HW1_part3

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1 CS 84020 Neural Networks and Deep Learning

Homework 1

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2 PART3

3 Listing 8

Load libraries. Load the Wisconsin Diagnostic Breast Cancer dataset. Complete any 8 calculations and plottings using Seaborn package which are not included into the previous calculations and plottings with matplotlib. Two of these might be related to PCA. 1 Bivariate Density Plot

2) Categorized Empirical Cumulative Distribution Plot
3) Empirical Cumulative Distribution Plot
4) PCA Plot
5) Violin Plot
6) Strip Plot
7) Box Plot
8) Feature Selection, Prediction and Confusion Matrix

Analysis From the Bivariate density plot of the first 10 features, we can see that only two feature can somehow reflect the difference between two labels(green and pink). For example, 'compactness_mean' and 'perimeter_mean' density plot shows two highly separated distributions of two labels (green and pink). However, 'compactness_mean' and 'smoothness_mean' formed same distribution of two labels which means it's hard to distinguish two class by these two features. Categorized empirical cumulative distribution also shows different distribution of two labels. 'perimeter_mean' has extremely different distribution between two labels. Empirical cumulative distribution plot shows the unique distribution of each feature. PCA(2 components) shows how well the best two features can do to classify the categories. From the plot, we can see that blue spots and orange spots are nearly separated by two features in a 2 dimension space.

The correlation matrix from Part 2: Listing 6, violin plots, strip plots, and bar plot below shed light on which features are least correlated to the diagnosis and to which there is little variation between the benign and malignant interquartiles. This, in addition to the dependent features ('perimeter_*' and 'area_*') described earlier, informs us in the dropping of some features in feature selection: 'fractal_dimension_mean', 'texture_se', 'smoothness_se', 'symmetry_se', 'fractal_dimension_se'. Rerunning the model afterwards yields improved performance for every model, except linear discriminant analysis and naive bayes. For our purpose of diagnosing malignancies with the least amount of misses, the decision tree classifier performs the best, yielding a recall of 97% for the malignant class.

a) Load libraries.

[27]:
```
# Load libraries
from pandas import read_csv, set_option
from pandas.plotting import scatter_matrix
from matplotlib import pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
from google.colab import data_table
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn import decomposition
```

[28]:
```
# Set options
set_option('display.max_columns', 32)
# plt.style.use('seaborn-talk')
plt.style.use('seaborn-white')
```

b) Load the dataset.

[29]:
```
# Load dataset
filename = 'http://archive.ics.uci.edu/ml/machine-learning-databases/
↪breast-cancer-wisconsin/wdbc.data'
colnames = ['id', 'diagnosis',
         'radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean',
         'smoothness_mean', 'compactness_mean', 'concavity_mean',
```

```
            'concave_points_mean', 'symmetry_mean', 'fractal_dimension_mean',
            'radius_se', 'texture_se', 'perimeter_se', 'area_se',
            'smoothness_se', 'compactness_se', 'concavity_se',
            'concave_points_se', 'symmetry_se', 'fractal_dimension_se',
            'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst',
            'smoothness_worst', 'compactness_worst', 'concavity_worst',
            'concave_points_worst', 'symmetry_worst', 'fractal_dimension_worst']
dataset = read_csv(filename, names=colnames, header=None)
```

[30]:

```
# drop `id` identifier
dataset = dataset.drop(['id'], 1)

# recode target labels to 0 and 1
dataset['diagnosis'] = dataset['diagnosis'].map({'B':0, 'M':1})

# Standardization
Y = dataset.iloc[:,0]
X_orig = dataset.iloc[:,1:]
X = (X_orig - X_orig.mean()) / (X_orig.std())

# X_orig = dataset.values[:, 1:]
# Y = dataset.values[:, 0]
# scaler_standardized = StandardScaler()
# X = scaler_standardized.fit_transform(X_orig)
X
```

[30]:

```
     radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0       1.096100     -2.071512        1.268817   0.983510         1.567087
1       1.828212     -0.353322        1.684473   1.907030        -0.826235
2       1.578499      0.455786        1.565126   1.557513         0.941382
3      -0.768233      0.253509       -0.592166  -0.763792         3.280667
4       1.748758     -1.150804        1.775011   1.824624         0.280125
..           …             …             …          …               …
564     2.109139      0.720838        2.058974   2.341795         1.040926
565     1.703356      2.083301        1.614511   1.722326         0.102368
566     0.701667      2.043775        0.672084   0.577445        -0.839745
567     1.836725      2.334403        1.980781   1.733693         1.524426
568    -1.806811      1.220718       -1.812793  -1.346604        -3.109349

     compactness_mean  concavity_mean  concave_points_mean  symmetry_mean  \
0            3.280628        2.650542             2.530249       2.215566
1           -0.486643       -0.023825             0.547662       0.001391
2            1.052000        1.362280             2.035440       0.938859
3            3.399917        1.914213             1.450431       2.864862
4            0.538866        1.369806             1.427237      -0.009552
..                …              …                    …              …
564          0.218868        1.945573             2.318924      -0.312314
```

565	-0.017817	0.692434	1.262558	-0.217473
566	-0.038646	0.046547	0.105684	-0.808406
567	3.269267	3.294046	2.656528	2.135315
568	-1.149741	-1.113893	-1.260710	-0.819349

	fractal_dimension_mean	radius_se	texture_se	perimeter_se	area_se	\
0	2.253764	2.487545	-0.564768	2.830540	2.485391	
1	-0.867889	0.498816	-0.875473	0.263095	0.741749	
2	-0.397658	1.227596	-0.779398	0.850180	1.180298	
3	4.906602	0.326087	-0.110312	0.286341	-0.288125	
4	-0.561956	1.269426	-0.789549	1.272070	1.189310	
..	…	…	…	…	…	
564	-0.930209	2.779634	0.070963	2.377491	2.601897	
565	-1.057681	1.299356	2.258951	1.155840	1.290429	
566	-0.894800	0.184730	-0.257145	0.276450	0.180539	
567	1.042778	1.156917	0.685485	1.437265	1.008615	
568	-0.560539	-0.070217	0.382756	-0.157311	-0.465742	

	smoothness_se	compactness_se	concavity_se	concave_points_se	\
0	-0.213814	1.315704	0.723390	0.660239	
1	-0.604819	-0.692317	-0.440393	0.259933	
2	-0.296744	0.814257	0.212889	1.423575	
3	0.689095	2.741868	0.818798	1.114027	
4	1.481763	-0.048477	0.827742	1.143199	
..	…	…	…	…	
564	1.085429	0.191637	0.665416	2.065360	
565	-0.423637	-0.069697	0.251980	0.807720	
566	-0.379008	0.660696	0.510377	0.611619	
567	-0.172848	2.015943	1.301140	0.785031	
568	0.049299	-1.162493	-1.056571	-1.911765	

	symmetry_se	fractal_dimension_se	radius_worst	texture_worst	\
0	1.147747	0.906286	1.885031	-1.358098	
1	-0.804742	-0.099356	1.804340	-0.368879	
2	0.236827	0.293301	1.510541	-0.023953	
3	4.728520	2.045711	-0.281217	0.133866	
4	-0.360775	0.498889	1.297434	-1.465481	
..	…	…	…	…	
564	-1.137415	0.167832	1.899514	0.117596	
565	-0.188995	-0.490124	1.535369	2.045599	
566	-0.890632	0.036694	0.560868	1.373645	
567	0.326346	0.903262	1.959515	2.235958	
568	0.752168	-0.382418	-1.409652	0.763518	

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
0	2.301575	1.999478	1.306537	2.614365	
1	1.533776	1.888827	-0.375282	-0.430066	

```
2           1.346291    1.455004           0.526944             1.081980
3          -0.249720   -0.549538           3.391291             3.889975
4           1.337363    1.219651           0.220362            -0.313119
..               …           …                …                    …
564         1.751022    2.013529           0.378033            -0.273077
565         1.420690    1.493644          -0.690623            -0.394473
566         0.578492    0.427529          -0.808876             0.350427
567         2.301575    1.651717           1.429169             3.901415
568        -1.431475   -1.074867          -1.857384            -1.206491

     concavity_worst  concave_points_worst  symmetry_worst  \
0           2.107672              2.294058        2.748204
1          -0.146620              1.086129       -0.243675
2           0.854222              1.953282        1.151242
3           1.987839              2.173873        6.040726
4           0.612640              0.728618       -0.867590
..               …                    …              …
564         0.663928              1.627719       -1.358963
565         0.236365              0.733182       -0.531387
566         0.326479              0.413705       -1.103578
567         3.194794              2.287972        1.917396
568        -1.304683             -1.743529       -0.048096

     fractal_dimension_worst
0                   1.935312
1                   0.280943
2                   0.201214
3                   4.930672
4                  -0.396751
..                       …
564                -0.708467
565                -0.973122
566                -0.318129
567                 2.217684
568                -0.750546

[569 rows x 30 columns]
```

c) Data visualization.

1 Bivariate Density Plot (first 10 features)

[31]:
```
#maximum absolute scaling
df_scaled = dataset.copy()

for column in df_scaled.columns[1:32]:
    df_scaled[column] = df_scaled[column]  / df_scaled[column].abs().max()
df_scaled
```

[31]:

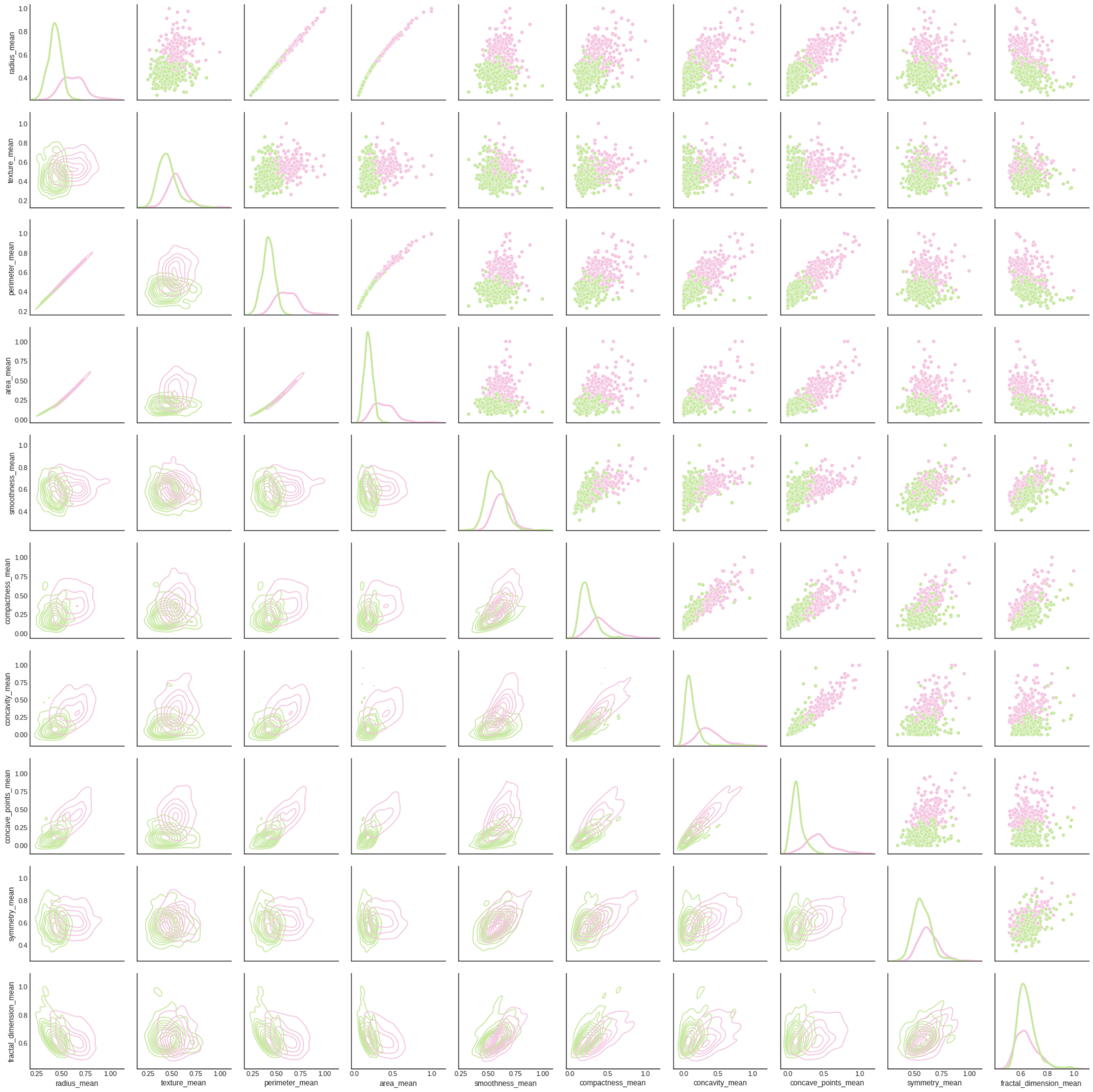
```
     diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0            1     0.639986      0.264257        0.651459   0.400240
1            1     0.731768      0.452393        0.705040   0.530188
2            1     0.700462      0.540988        0.689655   0.481008
3            1     0.406261      0.518839        0.411565   0.154378
4            1     0.721807      0.365071        0.716711   0.518593
..         …          …            …             …         …
564          1     0.766987      0.570010        0.753316   0.591363
565          1     0.716115      0.719196        0.696021   0.504198
566          1     0.590537      0.714868        0.574536   0.343103
567          1     0.732835      0.746690        0.743236   0.505798
568          0     0.276058      0.624745        0.254218   0.072371

     smoothness_mean  compactness_mean  concavity_mean  concave_points_mean  \
0           0.724602          0.803706        0.703140             0.731113
1           0.518605          0.227678        0.203608             0.348757
2           0.670747          0.462942        0.462512             0.635686
3           0.872093          0.821946        0.565604             0.522863
4           0.613831          0.384482        0.463918             0.518390
..               …                 …               …                    …
564         0.679315          0.335553        0.571462             0.690358
565         0.598531          0.299363        0.337395             0.486630
566         0.517442          0.296178        0.216753             0.263519
567         0.720930          0.801969        0.823336             0.755467
568         0.322093          0.126288        0.000000             0.000000

     symmetry_mean  fractional_dimension_mean  radius_se  texture_se  \
0         0.795724                   0.807779   0.381135    0.185322
1         0.596053                   0.581589   0.189175    0.150235
2         0.680592                   0.615661   0.259520    0.161085
3         0.854276                   1.000000   0.172503    0.236643
4         0.595066                   0.603756   0.263557    0.159939
..             …                         …          …           …
564       0.567763                   0.577073   0.409328    0.257114
565       0.576316                   0.567837   0.266446    0.504197
566       0.523026                   0.579639   0.158858    0.220061
567       0.788487                   0.720033   0.252698    0.326510
568       0.522039                   0.603859   0.134250    0.292323

     perimeter_se   area_se  smoothness_se  compactness_se  concavity_se  \
0        0.390764  0.282921       0.205557        0.362186      0.135682
1        0.154595  0.136629       0.167845        0.096603      0.046970
2        0.208599  0.173423       0.197559        0.295864      0.096768
3        0.156733  0.050221       0.292644        0.550812      0.142955
4        0.247407  0.174179       0.369097        0.181758      0.143636
..            …         …              …               …             …
564      0.349090  0.292696       0.330871        0.213516      0.131263
```

```
565      0.236715  0.182663       0.185320        0.178951       0.099747
566      0.155823  0.089543       0.189624        0.275554       0.119444
567      0.262602  0.159019       0.209509        0.454801       0.179722
568      0.115924  0.035319       0.230935        0.034417       0.000000

     concave_points_se  symmetry_se  fractal_dimension_se  radius_worst  \
0             0.300625     0.380367              0.207540      0.704218
1             0.253836     0.175934              0.118365      0.693396
2             0.389847     0.284991              0.153184      0.653996
3             0.353665     0.755288              0.308579      0.413707
4             0.357075     0.222419              0.171414      0.625416
..                 …            …                   …             …
564           0.464861     0.141102              0.142058      0.706160
565           0.317863     0.240405              0.083713      0.657325
566           0.294942     0.166941              0.130429      0.526637
567           0.315211     0.294364              0.207272      0.714206
568           0.000000     0.338949              0.093264      0.262375

     texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0         0.349818         0.734873    0.474612          0.728661
1         0.472547         0.632166    0.459803          0.556155
2         0.515341         0.607086    0.401740          0.648697
3         0.534921         0.393591    0.133451          0.942498
4         0.336496         0.605892    0.370240          0.617251
..             …                …           …                 …
564       0.532903         0.661226    0.476493          0.633423
565       0.772103         0.617038    0.406911          0.523810
566       0.688736         0.504379    0.264222          0.511680
567       0.795721         0.734873    0.428068          0.741240
568       0.613040         0.235510    0.063141          0.404133

     compactness_worst  concavity_worst  concave_points_worst  symmetry_worst  \
0             0.629112         0.568610              0.912027        0.693130
1             0.176371         0.192971              0.639175        0.414281
2             0.401229         0.359744              0.835052        0.544290
3             0.818809         0.548642              0.884880        1.000000
4             0.193762         0.319489              0.558419        0.356131
..                 …                …                   …               …
564           0.199716         0.328035              0.761512        0.310334
565           0.181664         0.256789              0.559450        0.387466
566           0.292439         0.271805              0.487285        0.334137
567           0.820510         0.749760              0.910653        0.615697
568           0.060907         0.000000              0.000000        0.432510

     fractal_dimension_worst
0                   0.573012
1                   0.429012
```

```
2                    0.422072
3                    0.833735
4                    0.370024
..                        ...
564                  0.342892
565                  0.319855
566                  0.376867
567                  0.597590
568                  0.339229

[569 rows x 31 columns]
```

[32]:
```python
features = list(dataset.columns[0:11])
data = df_scaled[features]

g = sns.PairGrid(data, hue='diagnosis', palette = 'PiYG_r')
# g.map(sns.scatterplot)
g.map_upper(sns.scatterplot)
g.map_lower(sns.kdeplot)
g.map_diag(sns.kdeplot, lw=3, legend=False)
```

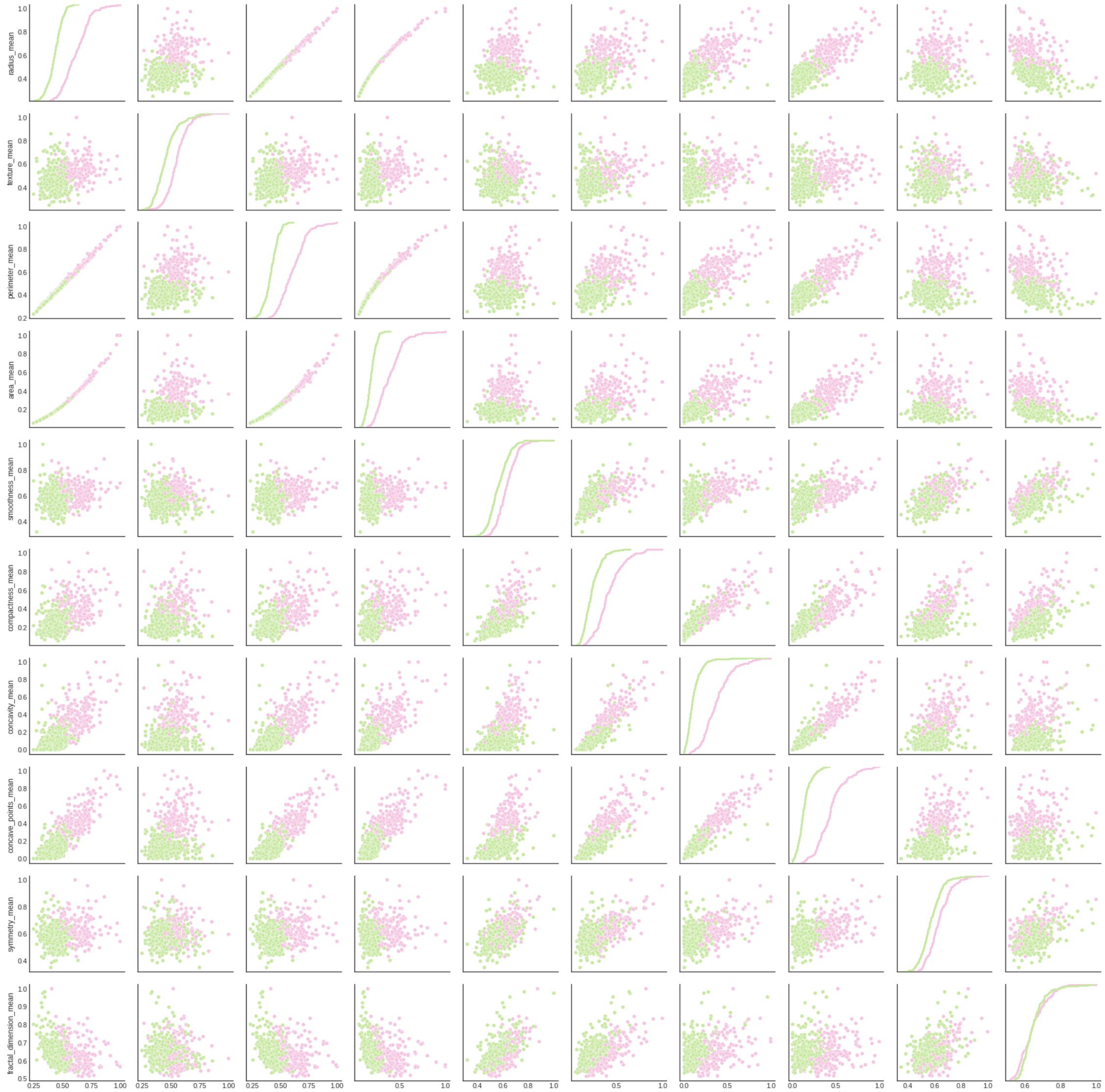
[32]:
```
<seaborn.axisgrid.PairGrid at 0x7f7eccbf6810>
```



2) Categorized Empirical Cumulative Distribution Plot

```
[33]: # g2 = sns.PairGrid(data, hue='diagnosis', palette = 'PiYG_r')
      g2 = sns.PairGrid(data, hue='diagnosis', palette = 'PiYG_r')
      g2.map_diag(sns.ecdfplot, lw=3, legend=False)
      g2.map_offdiag(sns.scatterplot)
```

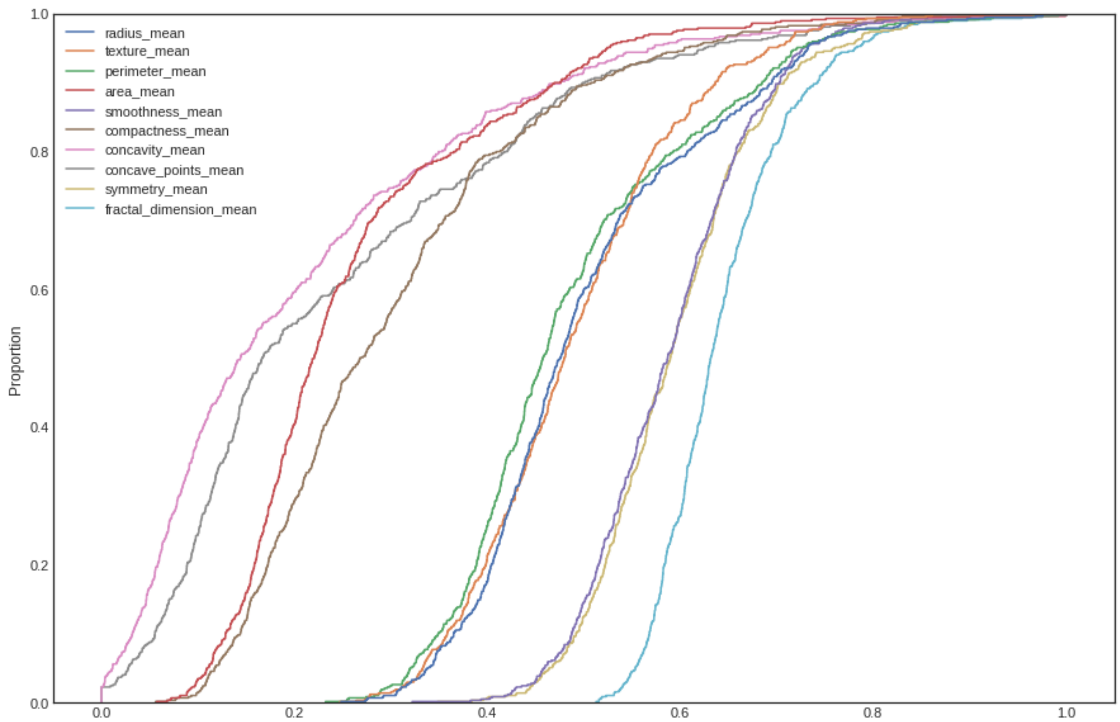
```
[33]: <seaborn.axisgrid.PairGrid at 0x7f7eccbda810>
```



3) Empirical Cumulative Distribution Plot

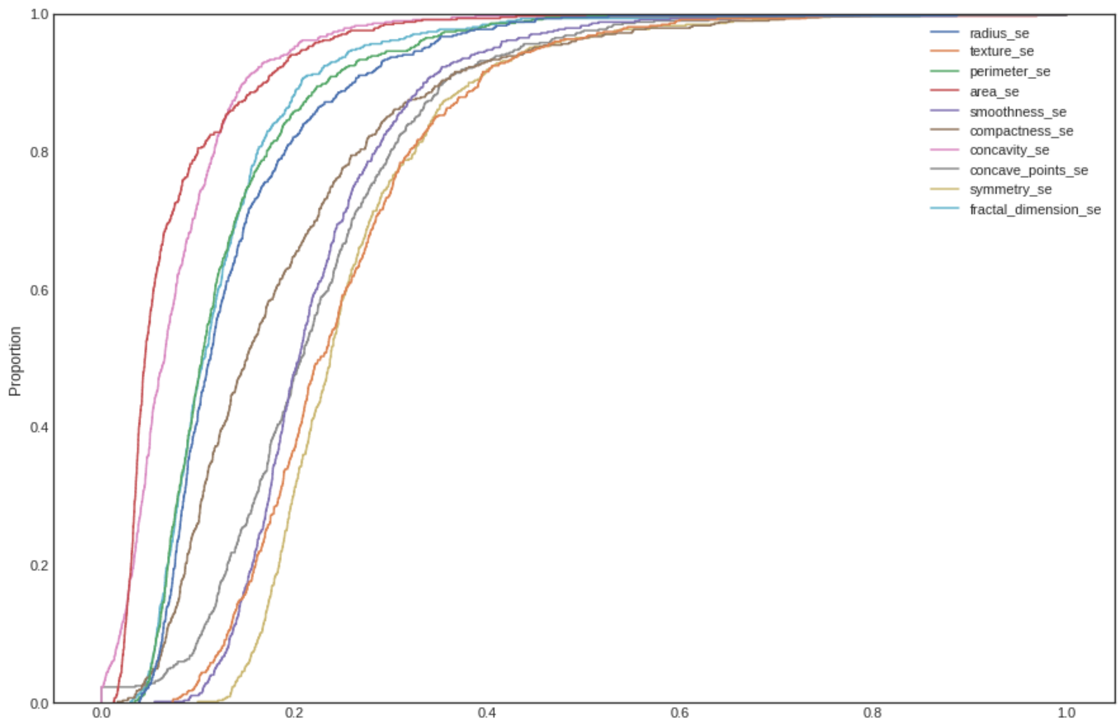
[34]:
```
features1 = list(dataset.columns[1:11])
data1 = df_scaled[features1]
plt.figure(figsize=(15, 10))
sns.ecdfplot(data1)
```

[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ec7f90f90>



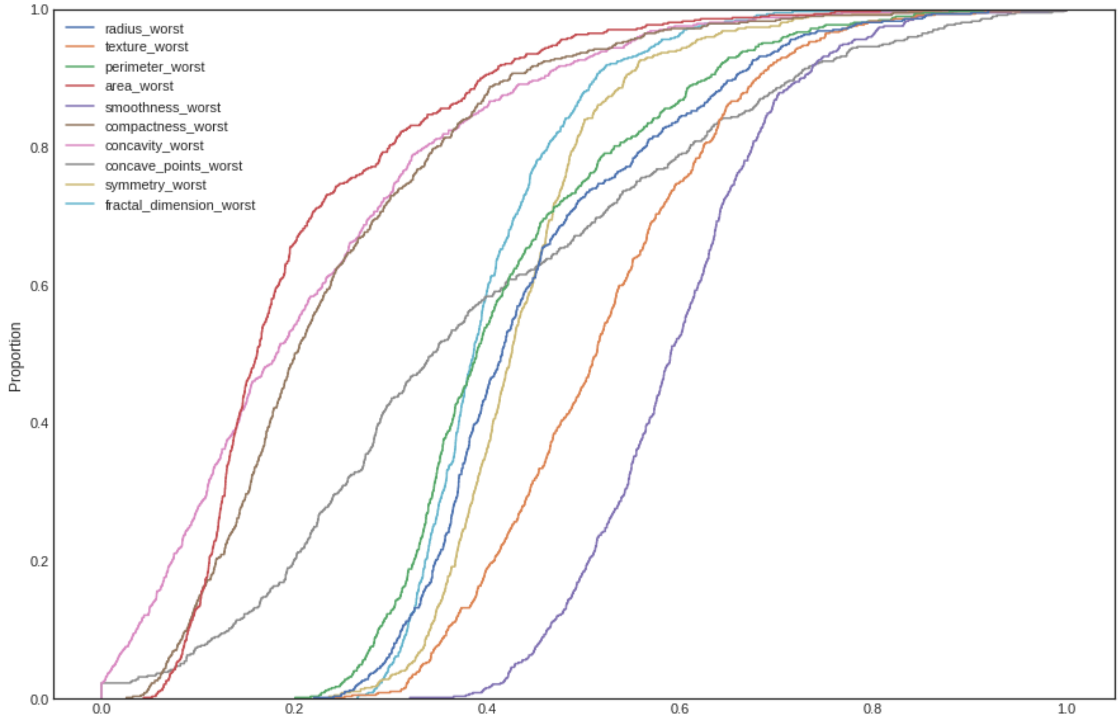
[35]:
```
features2 = list(dataset.columns[11:21])
data2 = df_scaled[features2]
plt.figure(figsize=(15, 10))
sns.ecdfplot(data2)
```

[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ecff065d0>



[36]:
```
features3 = list(dataset.columns[21:31])
data3 = df_scaled[features3]
plt.figure(figsize=(15, 10))
sns.ecdfplot(data3)
```

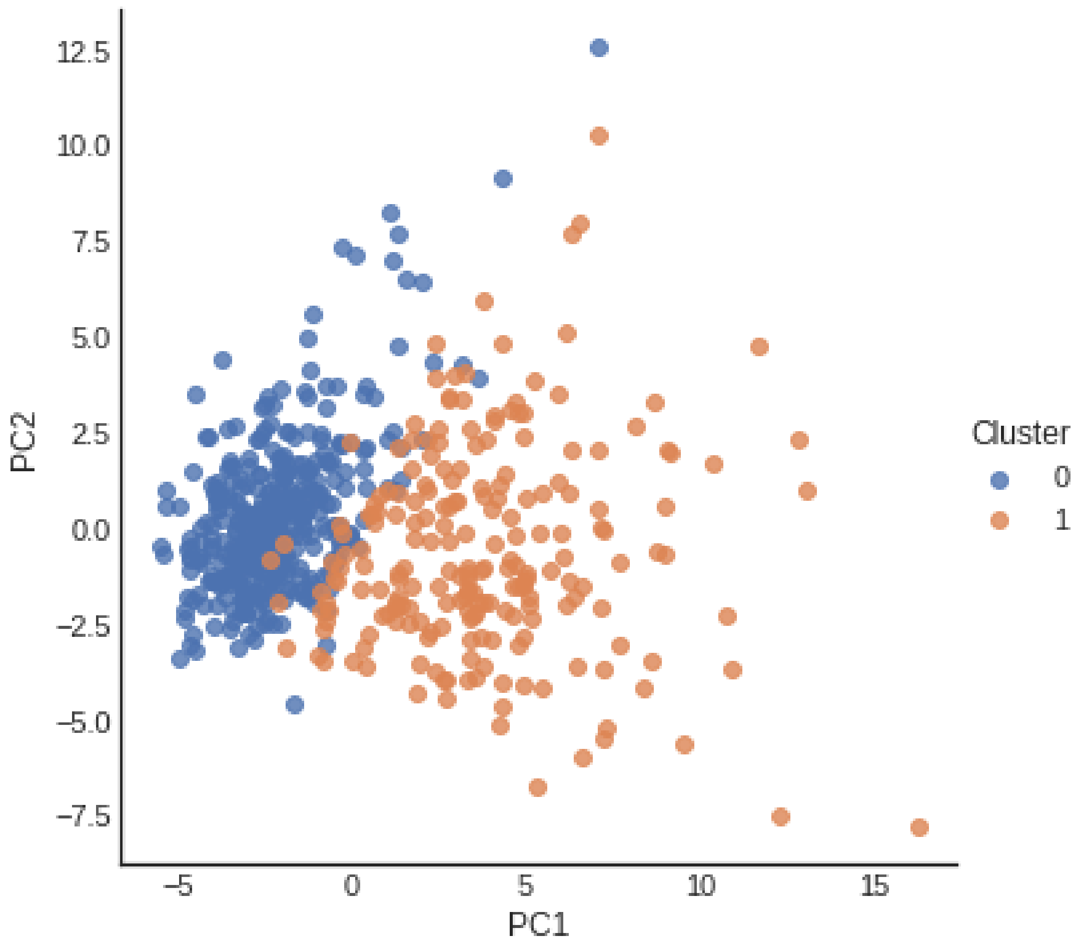
[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ecff06990>



4) PCA plot (2 components)

[37]:
```
pca = decomposition.PCA(n_components=2)
pc = pca.fit_transform(X)
pc_df = pd.DataFrame(data = pc ,
        columns = ['PC1', 'PC2'])
pc_df['Cluster'] = df_scaled['diagnosis']
sns.lmplot( x="PC1", y="PC2",
  data=pc_df,
  fit_reg=False,
  hue='Cluster', # color by cluster
  legend=True,
  )
```

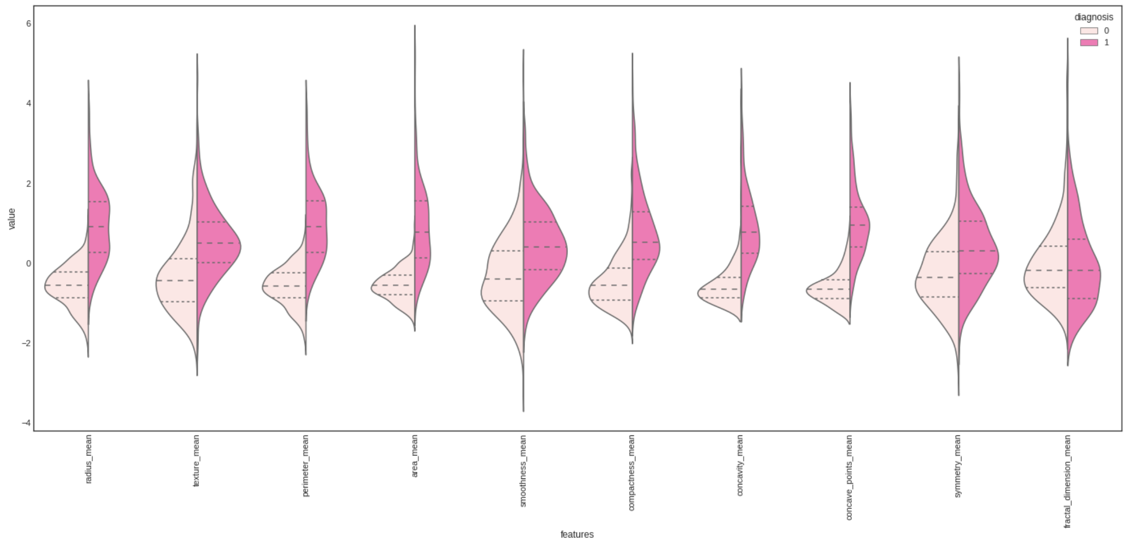
[37]: <seaborn.axisgrid.FacetGrid at 0x7f7ec7e14f10>



5) Violin Plot

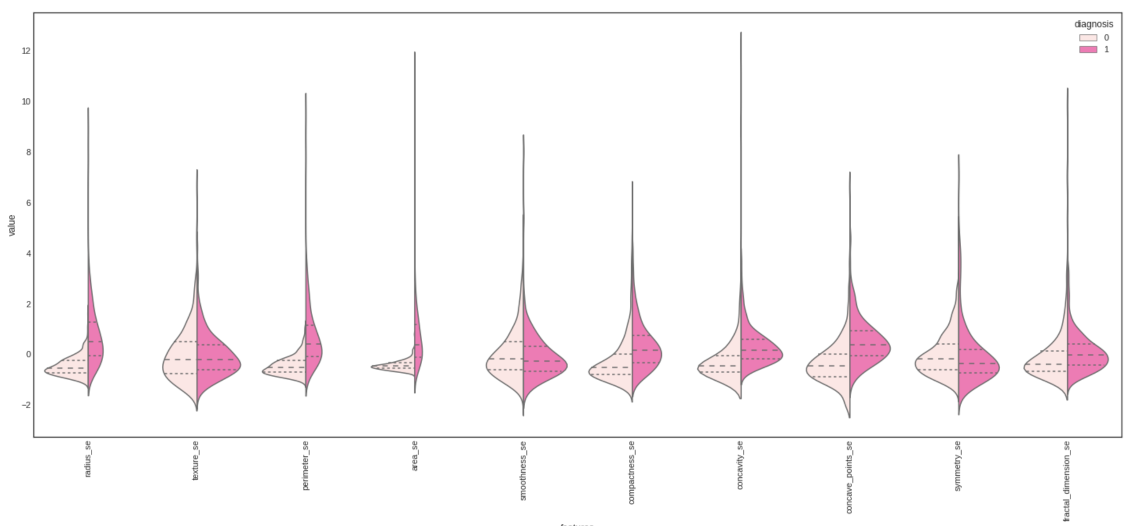
[38]:
```
data1_10 = pd.concat([Y, X.iloc[:,0:10]],axis=1)
data1_10 = pd.melt(data1_10, id_vars="diagnosis",
                    var_name="features",
                    value_name='value')
plt.figure(figsize=(25,10))
sns.violinplot(x="features", y="value", hue="diagnosis", data=data1_10,␣
 ↪split=True,
               inner="quartile", palette={0: "mistyrose", 1: "hotpink"})
plt.xticks(rotation=90)
```

[38]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 <a list of 10 Text major ticklabel objects>)
```



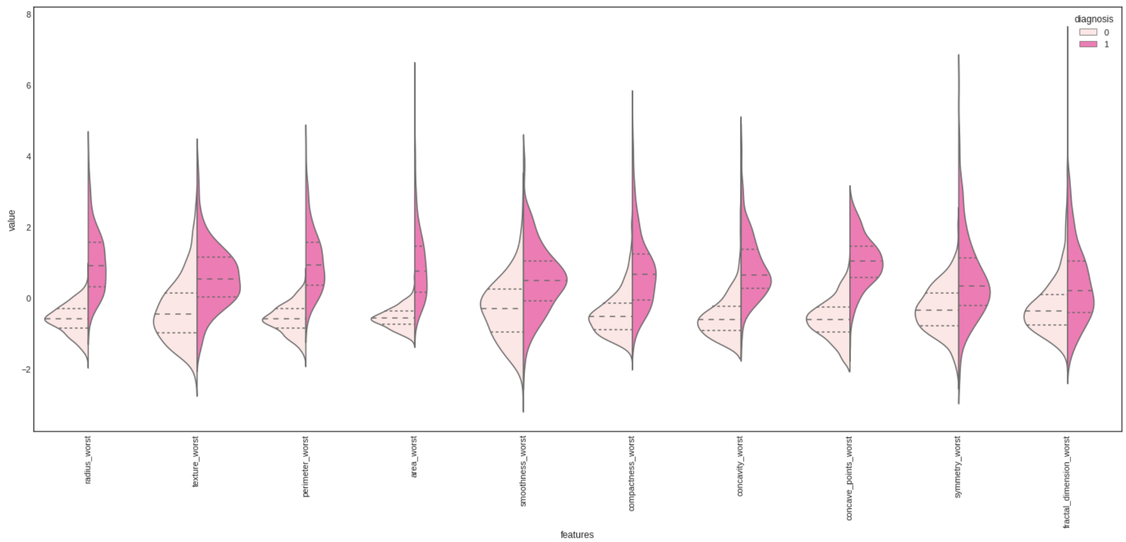
[39]:
```python
data11_20 = pd.concat([Y, X.iloc[:,10:20]],axis=1)
data11_20 = pd.melt(data11_20, id_vars="diagnosis",
                    var_name="features",
                    value_name='value')
plt.figure(figsize=(25,10))
sns.violinplot(x="features", y="value", hue="diagnosis", data=data11_20,␣
 ↪split=True,
               inner="quartile", palette={0: "mistyrose", 1: "hotpink"})
plt.xticks(rotation=90)
```

[39]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 <a list of 10 Text major ticklabel objects>)
```



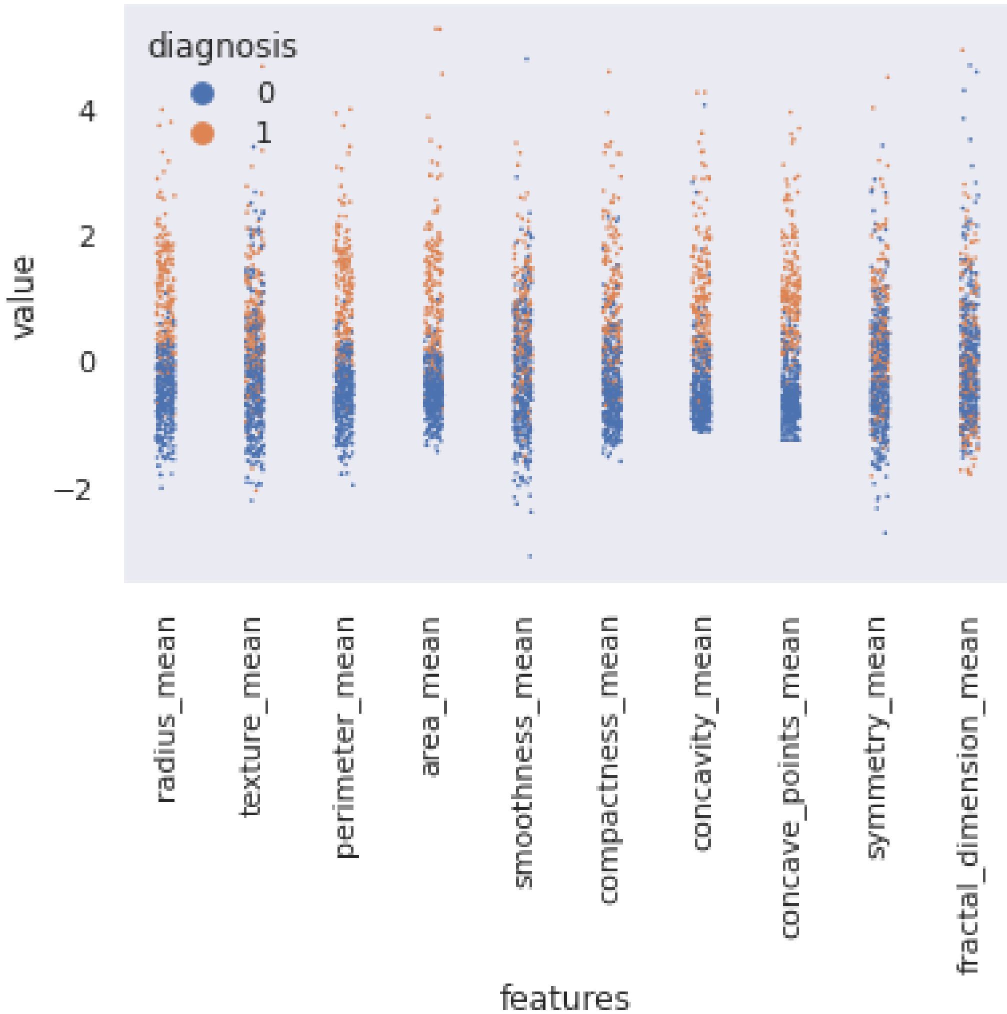
[40]:
```
data21_30 = pd.concat([Y, X.iloc[:,20:]],axis=1)
data21_30 = pd.melt(data21_30, id_vars="diagnosis",
                    var_name="features",
                    value_name='value')
plt.figure(figsize=(25,10))
sns.violinplot(x="features", y="value", hue="diagnosis", data=data21_30,␣
↪split=True,
               inner="quartile", palette={0: "mistyrose", 1: "hotpink"})
plt.xticks(rotation=90)
```

[40]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 <a list of 10 Text major ticklabel objects>)
```



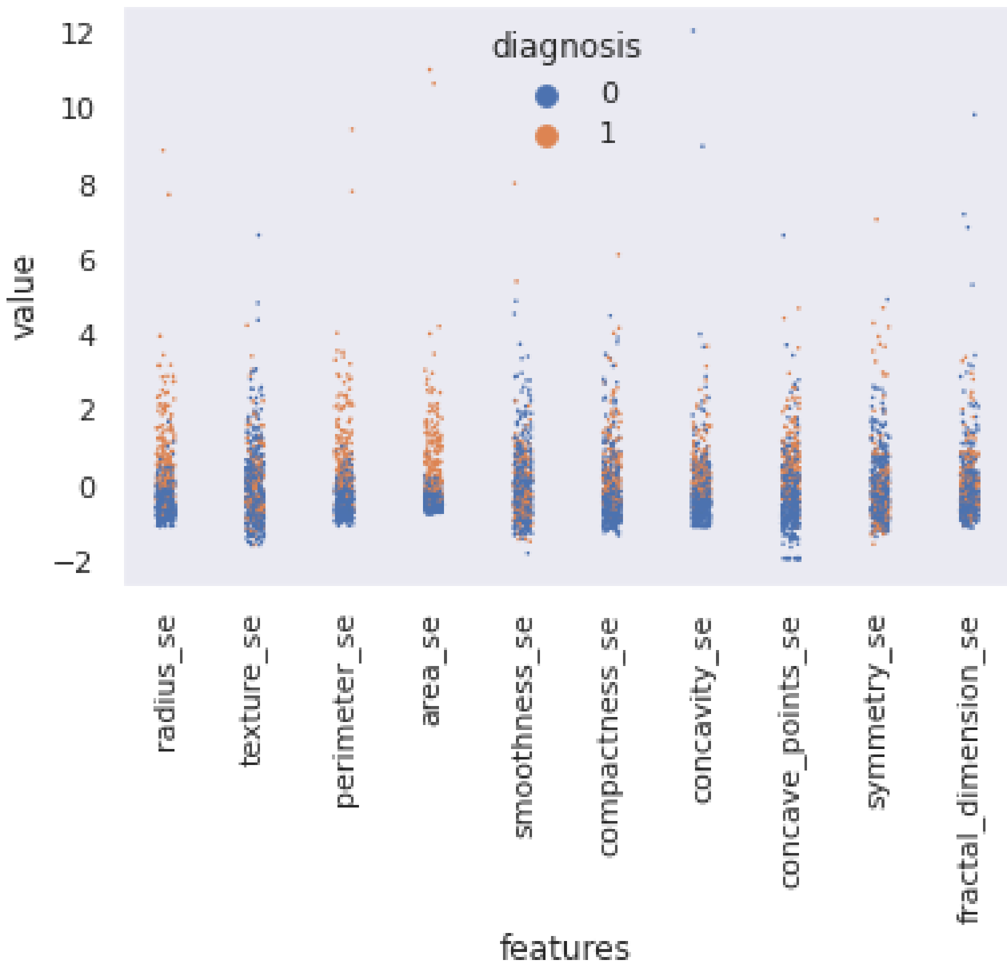
6) Strip Plot

[41]:
```
sns.set(style = 'dark')
sns.stripplot(x='features', y='value', data=data1_10, hue='diagnosis', size=1.5)
plt.xticks(rotation=90)
plt.show()
```

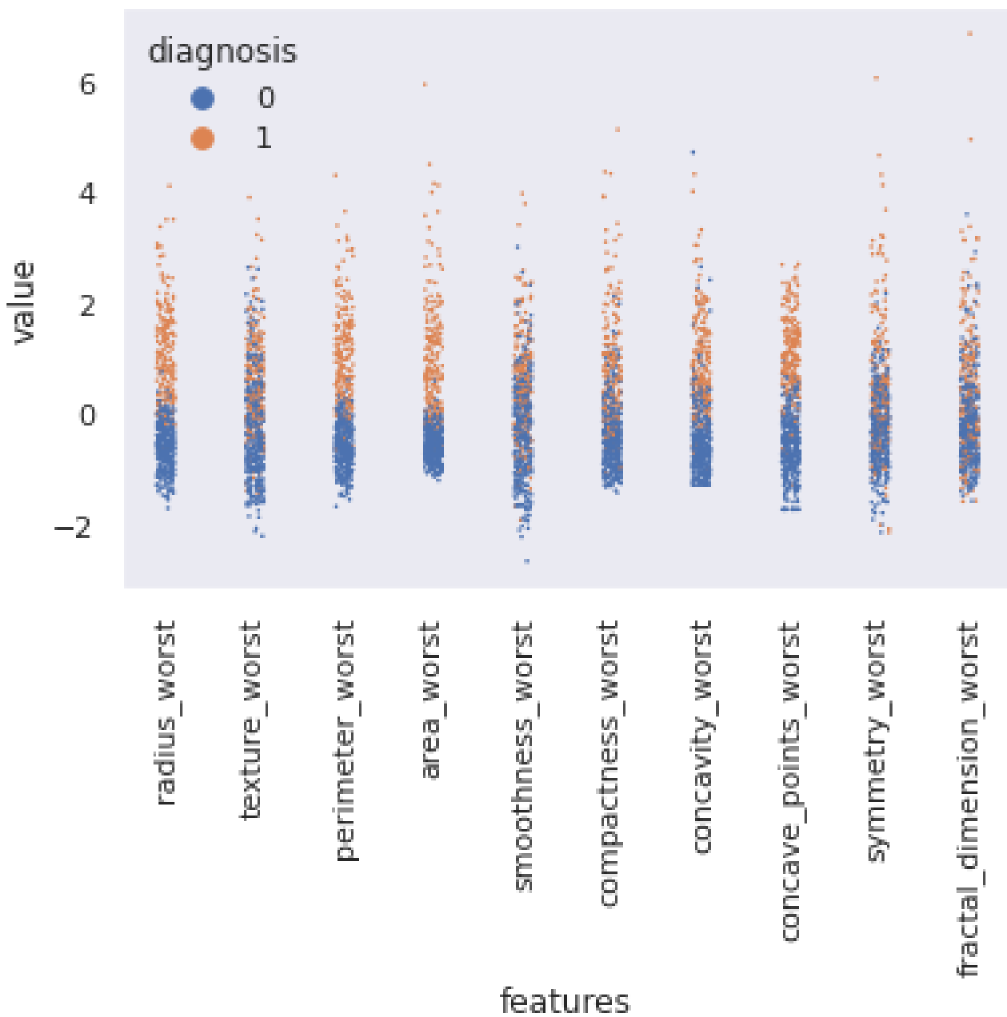


[42]:

```
sns.stripplot(x='features', y='value', data=data11_20, hue='diagnosis', size=1.
 ↪5)
plt.xticks(rotation=90)
plt.show()
```

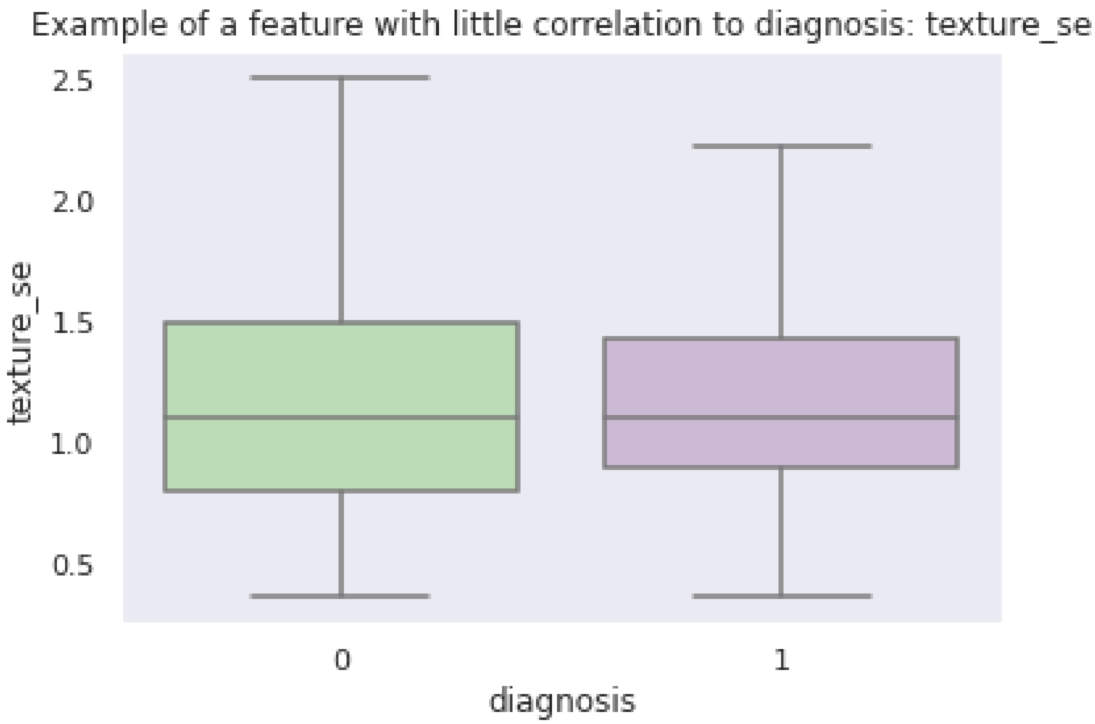


[43]:
```
sns.stripplot(x='features', y='value', data=data21_30, hue='diagnosis', size=1.
 ↪5)
plt.xticks(rotation=90)
plt.show()
```



7) Box Plot

[44]:
```
bp = sns.boxplot(x='diagnosis', y='texture_se', data=dataset, showfliers=False,␣
 ↪palette='PRGn_r')
bp.set_title('Example of a feature with little correlation to diagnosis:␣
 ↪texture_se')
plt.show()
```



8) Feature Selection and Confusion Matrix

[45]:
```
# Based on dependence determined, drop perimeter and area features.
# Based on the correlation matrix and violin plots, drop features that have␣
 ↪very little correlation to the target.
drop_list = ['perimeter_mean', 'area_mean', 'perimeter_se', 'area_se',␣
 ↪'perimeter_worst', 'area_worst',
'fractal_dimension_mean', 'texture_se', 'smoothness_se', 'symmetry_se',␣
 ↪'fractal_dimension_se']

X_fs = X.drop(drop_list,axis=1)
X_fs.head()
```

[45]:
```
   radius_mean  texture_mean  smoothness_mean  compactness_mean  \
0     1.096100     -2.071512         1.567087          3.280628
1     1.828212     -0.353322        -0.826235         -0.486643
2     1.578499      0.455786         0.941382          1.052000
3    -0.768233      0.253509         3.280667          3.399917
4     1.748758     -1.150804         0.280125          0.538866

   concavity_mean  concave_points_mean  symmetry_mean  radius_se  \
0        2.650542             2.530249       2.215566   2.487545
1       -0.023825             0.547662       0.001391   0.498816
```

```
2        1.362280             2.035440       0.938859   1.227596
3        1.914213             1.450431       2.864862   0.326087
4        1.369806             1.427237      -0.009552   1.269426

   compactness_se  concavity_se  concave_points_se  radius_worst  \
0        1.315704      0.723390           0.660239      1.885031
1       -0.692317     -0.440393           0.259933      1.804340
2        0.814257      0.212889           1.423575      1.510541
3        2.741868      0.818798           1.114027     -0.281217
4       -0.048477      0.827742           1.143199      1.297434

   texture_worst  smoothness_worst  compactness_worst  concavity_worst  \
0      -1.358098          1.306537           2.614365         2.107672
1      -0.368879         -0.375282          -0.430066        -0.146620
2      -0.023953          0.526944           1.081980         0.854222
3       0.133866          3.391291           3.889975         1.987839
4      -1.465481          0.220362          -0.313119         0.612640

   concave_points_worst  symmetry_worst  fractal_dimension_worst
0              2.294058        2.748204                 1.935312
1              1.086129       -0.243675                 0.280943
2              1.953282        1.151242                 0.201214
3              2.173873        6.040726                 4.930672
4              0.728618       -0.867590                -0.396751
```

[46]:

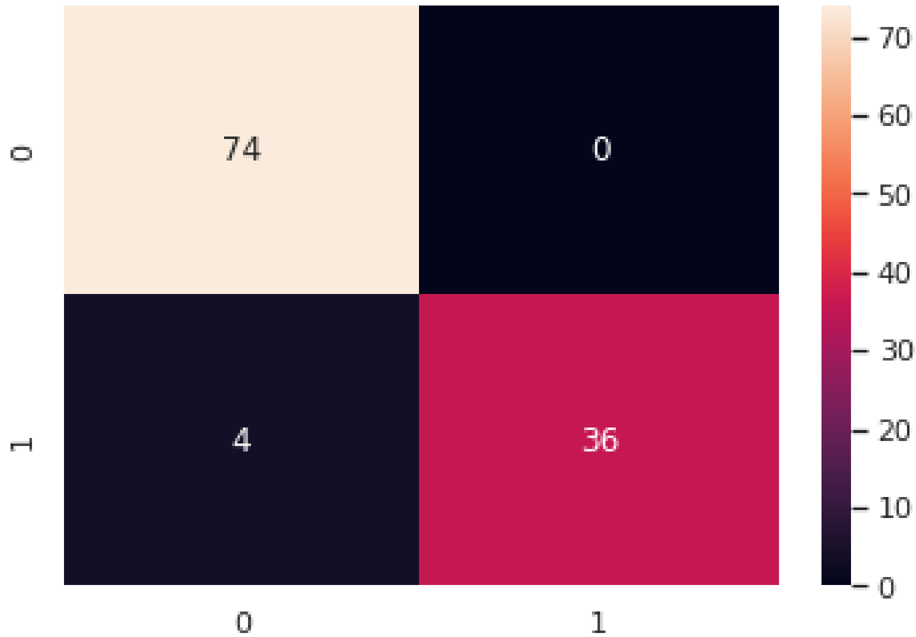
```python
val_size = 0.20
seed = 7
X_train, X_val, Y_train, Y_val = train_test_split(X_fs, Y, test_size=val_size,␣
 ↪random_state=seed)

def model_predict(name, model):
    model.fit(X_train, Y_train)
    pred = model.predict(X_val)
    print("%s: %f" % (name, accuracy_score(Y_val, pred)))
    cm = confusion_matrix(Y_val, pred)
    sns.heatmap(cm, annot=True, fmt="d")
    print(classification_report(Y_val, pred))

    return pred
```

[47]:

```python
pred_lr = model_predict('LR', LogisticRegression(solver='liblinear'))
```

```
LR: 0.964912
              precision    recall  f1-score   support

           0       0.95      1.00      0.97        74
           1       1.00      0.90      0.95        40
```

```
    accuracy                           0.96       114
   macro avg       0.97      0.95      0.96       114
weighted avg       0.97      0.96      0.96       114
```

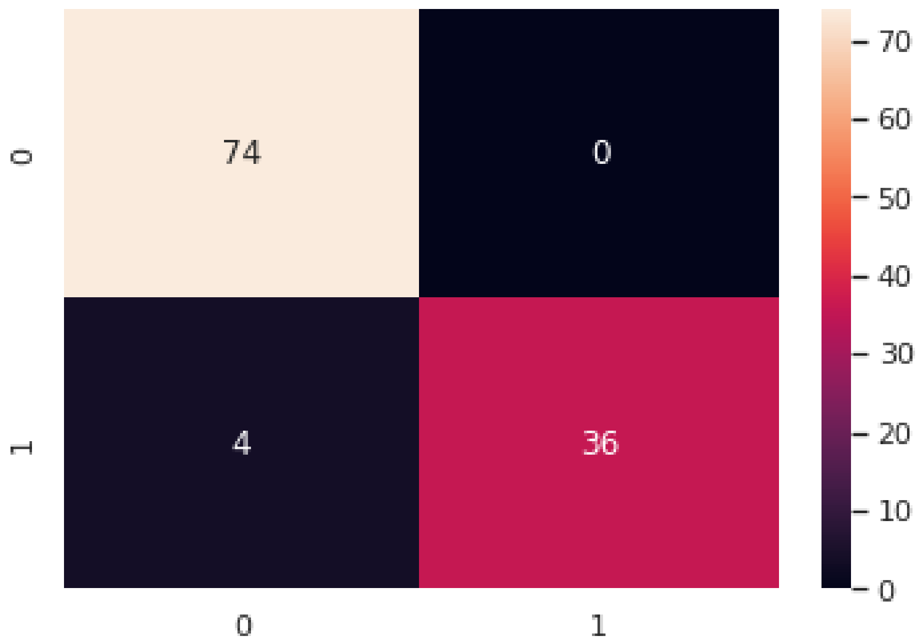


[48]:
```
pred_lda = model_predict('LDA', LinearDiscriminantAnalysis())
```

```
LDA: 0.938596
              precision    recall  f1-score   support

           0       0.91      1.00      0.95        74
           1       1.00      0.82      0.90        40

    accuracy                           0.94       114
   macro avg       0.96      0.91      0.93       114
weighted avg       0.94      0.94      0.94       114
```

[49]:
```
pred_knn = model_predict('KNN', KNeighborsClassifier())
```

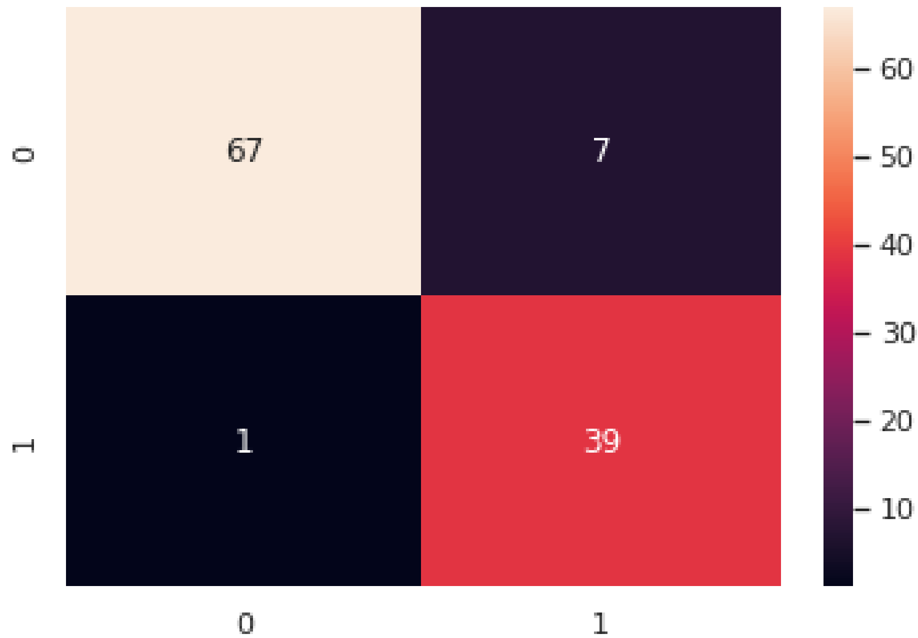
```
KNN: 0.964912
              precision    recall  f1-score   support

           0       0.95      1.00      0.97        74
           1       1.00      0.90      0.95        40

    accuracy                           0.96       114
   macro avg       0.97      0.95      0.96       114
weighted avg       0.97      0.96      0.96       114
```



[50]:

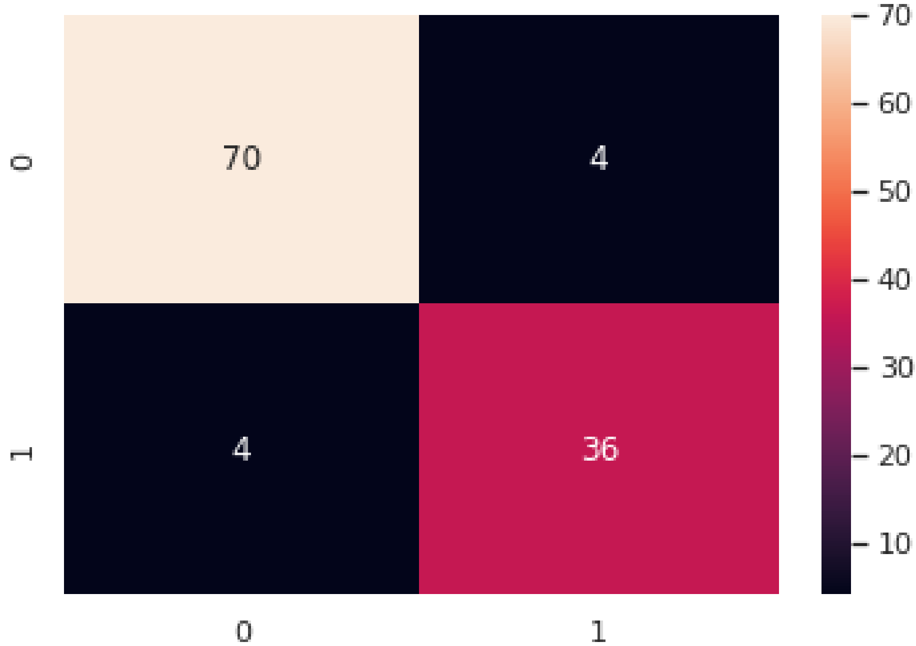
```
pred_cart = model_predict('CART', DecisionTreeClassifier(random_state=seed))
```

```
CART: 0.929825
              precision    recall  f1-score   support

           0       0.99      0.91      0.94        74
           1       0.85      0.97      0.91        40

    accuracy                           0.93       114
   macro avg       0.92      0.94      0.93       114
weighted avg       0.94      0.93      0.93       114
```



[51]:
```
pred_nb = model_predict('NB', GaussianNB())
```

```
NB: 0.929825
              precision    recall  f1-score   support

           0       0.95      0.95      0.95        74
           1       0.90      0.90      0.90        40

    accuracy                           0.93       114
   macro avg       0.92      0.92      0.92       114
weighted avg       0.93      0.93      0.93       114
```



[52]:
```
pred_svm = model_predict('SVM', SVC())
```

```
SVM: 0.973684
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        74
           1       1.00      0.93      0.96        40

    accuracy                           0.97       114
   macro avg       0.98      0.96      0.97       114
weighted avg       0.97      0.97      0.97       114
```


74
0
3
37
0
1
0
1
70
60
50
40
30
20
10
0