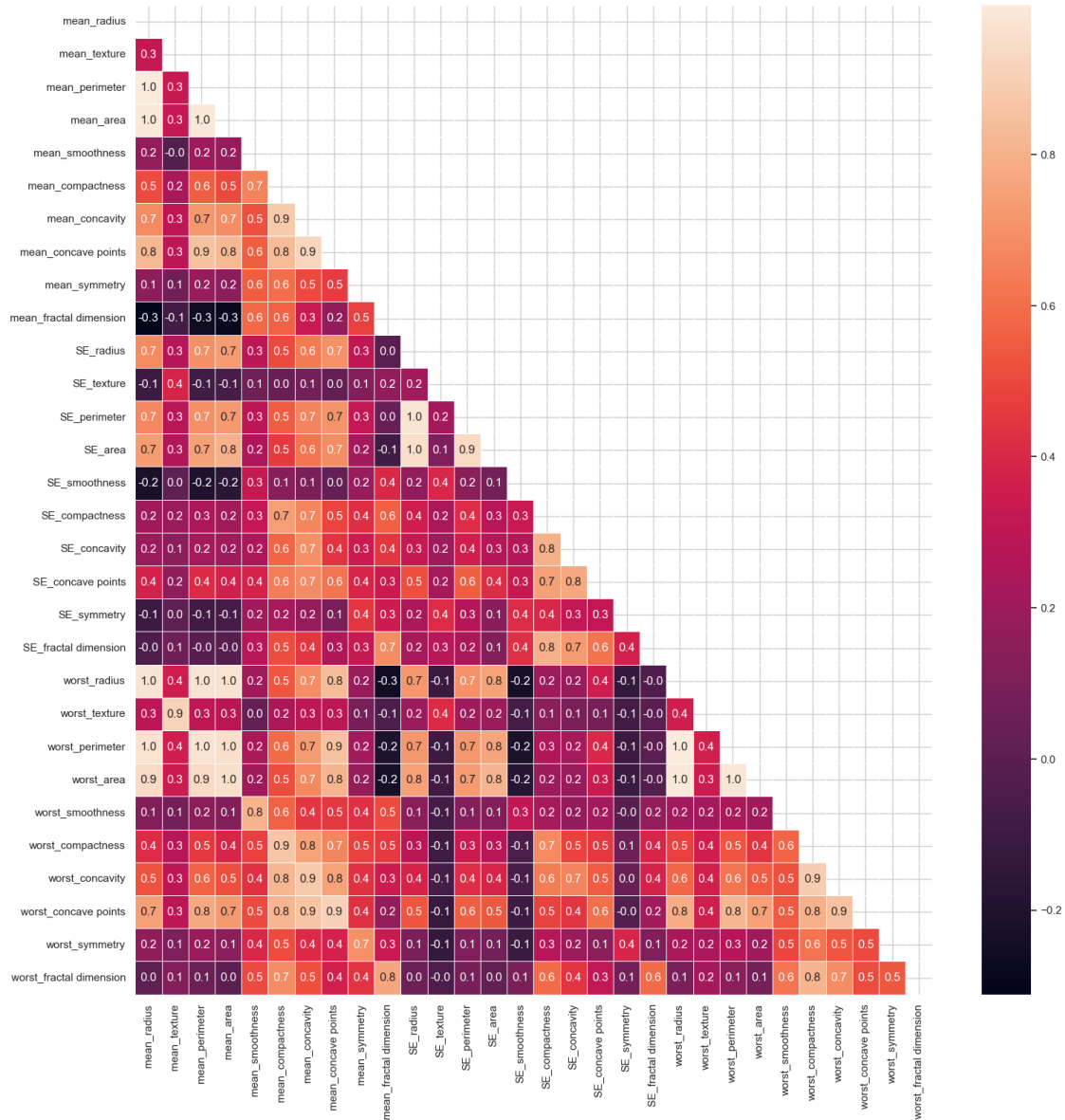
```
[283]: data=pd.concat([y,data_n.iloc[:,20:31]],axis=1)
data=pd.melt(data,id_vars='diagnosis',var_name='features',value_name='value')
plt.figure(figsize=(10,10))
tic=time.time()
sns.swarmplot(x='features',y='value',hue='diagnosis',data=data)
plt.xticks(rotation=90)
```

```
[283]: ([0, 1, 2, 3, 4, 5, 6, 7, 8, 9],
[Text(0, 0, 'worst_radius'),
Text(1, 0, 'worst_texture'),
Text(2, 0, 'worst_perimeter'),
Text(3, 0, 'worst_area'),
Text(4, 0, 'worst_smoothness'),
Text(5, 0, 'worst_compactness'),
Text(6, 0, 'worst_concavity'),
Text(7, 0, 'worst_concave points'),
Text(8, 0, 'worst_symmetry'),
Text(9, 0, 'worst_fractal dimension')])
```



```
[284]: f,ax = plt.subplots(figsize=(18, 18))
matrix = np.triu(x.corr())
sns.heatmap(x.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax, mask=matrix)
```

```
[284]: <Axes: >
```



```
[285]: # Create correlation matrix
corr_matrix = x.corr().abs() # Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

# Find index of feature columns with correlation greater than 0.8
to_drop = [column for column in upper.columns if any(upper[column] > 0.8)]
```

```
[286]: to_drop
```

```
[286]: ['mean_perimeter',
        'mean_area',
        'mean_concavity',
        'mean_concave points',
        'SE_perimeter',
        'SE_area',
        'SE_concavity',
        'SE_fractal dimension',
        'worst_radius',
        'worst_texture',
        'worst_perimeter',
        'worst_area',
        'worst_smoothness',
        'worst_compactness',
        'worst_concavity',
        'worst_concave points',
        'worst_fractal dimension']
```

```
[287]: # Drop features
x1 = x.drop(x[to_drop], axis=1)
x1.columns
```

```
[287]: Index(['mean_radius', 'mean_texture', 'mean_smoothness', 'mean_compactness',
        'mean_symmetry', 'mean_fractal dimension', 'SE_radius', 'SE_texture',
        'SE_smoothness', 'SE_compactness', 'SE_concave points', 'SE_symmetry',
        'worst_symmetry'],
        dtype='object')
```

```
[288]: x1.head()
```

```
[288]:
```

	mean_radius	mean_texture	mean_smoothness	mean_compactness	
0	17.99	10.38	0.11840	0.27760	\
1	20.57	17.77	0.08474	0.07864	
2	19.69	21.25	0.10960	0.15990	
3	11.42	20.38	0.14250	0.28390	
4	20.29	14.34	0.10030	0.13280	

	mean_symmetry	mean_fractal dimension	SE_radius	SE_texture	
0	0.2419	0.07871	1.0950	0.9053	\
1	0.1812	0.05667	0.5435	0.7339	
2	0.2069	0.05999	0.7456	0.7869	
3	0.2597	0.09744	0.4956	1.1560	
4	0.1809	0.05883	0.7572	0.7813	

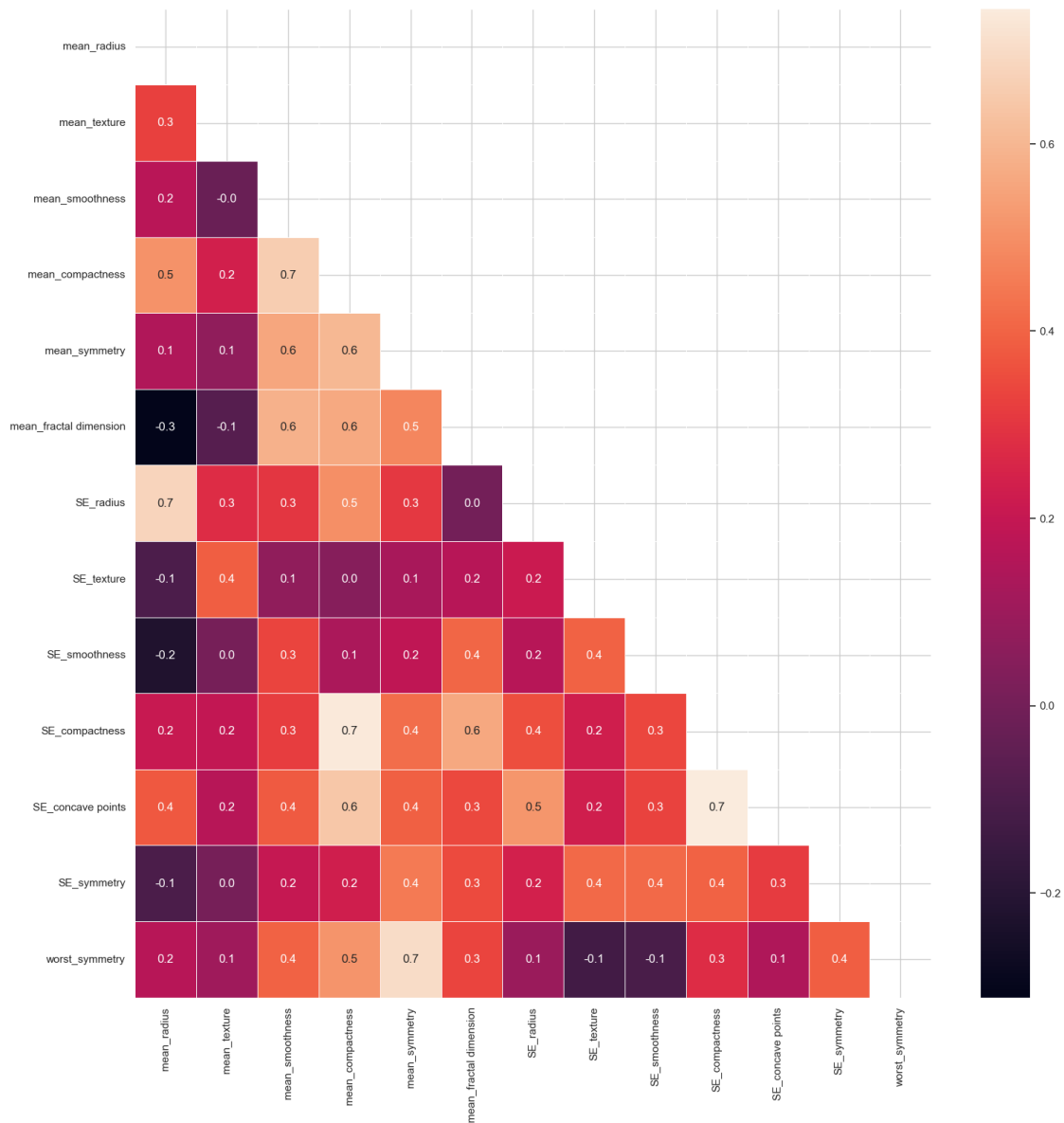
	SE_smoothness	SE_compactness	SE_concave points	SE_symmetry	
0	0.006399	0.04904	0.01587	0.03003	\
1	0.005225	0.01308	0.01340	0.01389	

2	0.006150	0.04006	0.02058	0.02250
3	0.009110	0.07458	0.01867	0.05963
4	0.011490	0.02461	0.01885	0.01756

	worst_symmetry
0	0.4601
1	0.2750
2	0.3613
3	0.6638
4	0.2364

```
[289]: f,ax = plt.subplots(figsize=(18, 18))
matrix = np.triu(x1.corr())
sns.heatmap(x1.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax, mask=matrix)
```

```
[289]: <Axes: >
```

```
[290]: from sklearn.model_selection import train_test_split
```

```
[291]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
        ↪3,random_state=42)
```

```
[292]: from sklearn.ensemble import RandomForestClassifier
        from sklearn.metrics import f1_score,confusion_matrix
        from sklearn.metrics import accuracy_score
```

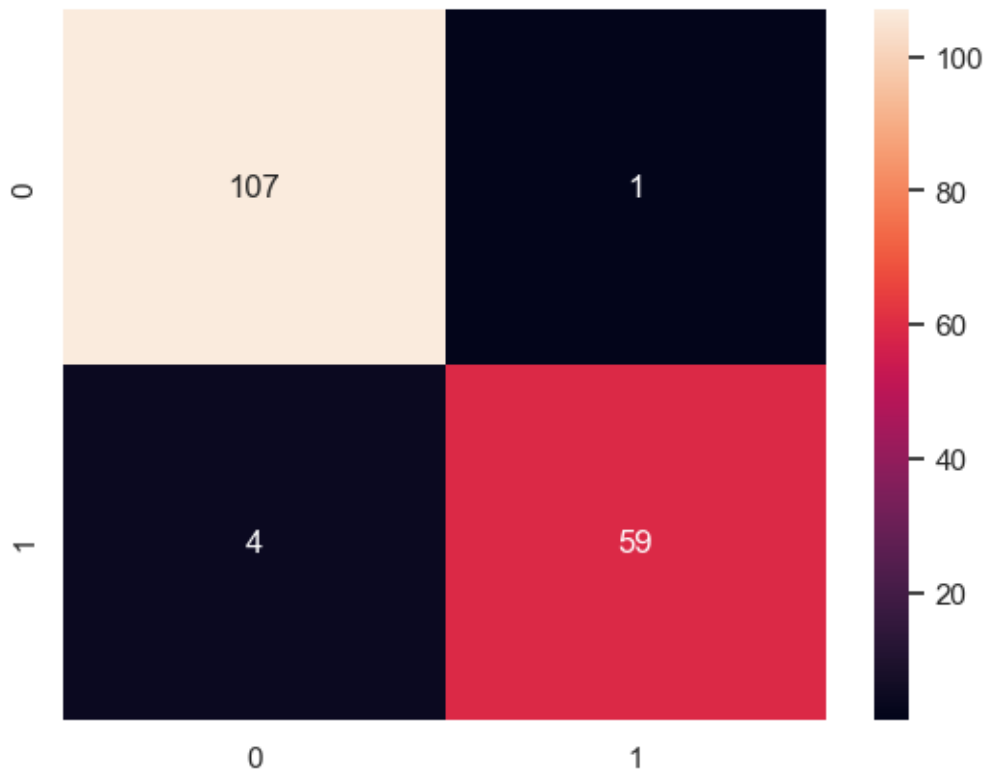
```

RFC1=RandomForestClassifier(random_state=42)
RFC1=RFC1.fit(x_train,y_train)
acc=accuracy_score(y_test,RFC1.predict(x_test))
print('Accuracy is:',acc)
cm=confusion_matrix(y_test,RFC1.predict(x_test))
sns.heatmap(cm,annot=True,fmt='d')

```

Accuracy is: 0.9707602339181286

[292]: <Axes: >



```

[293]: from sklearn.feature_selection import SelectKBest
       from sklearn.feature_selection import chi2

```

```

[294]: feature_select=SelectKBest(chi2,k=5).fit(x_train,y_train)
       print('Score list:',feature_select.scores_)
       print('Feature list:',x_train.columns)

```

Score list: [1.77946492e+02 6.06916433e+01 1.34061092e+03 3.66899557e+04
1.00015175e-01 3.41839493e+00 1.30547650e+01 7.09766457e+00
1.95982847e-01 3.42575072e-04 2.45882967e+01 4.07131026e-02
1.72696840e+02 6.12741067e+03 1.32470372e-03 3.74071521e-01]

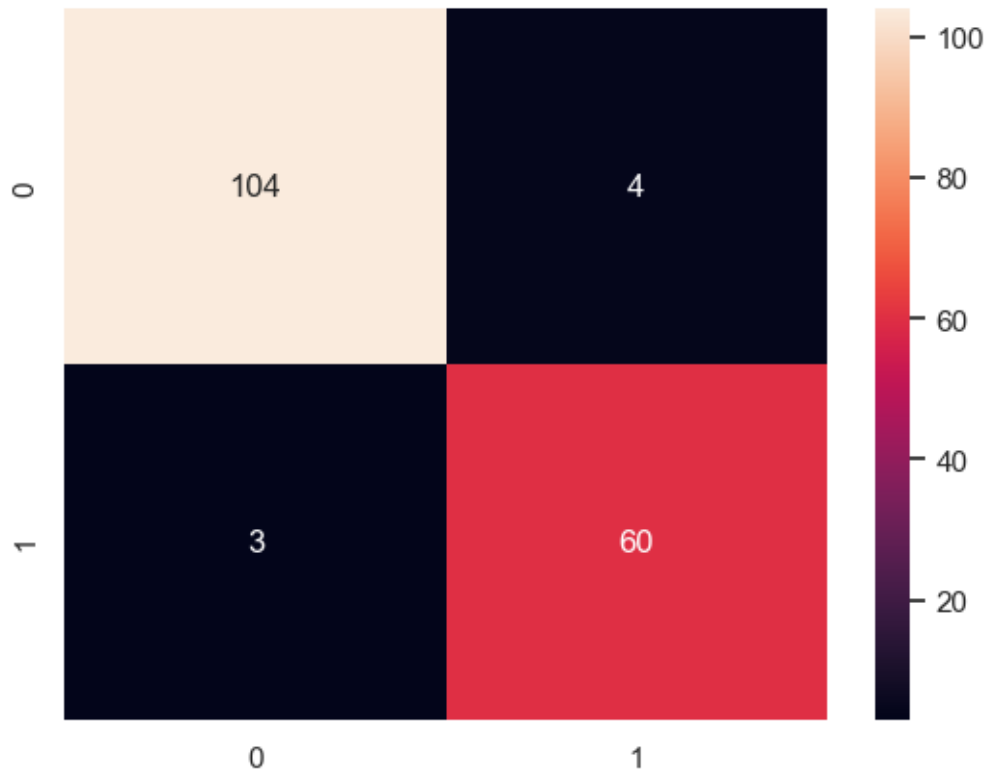
```
6.92896719e-01 2.01587194e-01 1.39557806e-03 2.65927071e-03
3.25782599e+02 1.16958562e+02 2.40512835e+03 7.50217341e+04
2.63226314e-01 1.19077581e+01 2.58858117e+01 8.90751003e+00
1.00635138e+00 1.23087347e-01]
```

```
Feature list: Index(['mean_radius', 'mean_texture', 'mean_perimeter',
'mean_area',
'mean_smoothness', 'mean_compactness', 'mean_concavity',
'mean_concave points', 'mean_symmetry', 'mean_fractal dimension',
'SE_radius', 'SE_texture', 'SE_perimeter', 'SE_area', 'SE_smoothness',
'SE_compactness', 'SE_concavity', 'SE_concave points', 'SE_symmetry',
'SE_fractal dimension', 'worst_radius', 'worst_texture',
'worst_perimeter', 'worst_area', 'worst_smoothness',
'worst_compactness', 'worst_concavity', 'worst_concave points',
'worst_symmetry', 'worst_fractal dimension'],
dtype='object')
```

```
[295]: x_train_2=feature_select.transform(x_train)
x_test_2=feature_select.transform(x_test)
RFC12=RandomForestClassifier()
RFC12.fit(x_train_2,y_train)
acc2=accuracy_score(y_test,RFC12.predict(x_test_2))
print('Accuracy is:',acc2)
cm2=confusion_matrix(y_test,RFC12.predict(x_test_2))
sns.heatmap(cm2,annot=True,fmt='d')
```

Accuracy is: 0.9590643274853801

```
[295]: <Axes: >
```



```
[296]: from sklearn.feature_selection import RFE
RFC13=RandomForestClassifier()

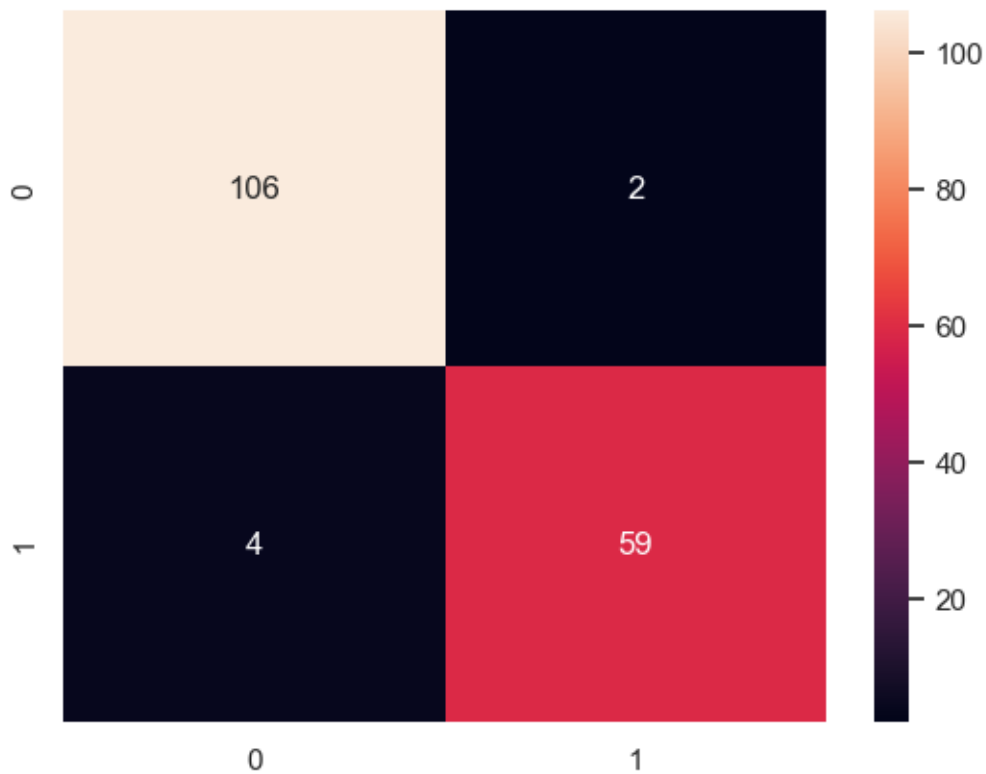
rfe=RFE(estimator=RFC13,n_features_to_select=5,step=1)
rfe=rfe.fit(x_train,y_train)
x_train_3=rfe.transform(x_train)
x_test_3=rfe.transform(x_test)
print('Chosen best 5 features by rfe:',x_train.columns[rfe.support_])
```

```
Chosen best 5 features by rfe: Index(['mean_concave points', 'worst_radius',
'worst_perimeter', 'worst_area',
'worst_concave points'],
dtype='object')
```

```
[300]: RFC13.fit(x_train_3,y_train)
acc3=accuracy_score(y_test,RFC13.predict(x_test_3))
print('Accuracy is:',acc3)
cm2=confusion_matrix(y_test,RFC13.predict(x_test_3))
sns.heatmap(cm2,annot=True,fmt='d')
```

```
Accuracy is: 0.9649122807017544
```

[300]: <Axes: >



```
[301]: from sklearn.feature_selection import RFECV
RFC14=RandomForestClassifier()
rfecv=RFECV(estimator=RFC14,step=1,cv=5,scoring='accuracy')
rfecv=rfecv.fit(x_train,y_train)
print('Optimal number of features:',rfecv.n_features_)
print('Best features:',x_train.columns[rfecv.support_])
```

```
Optimal number of features: 13
Best features: Index(['mean_radius', 'mean_texture', 'mean_perimeter',
'mean_area',
'mean_concavity', 'mean_concave points', 'SE_area', 'worst_radius',
'worst_texture', 'worst_perimeter', 'worst_area', 'worst_concavity',
'worst_concave points'],
dtype='object')
```

```
[302]: rfecv.fit(x_train,y_train)
x_train_4=rfecv.transform(x_train)
x_test_4=rfecv.transform(x_test)
RFC14.fit(x_train_4,y_train)
```

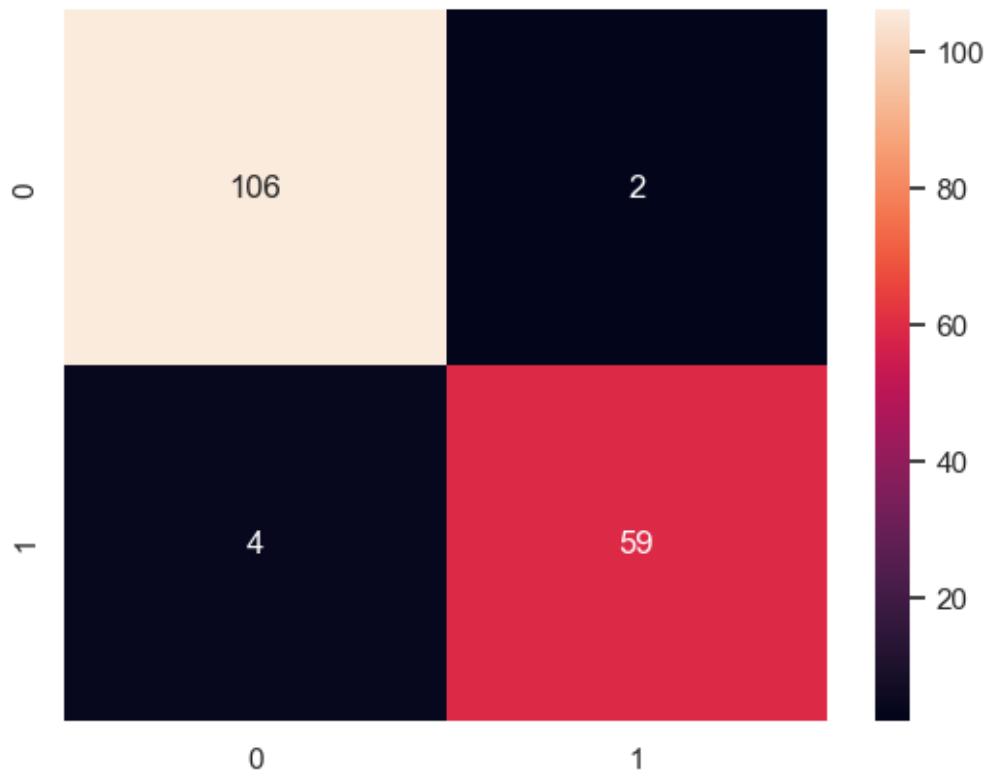
```

acc4=accuracy_score(y_test,RFC14.predict(x_test_4))
print('Accuracy is:',acc4)
cm2=confusion_matrix(y_test,RFC14.predict(x_test_4))
sns.heatmap(cm2,annot=True,fmt='d')

```

Accuracy is: 0.9649122807017544

[302]: <Axes: >



```

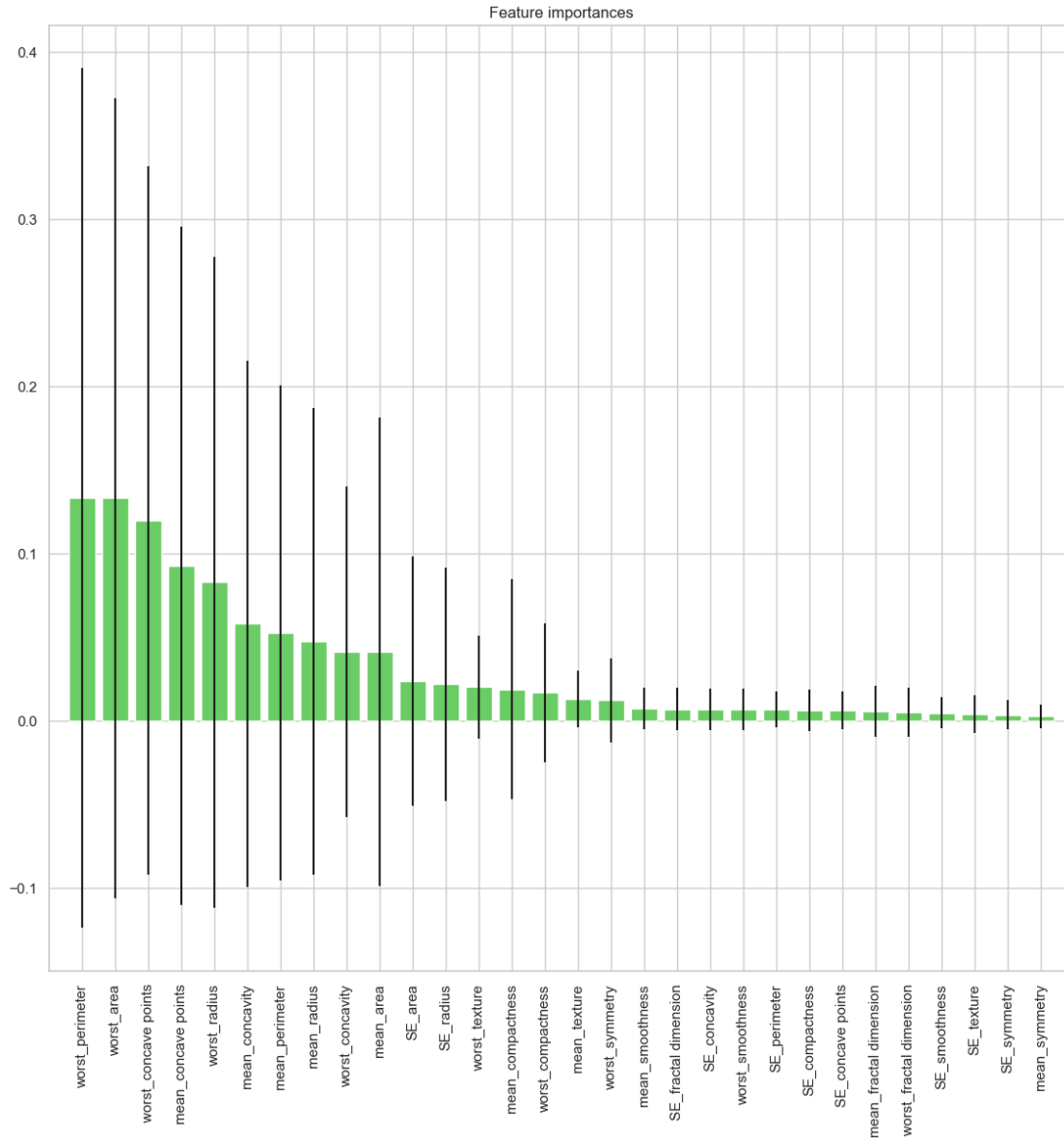
[303]: RFC15=RandomForestClassifier()
RFC15=RFC15.fit(x_train,y_train)
importances=RFC15.feature_importances_
std=np.std([tree.feature_importances_ for tree in RFC15.estimators_],axis=0)
indices=np.argsort(importances)[::-1]
print('Feature ranking:')
for f in range(x_train.shape[1]):
    print( '%d. feature %d )=(%f)' % (f+1,indices[f],importances[indices[f]]))
plt.figure(1,figsize=(14,13))
plt.title('Feature importances')
plt.bar(range(x_train.
    ↪shape[1]),importances[indices],color='g',yerr=std[indices],align='center')
plt.xticks(range(x_train.shape[1]),x_train.columns[indices],rotation=90)

```

```
plt.xlim([-1,x_train.shape[1]])  
plt.show()
```

Feature ranking:

1. feature 22)=(0.133143)
2. feature 23)=(0.133068)
3. feature 27)=(0.119613)
4. feature 7)=(0.092584)
5. feature 20)=(0.082885)
6. feature 6)=(0.057896)
7. feature 2)=(0.052447)
8. feature 0)=(0.047453)
9. feature 26)=(0.041349)
10. feature 3)=(0.041249)
11. feature 13)=(0.023812)
12. feature 10)=(0.021853)
13. feature 21)=(0.020053)
14. feature 5)=(0.018697)
15. feature 25)=(0.016667)
16. feature 1)=(0.012959)
17. feature 28)=(0.012210)
18. feature 4)=(0.007435)
19. feature 19)=(0.006828)
20. feature 16)=(0.006770)
21. feature 24)=(0.006609)
22. feature 12)=(0.006606)
23. feature 15)=(0.006181)
24. feature 17)=(0.006067)
25. feature 9)=(0.005679)
26. feature 29)=(0.005058)
27. feature 14)=(0.004739)
28. feature 11)=(0.003873)
29. feature 18)=(0.003526)
30. feature 8)=(0.002691)



[]: *#Since dimensionality reduction improved efficiency but not importance, we'll ↪ assess the results of the Random Forest algorithm using all features.*