data visualization

February 13, 2018

In [63]:
```
%matplotlib inline
from IPython.display import display 6
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import time
```

In [64]:
```
data = pd.read_csv('/Users/siddharth/Desktop/btp/BTP/week2/data.csv')
```

In [65]:
```
data.head(10)
```

Out[65]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	\
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	
5	843786	M	12.45	15.70	82.57	477.1	
6	844359	M	18.25	19.98	119.60	1040.0	
7	84458202	M	13.71	20.83	90.20	577.9	
8	844981	M	13.00	21.82	87.50	519.8	
9	84501001	M	12.46	24.04	83.97	475.9	

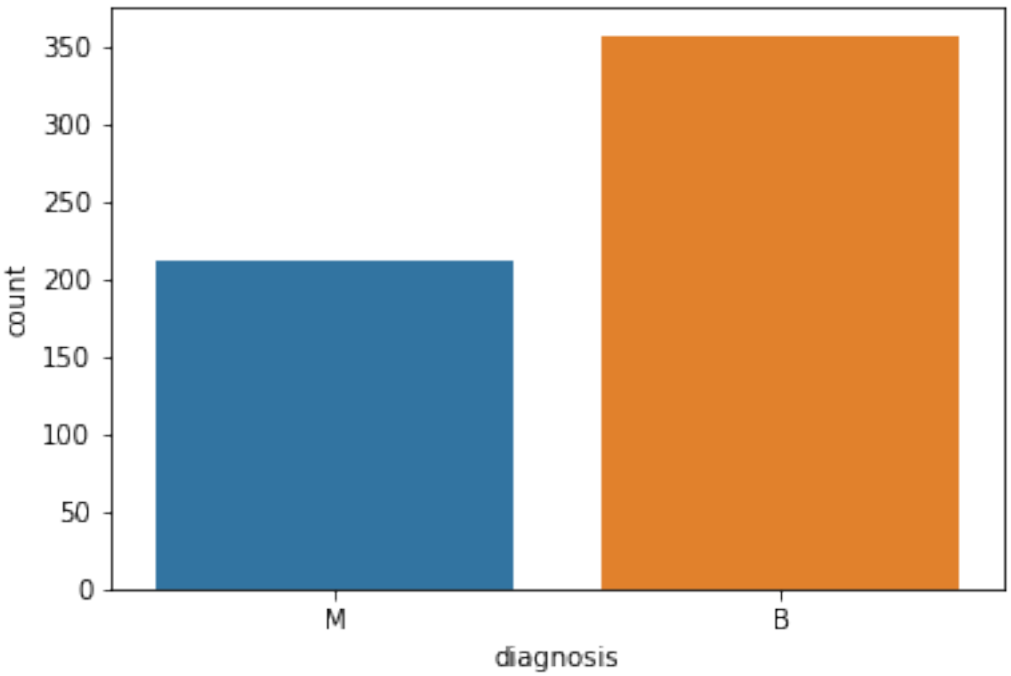
	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	0.11840	0.27760	0.30010	0.14710	
1	0.08474	0.07864	0.08690	0.07017	
2	0.10960	0.15990	0.19740	0.12790	
3	0.14250	0.28390	0.24140	0.10520	
4	0.10030	0.13280	0.19800	0.10430	
5	0.12780	0.17000	0.15780	0.08089	
6	0.09463	0.10900	0.11270	0.07400	
7	0.11890	0.16450	0.09366	0.05985	
8	0.12730	0.19320	0.18590	0.09353	
9	0.11860	0.23960	0.22730	0.08543	

	...	texture_worst	perimeter_worst	area_worst	smoothness_worst	\
0	...	17.33	184.60	2019.0	0.1622	
1	...	23.41	158.80	1956.0	0.1238	

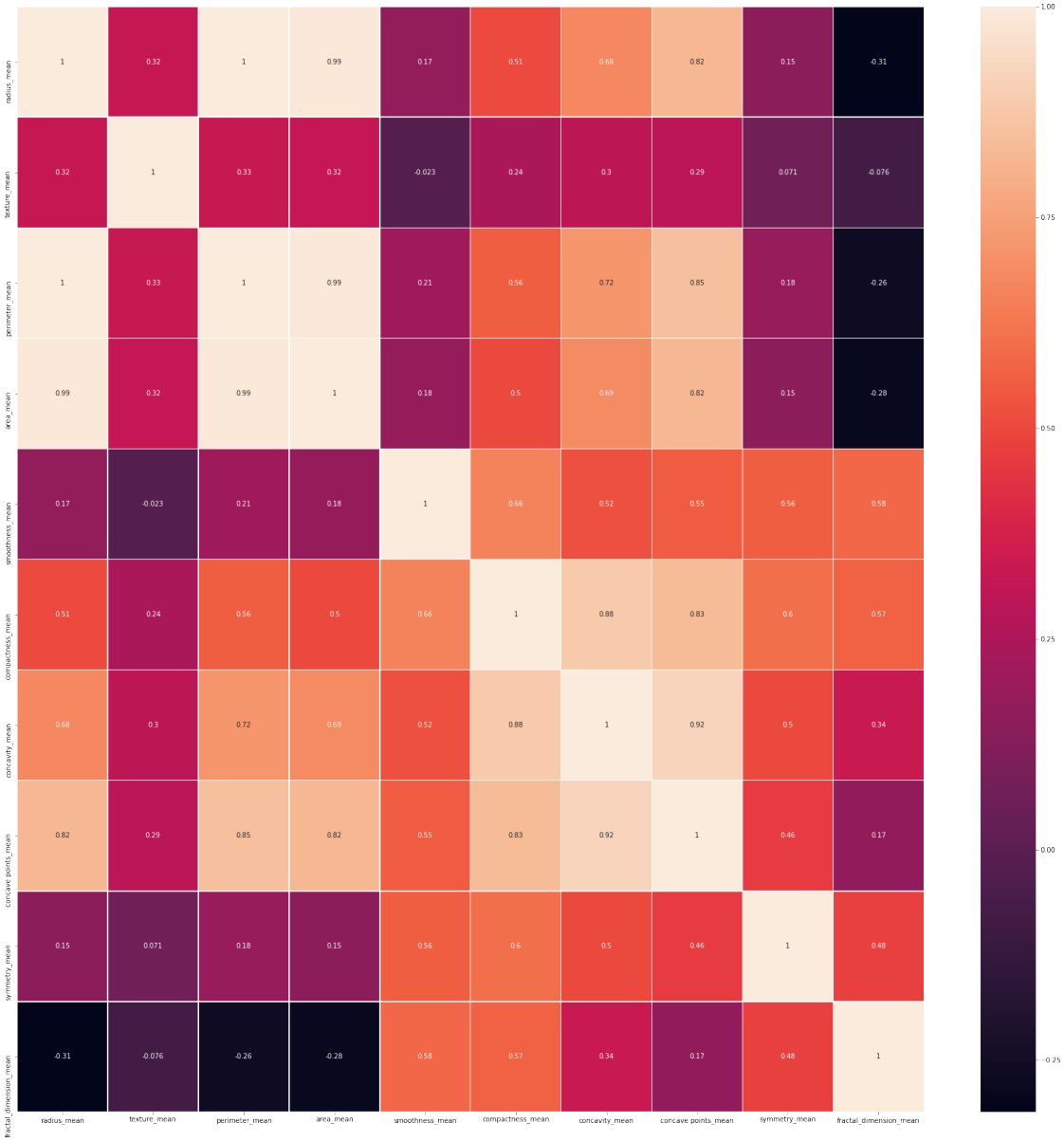
```
2     ...          25.53          152.50      1709.0           0.1444
3     ...          26.50           98.87       567.7           0.2098
4     ...          16.67          152.20      1575.0           0.1374
5     ...          23.75          103.40       741.6           0.1791
6     ...          27.66          153.20      1606.0           0.1442
7     ...          28.14          110.60       897.0           0.1654
8     ...          30.73          106.20       739.3           0.1703
9     ...          40.68           97.65       711.4           0.1853

   compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
4             0.2050           0.4000                0.1625          0.2364
5             0.5249           0.5355                0.1741          0.3985
6             0.2576           0.3784                0.1932          0.3063
7             0.3682           0.2678                0.1556          0.3196
8             0.5401           0.5390                0.2060          0.4378
9             1.0580           1.1050                0.2210          0.4366

   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN
5                  0.12440          NaN
6                  0.08368          NaN
7                  0.11510          NaN
8                  0.10720          NaN
9                  0.20750          NaN

[10 rows x 33 columns]
```

In [66]:
```
y = data.diagnosis
```

In [67]:
```
ax = sns.countplot(y,label="number of cases")
B, M = y.value_counts()
```



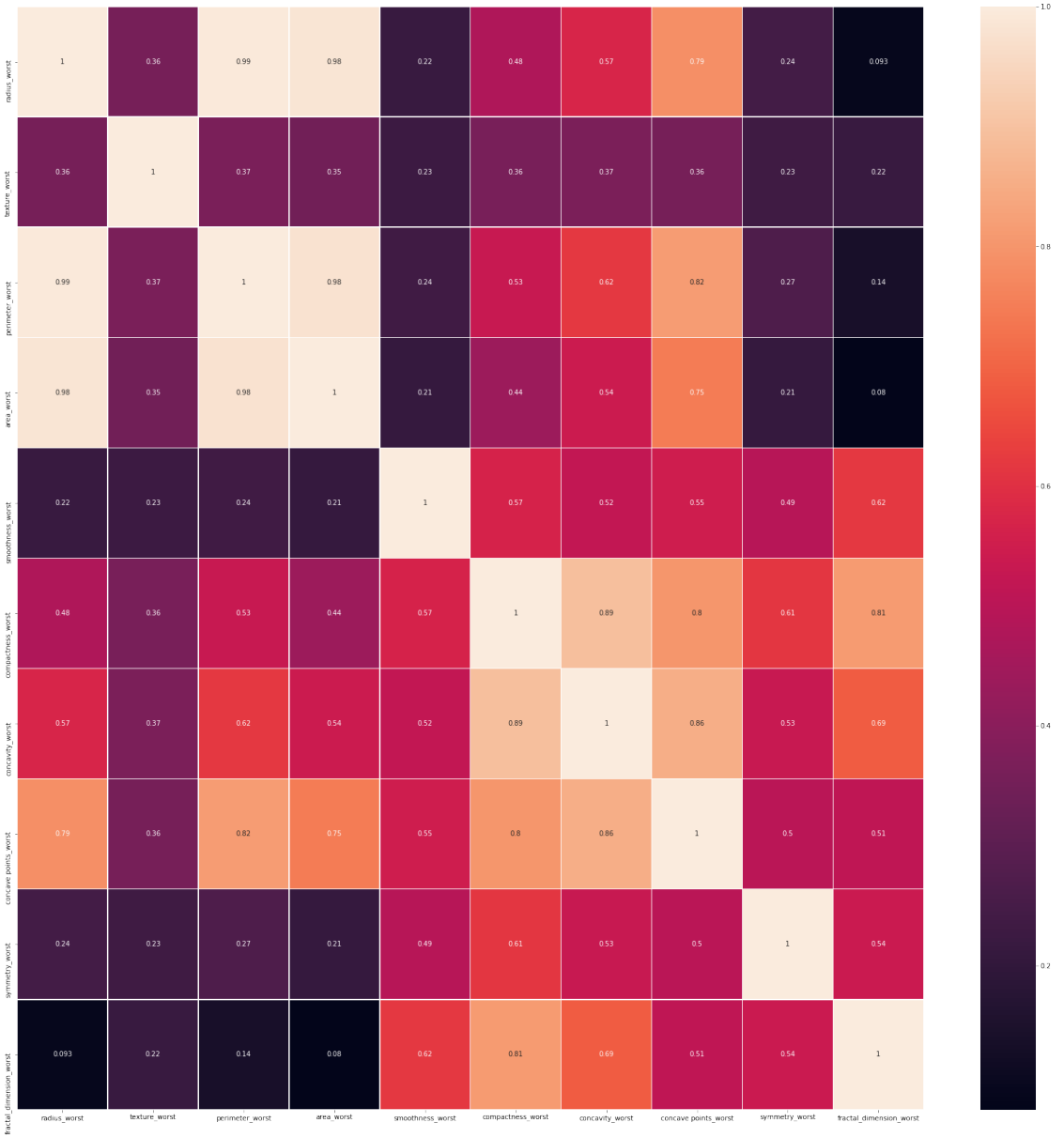

```
In [68]: x = data.drop(['Unnamed: 32','id','diagnosis','radius_se','texture_se','perimeter_se','

In [69]: plt.figure(figsize = (30,30))
         ax = sns.heatmap(x.corr(), linewidths=.5, annot=True)
```



The above heat map if for correlation between the means of all the standard parameters, this gives us a good idea about the actual impact for each parameter mean on the final result. Similar can be said for the below grpah which is for the worst parameters, hence giving us an idea about the edge cases.

```
In [70]: a = data.drop(['Unnamed: 32','id','diagnosis','radius_se','texture_se','perimeter_se','
```

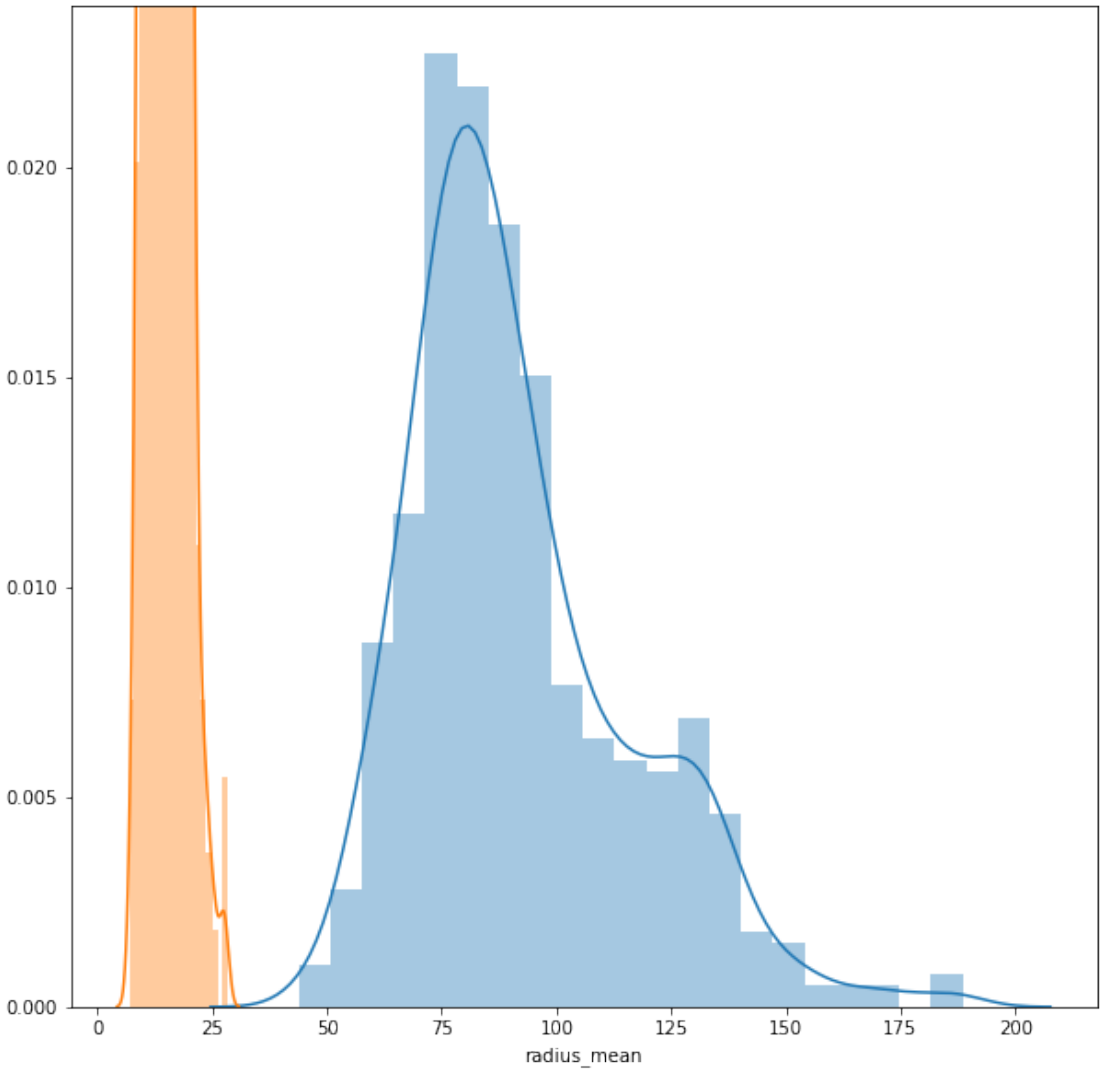
```
In [71]: plt.figure(figsize = (30,30))
         az = sns.heatmap(a.corr(), linewidths=.5, annot=True)
```



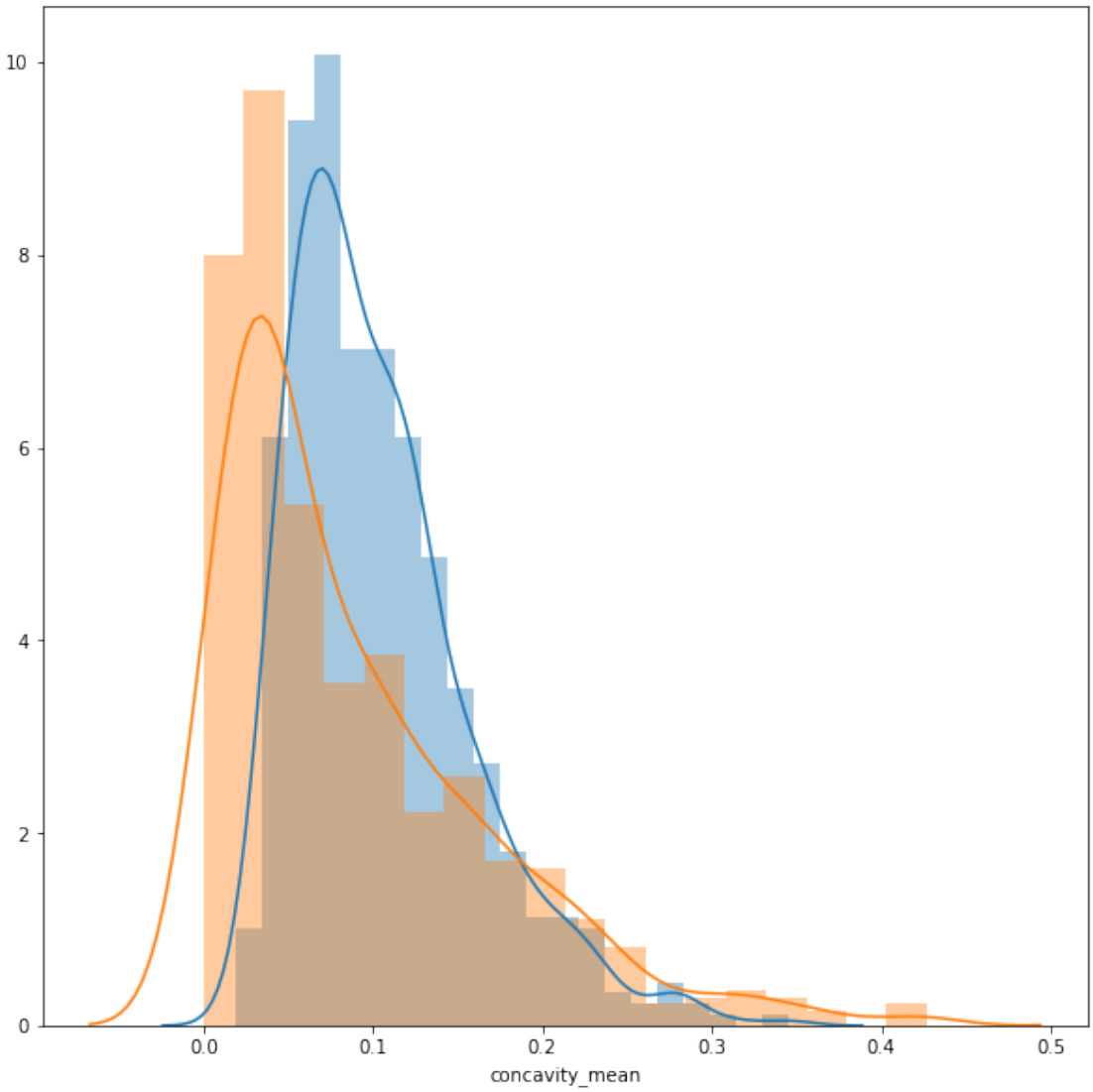
The following dist plots are useful for seeing the relative expanse of each parameters with one another. This will give us an idea on how to regularize the data to give the best results.

```
In [72]: #a4_dims = (11.7, 8.27)
         #ax = plt.subplots(figsize=a4_dims)
         plt.figure(figsize = (10,10))
         sns.distplot(data["perimeter_mean"])
         sns.distplot(data["radius_mean"])
```

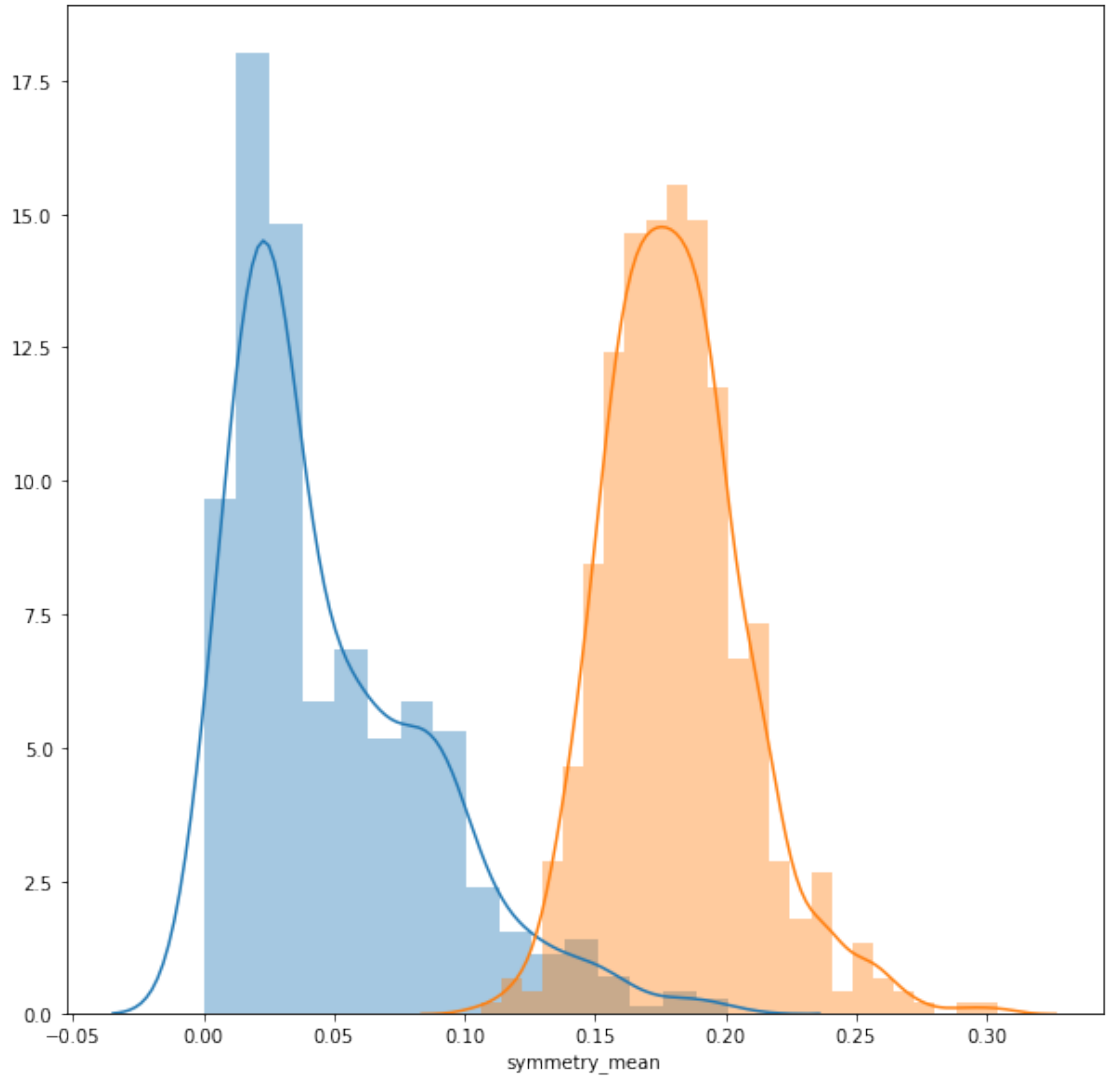
```
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1740d090>
```




```
In [73]: plt.figure(figsize = (10,10))
         sns.distplot(data["compactness_mean"])
         sns.distplot(data["concavity_mean"])

Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0x1a17643290>
```

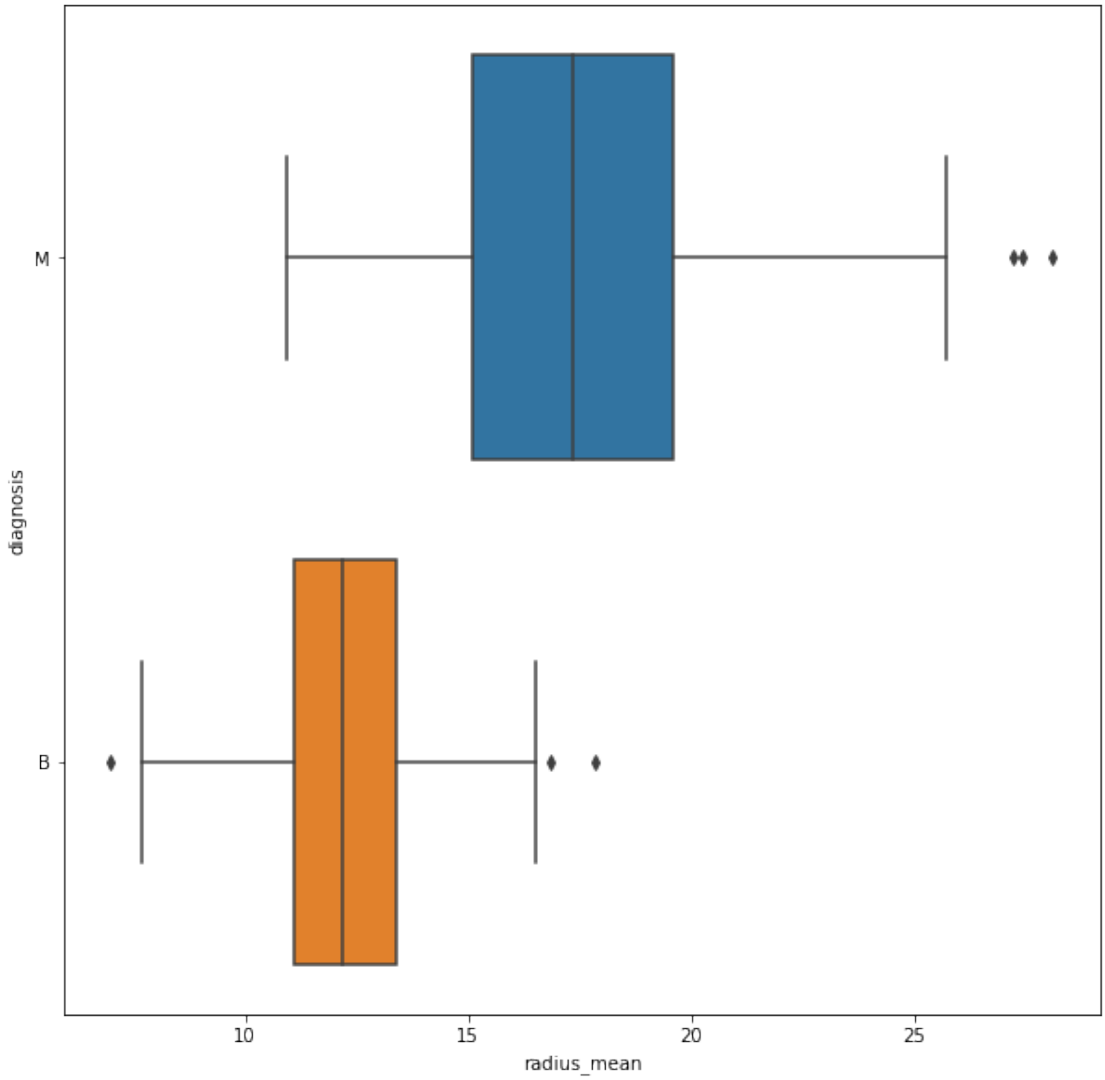



```
In [74]: plt.figure(figsize = (10,10))
         sns.distplot(data["concave points_mean"])
         sns.distplot(data["symmetry_mean"])

Out[74]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16d9f150>
```

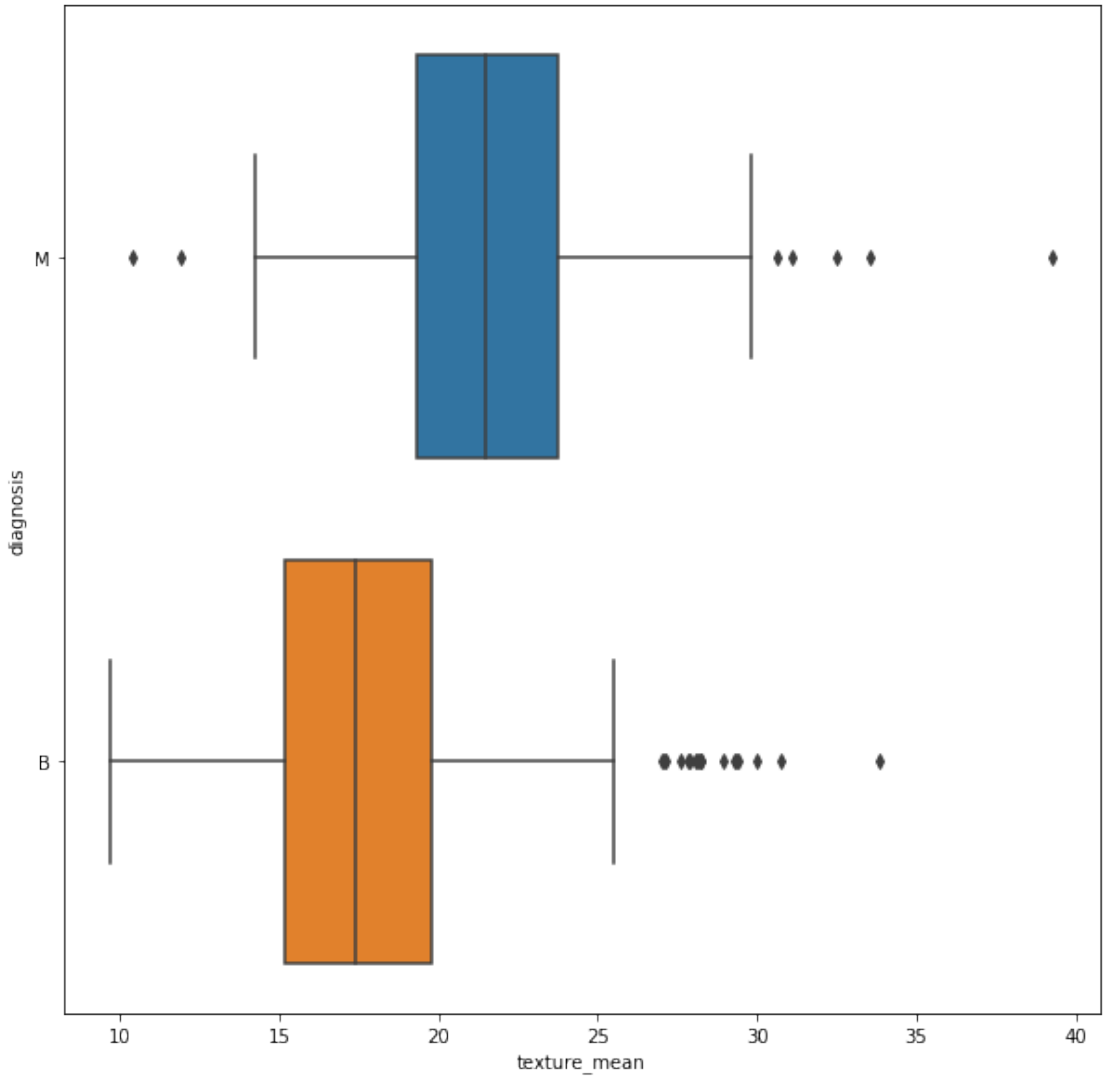


The following box plots are a crude representation of the 'range' of values of each parameter and the resultant answer. For ex, the plot for radius mean below, the means for M and B are seperated by a good margin and the correspoding 'box' i.e. deviation from the mean if although quite far yet not overlapping making it a very useful feature for us to include.

```
In [75]: #fig, (ax1, ax2) = plt.subplots(ncols=2, sharey=True)
         plt.figure(figsize = (10,10))

         sns.boxplot(data["radius_mean"],data["diagnosis"])

Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x1a17b8ce10>
```

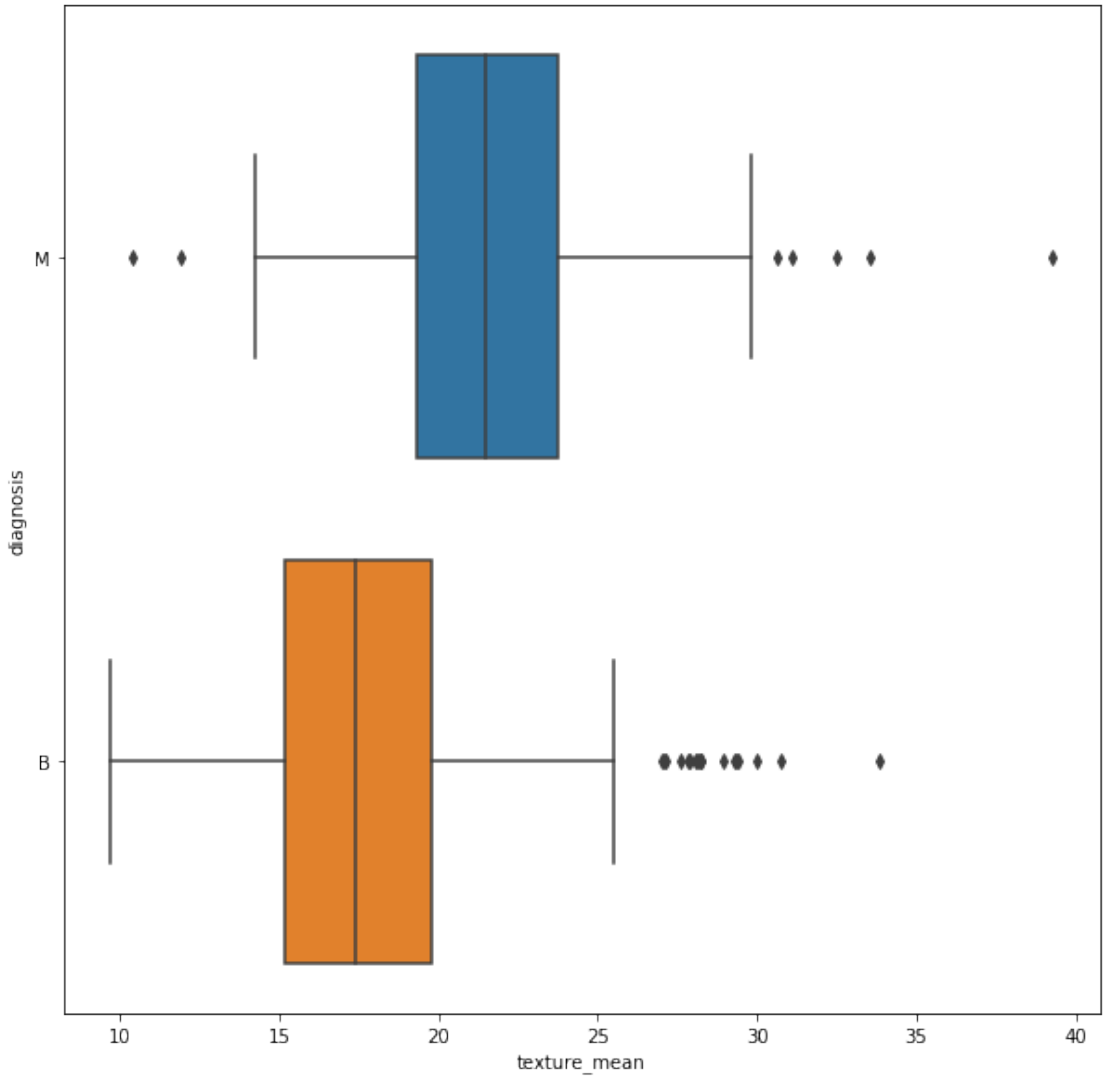



```
In [76]: plt.figure(figsize = (10,10))

         sns.boxplot(data["texture_mean"],data["diagnosis"])

Out[76]: <matplotlib.axes._subplots.AxesSubplot at 0x1a17b68810>
```



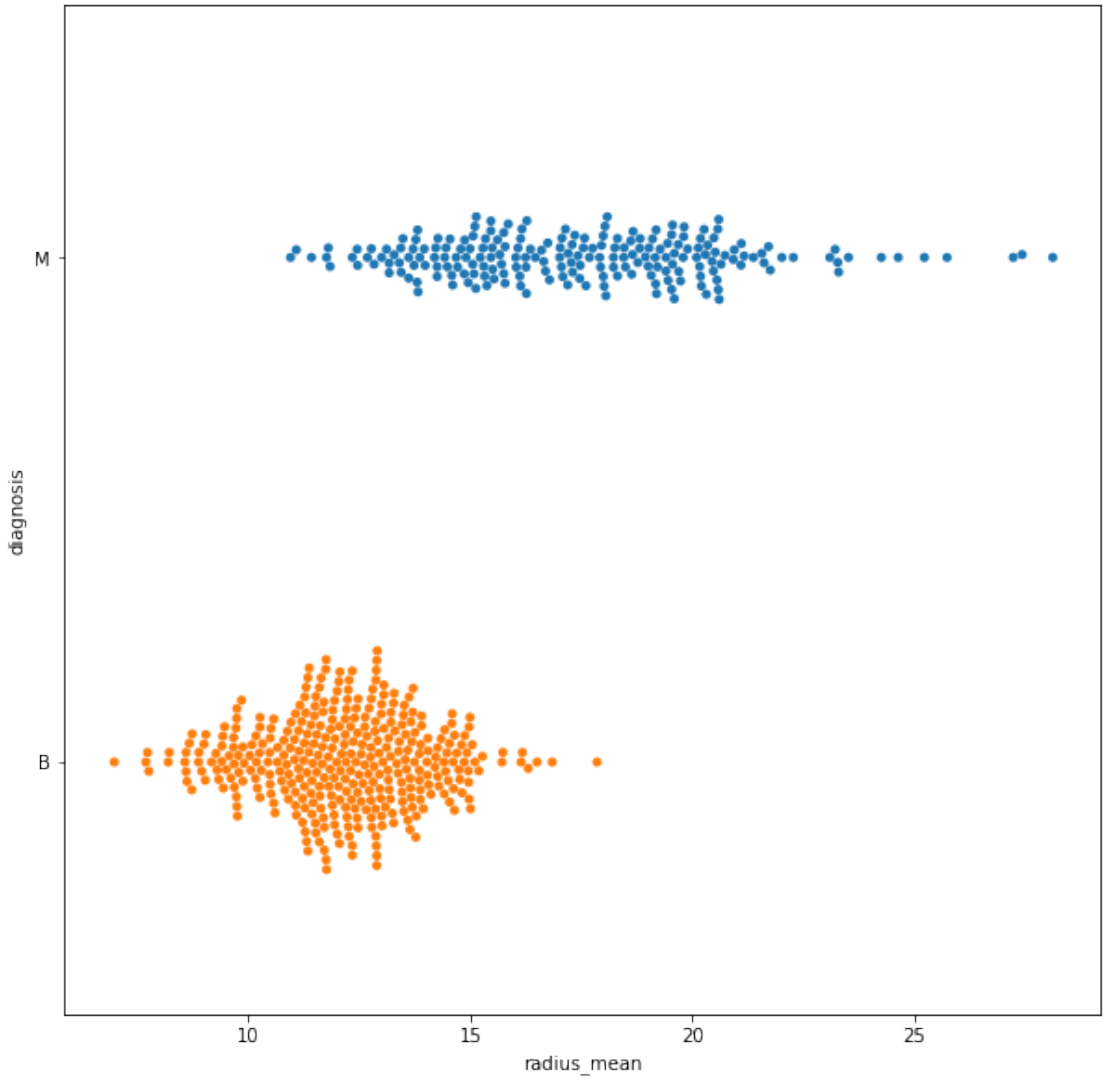

```
In [77]: plt.figure(figsize = (10,10))

         sns.boxplot(data["texture_mean"],data["diagnosis"])
         #sns.boxplot(data["perimeter_mean"],data["radius_mean"])
```

```
Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16981610>
```

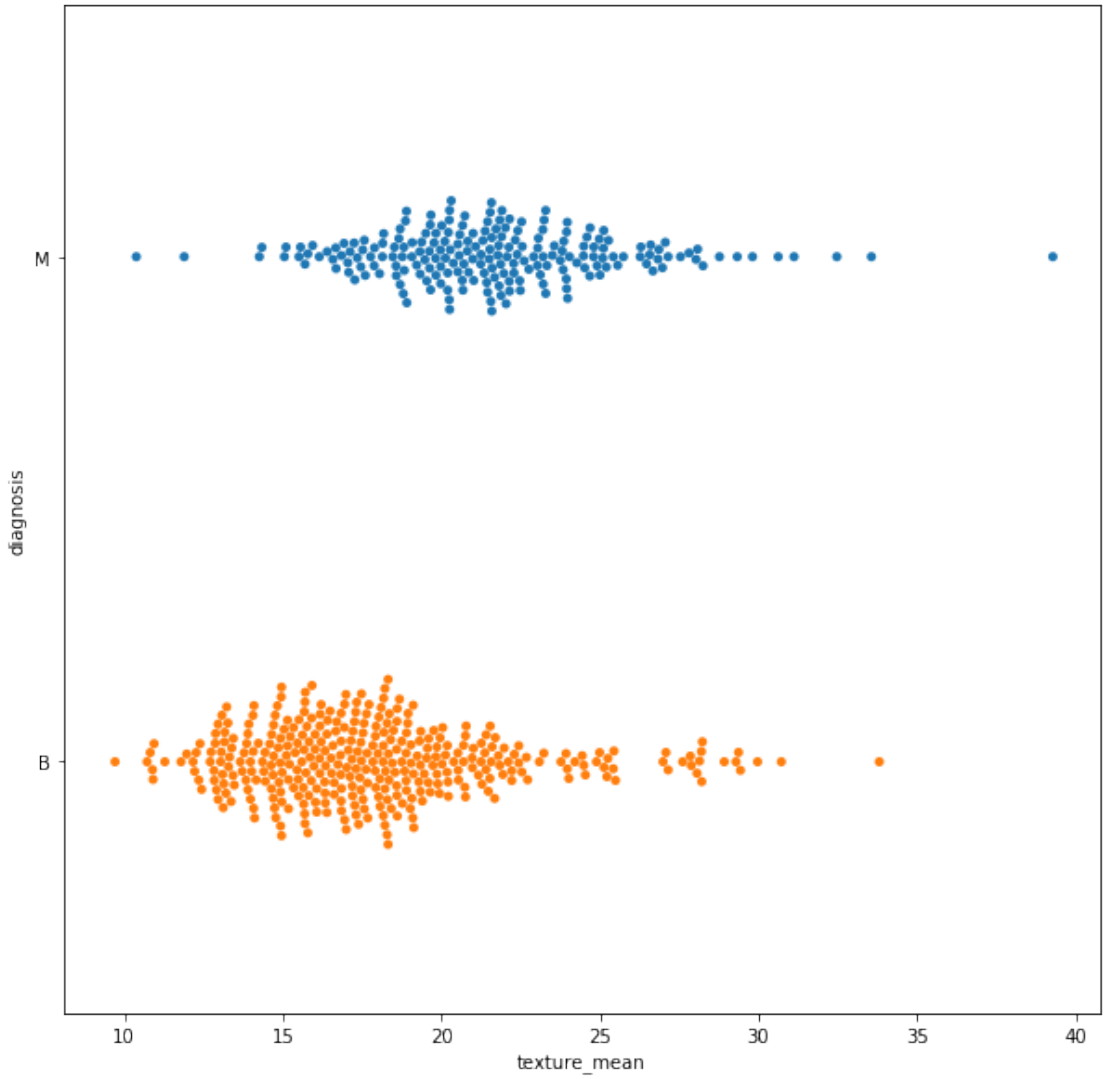


The following swarm plots are for each mean parameter and will give a clear idea for which features to include (eg concavity_mean) and which to not (eg fractal_mean).

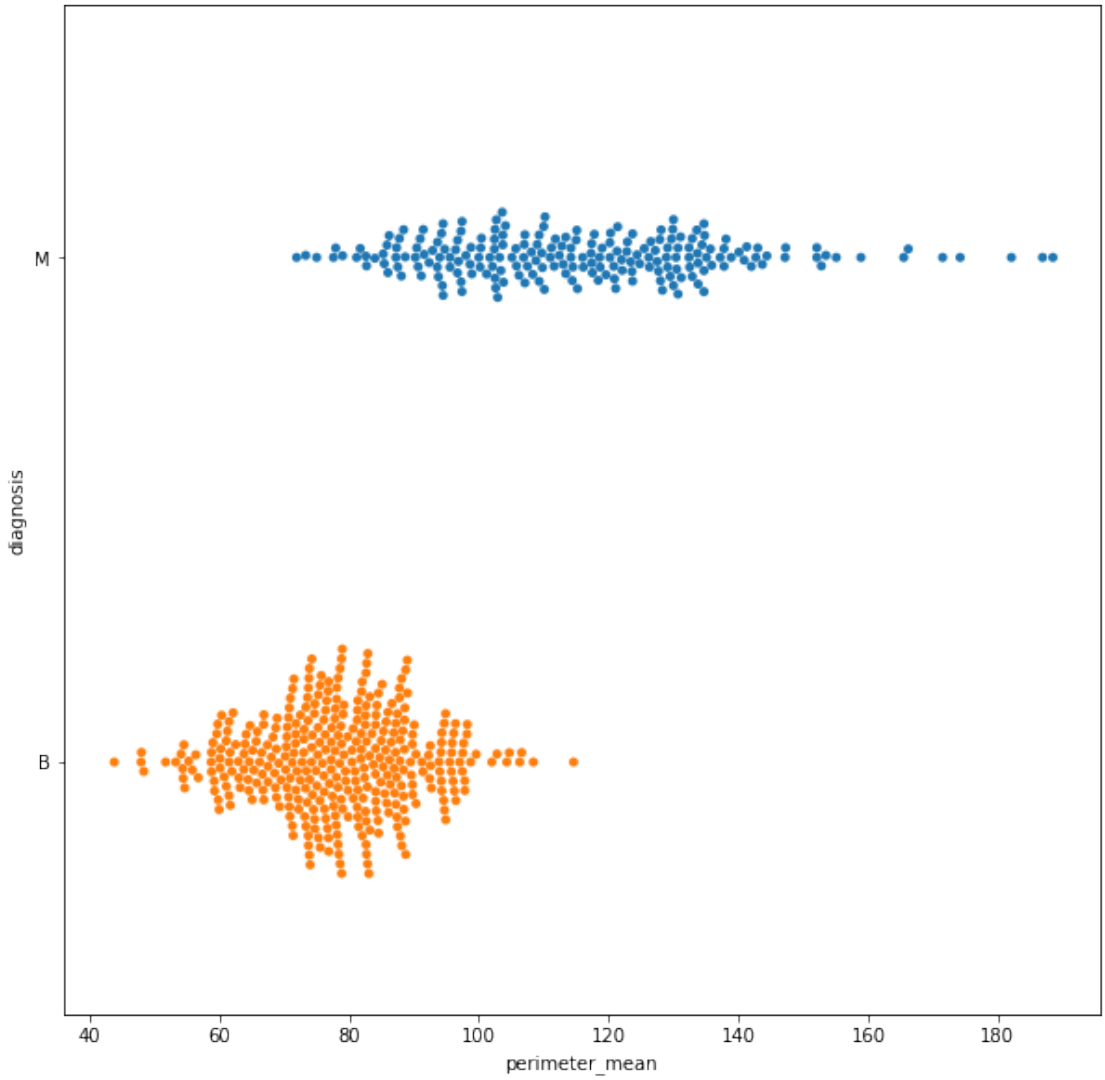
```
In [78]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["radius_mean"],data["diagnosis"])

Out[78]: <matplotlib.axes._subplots.AxesSubplot at 0x1a17a8d510>
```



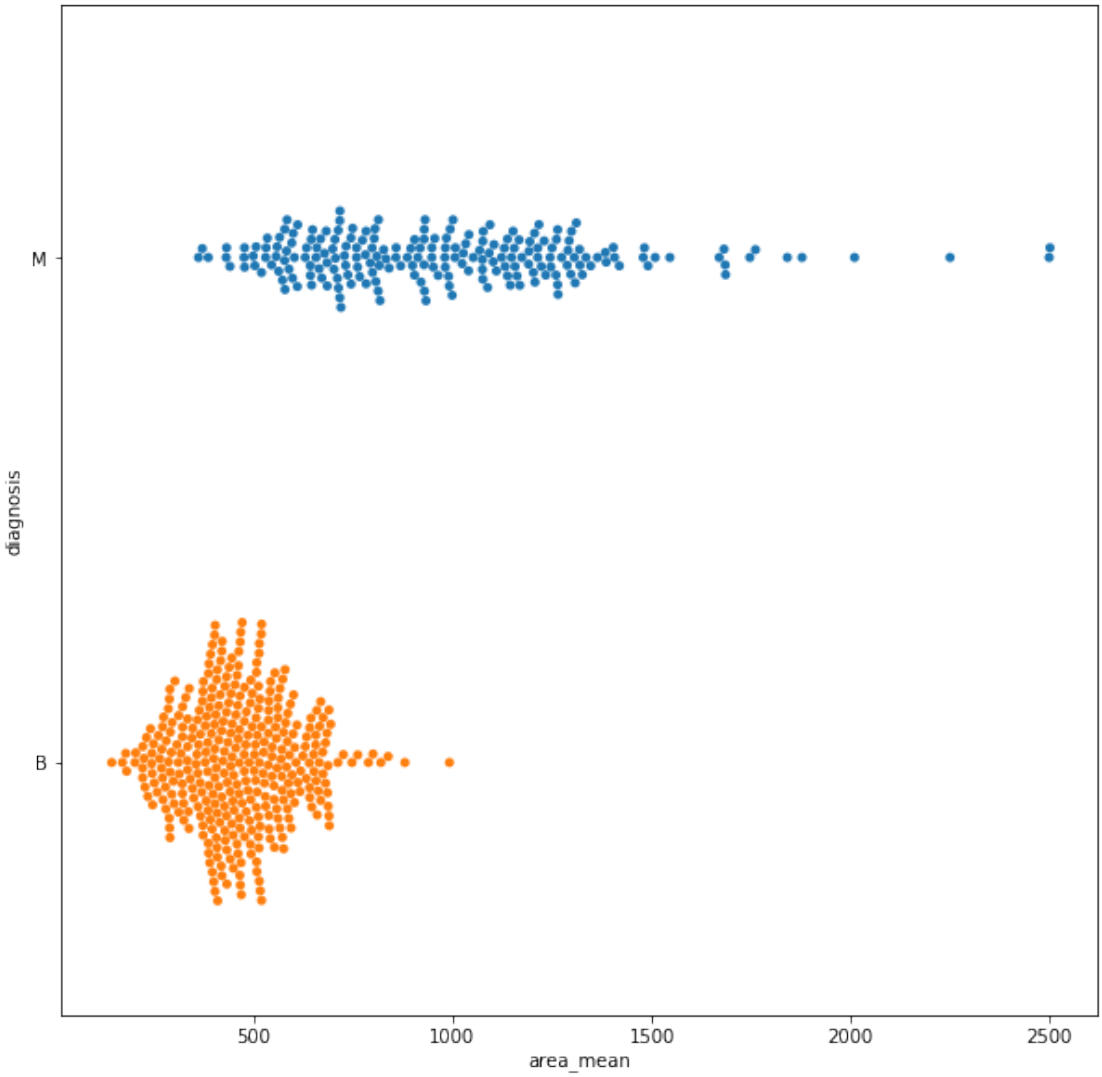

```
In [79]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["texture_mean"],data["diagnosis"])

Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x1a189e7910>
```



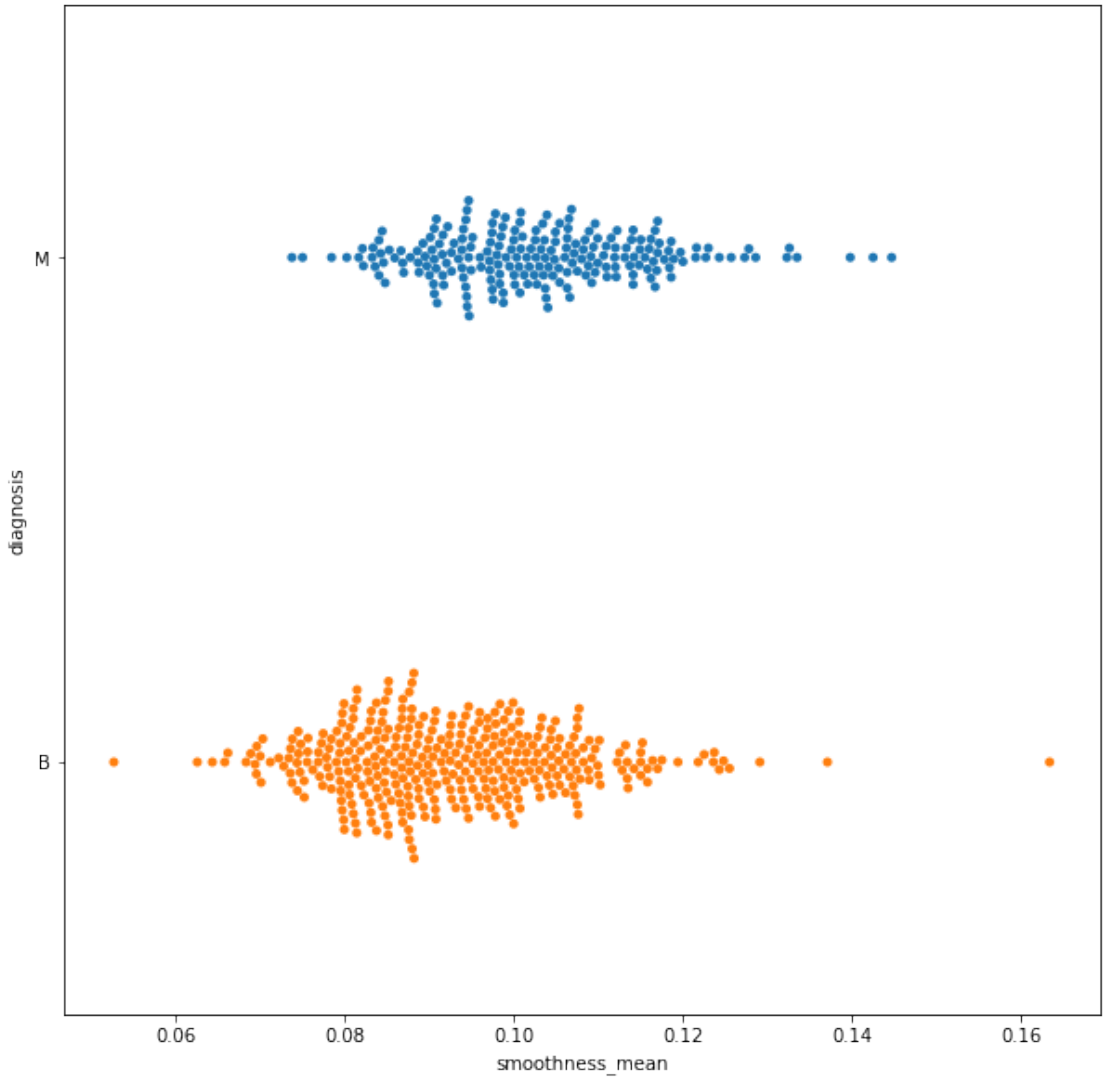

```
In [80]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["perimeter_mean"],data["diagnosis"])

Out[80]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1838ee50>
```



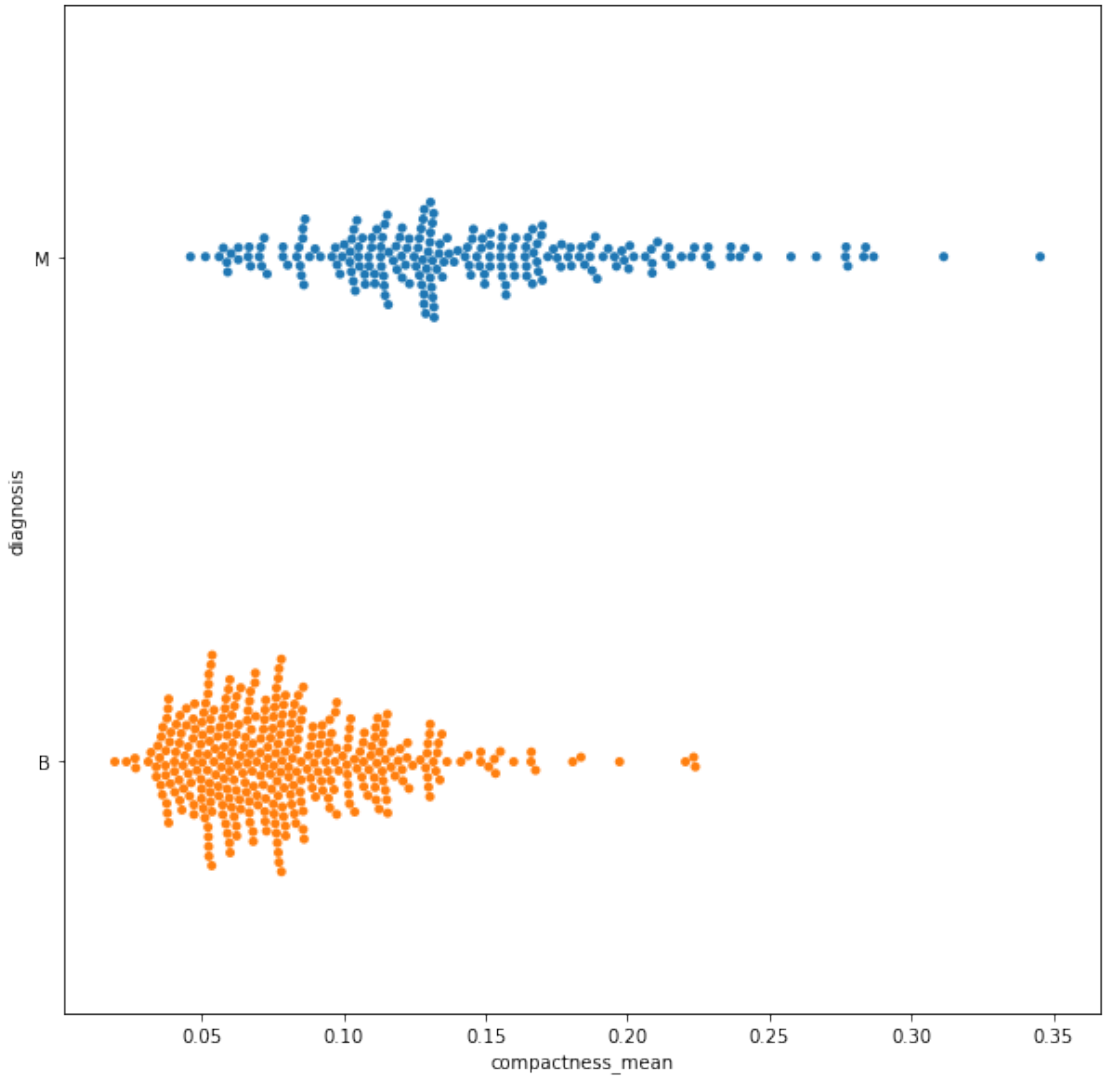

```
In [81]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["area_mean"],data["diagnosis"])

Out[81]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1abc6cd0>
```



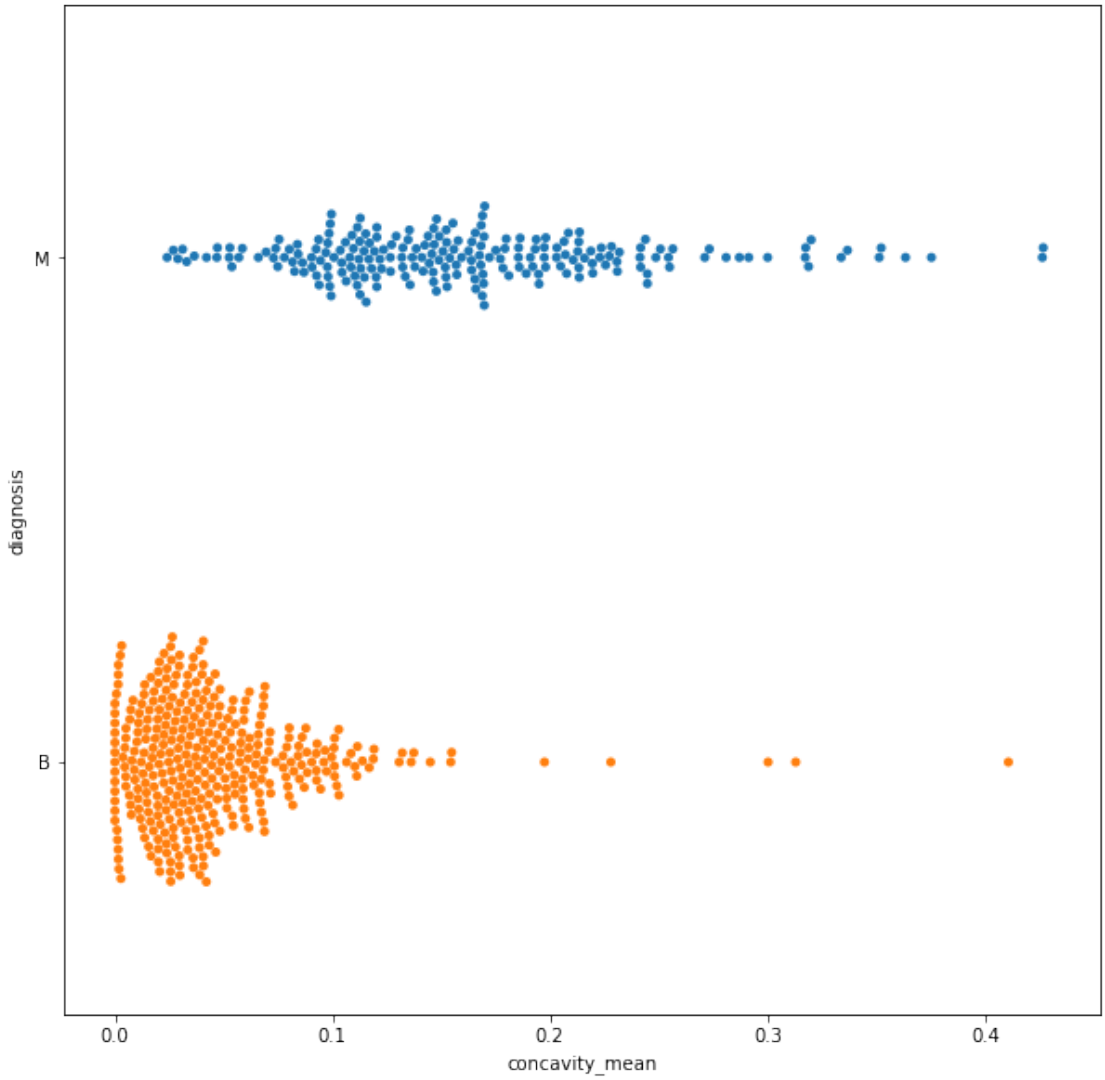

```
In [82]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["smoothness_mean"],data["diagnosis"])

Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16ce0910>
```



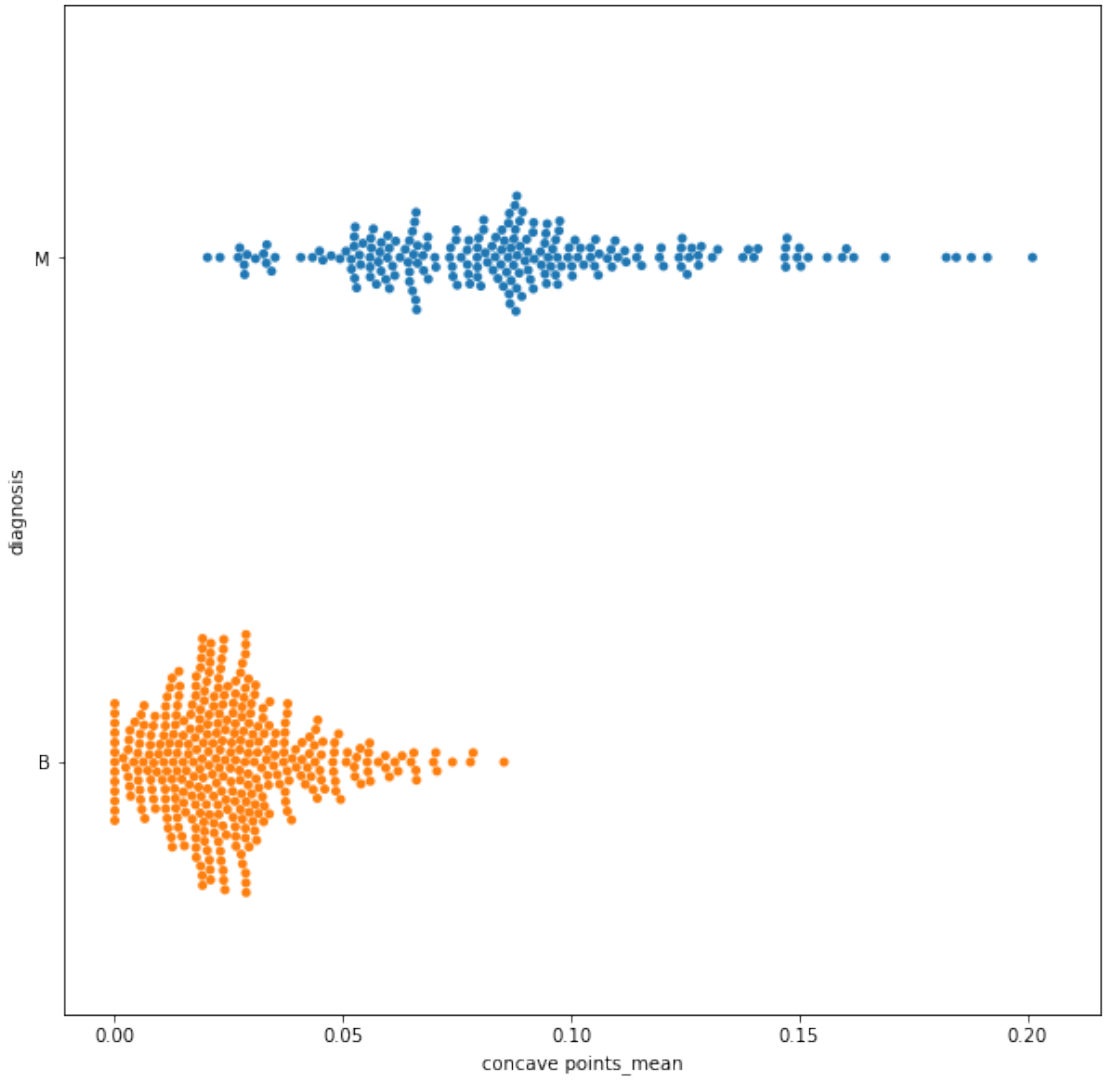

```
In [83]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["compactness_mean"],data["diagnosis"])

Out[83]: <matplotlib.axes._subplots.AxesSubplot at 0x1a18351d10>
```



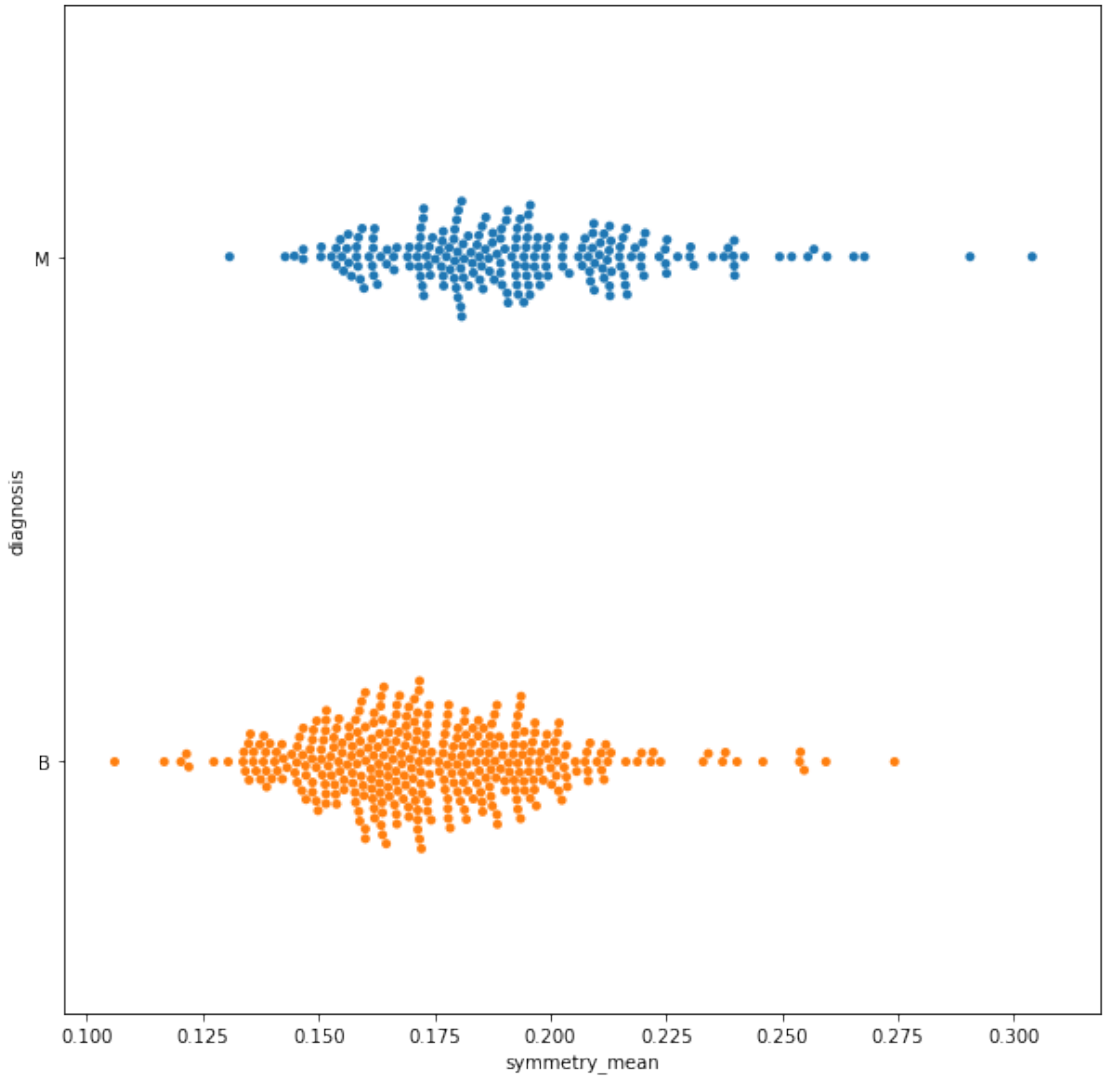

```
In [84]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["concavity_mean"],data["diagnosis"])

Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16d21d10>
```



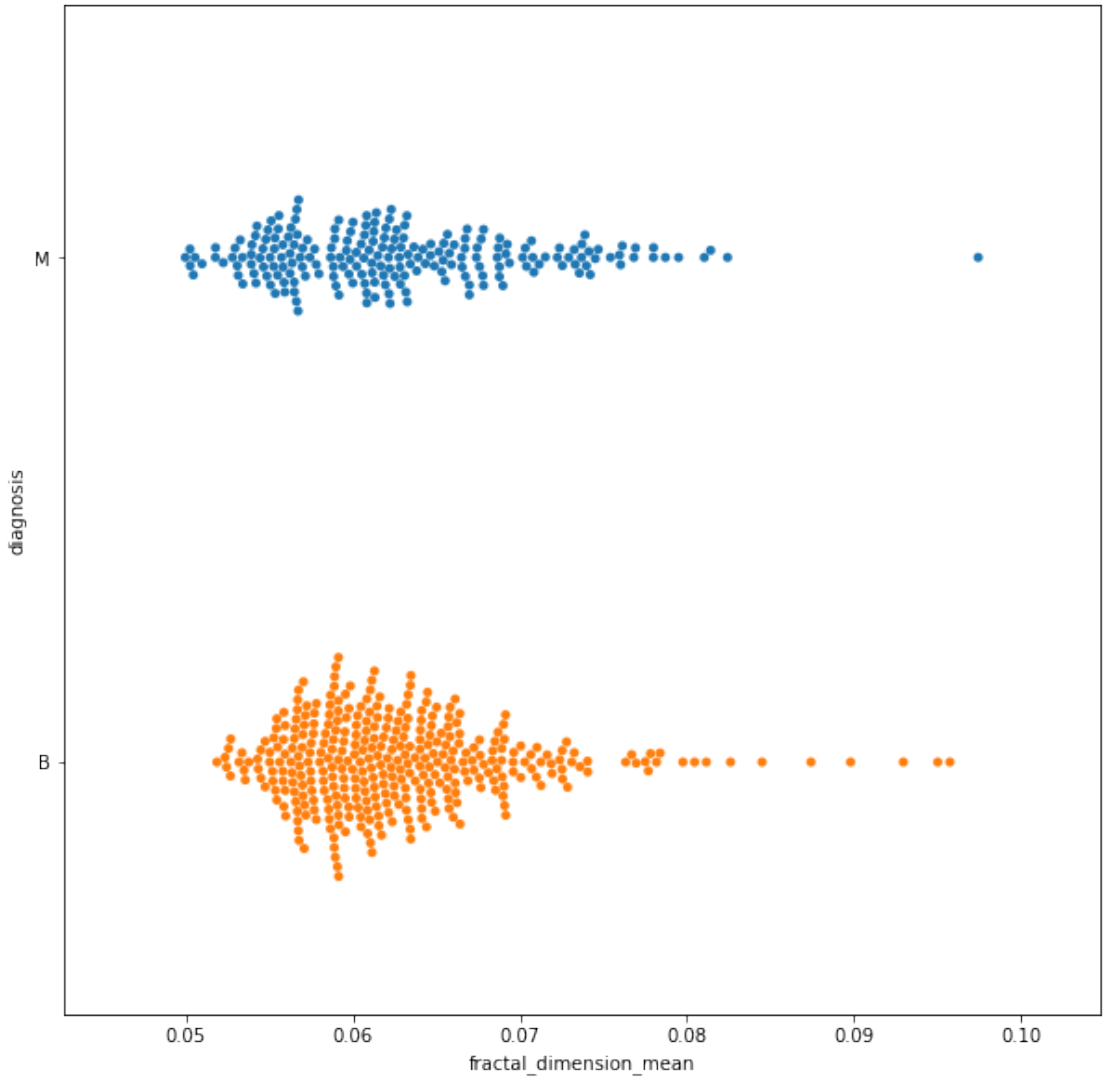

```
In [85]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["concave points_mean"],data["diagnosis"])

Out[85]: <matplotlib.axes._subplots.AxesSubplot at 0x1a176760d0>
```




```
In [86]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["symmetry_mean"],data["diagnosis"])

Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1748b790>
```




```
In [87]: plt.figure(figsize = (10,10))

         sns.swarmplot(data["fractal_dimension_mean"],data["diagnosis"])

Out[87]: <matplotlib.axes._subplots.AxesSubplot at 0x1a173bd690>
```



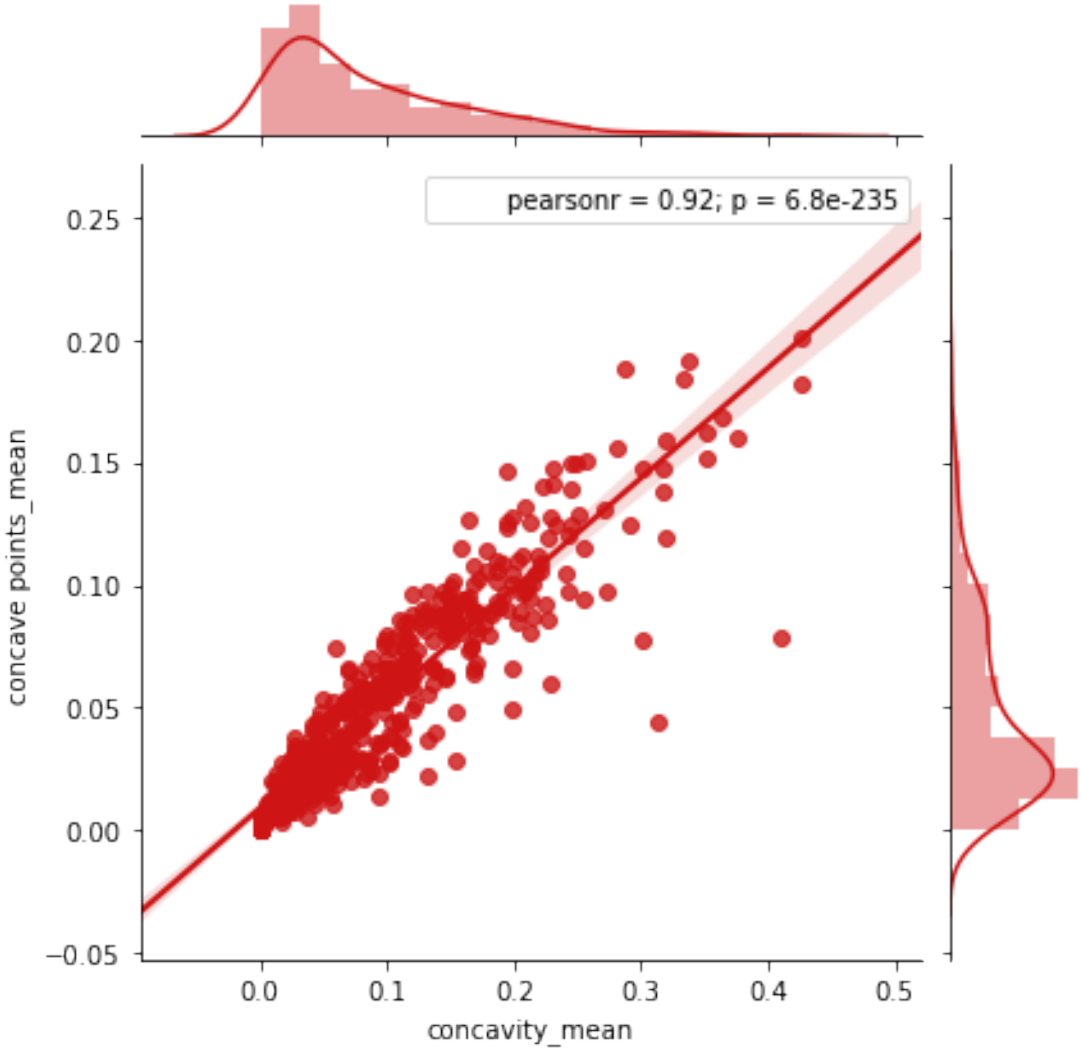
Variable of concavity_worst and concave point_worst looks like similar but how can we decide whether they are correlated with each other or not. (Not always true but, basically if the features are correlated with each other we can drop one of them)

In order to compare two features deeper, lets use joint plot. Look at this in joint plot below, it is really correlated. Pearsonr value is correlation value and 1 is the highest. Therefore, 0.92 is looks enough to say that they are correlated. Similarily radius with area and perimeter, there is a strong correlation in these parameters.

fractal_dimension_mean and texture_mean plot for eg, the personr value is negative, hence we can conculude these features aren't similar at all.

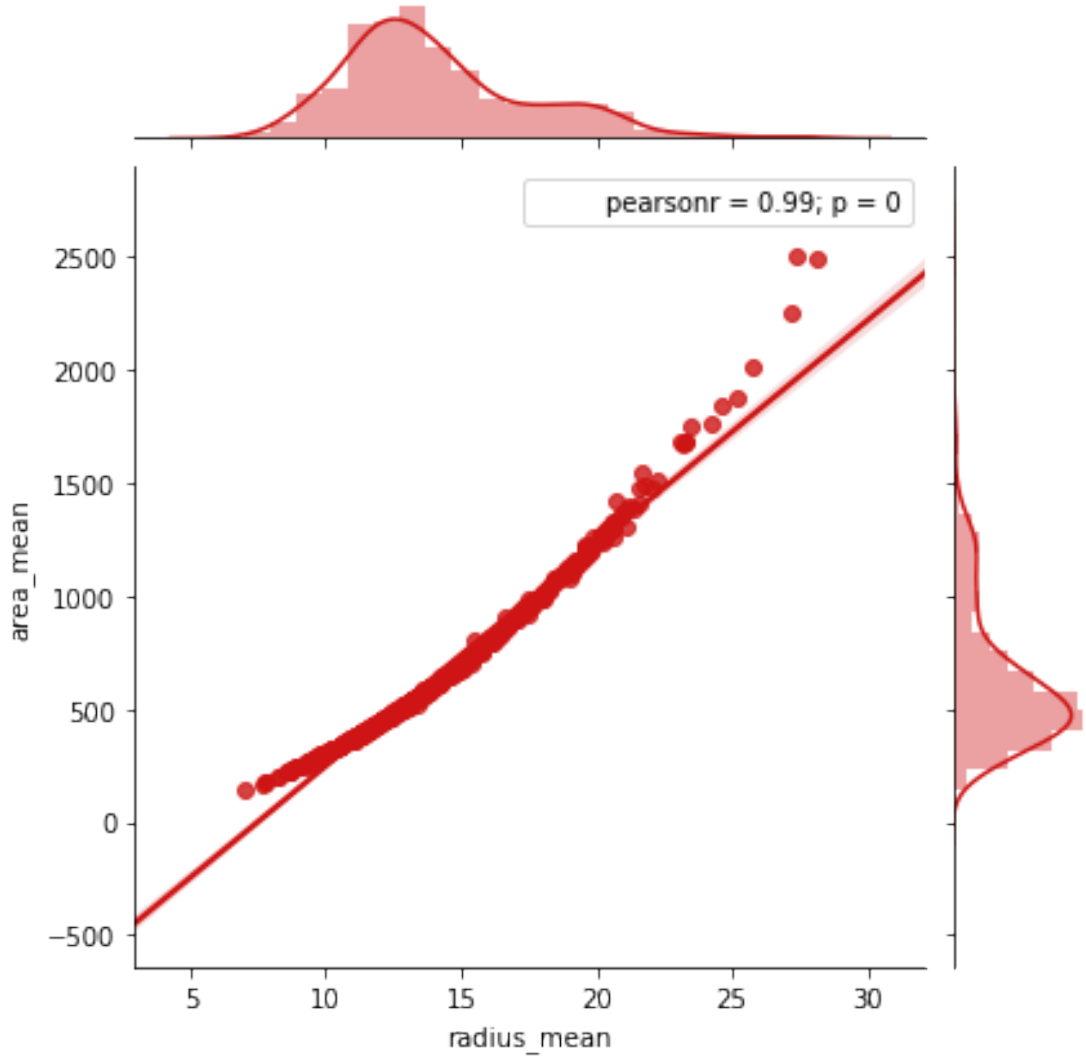
```
In [88]: sns.jointplot(x.loc[:,'concavity_mean'], x.loc[:,'concave points_mean'], kind="regg", c
```

```
Out[88]: <seaborn.axisgrid.JointGrid at 0x1a1733e790>
```



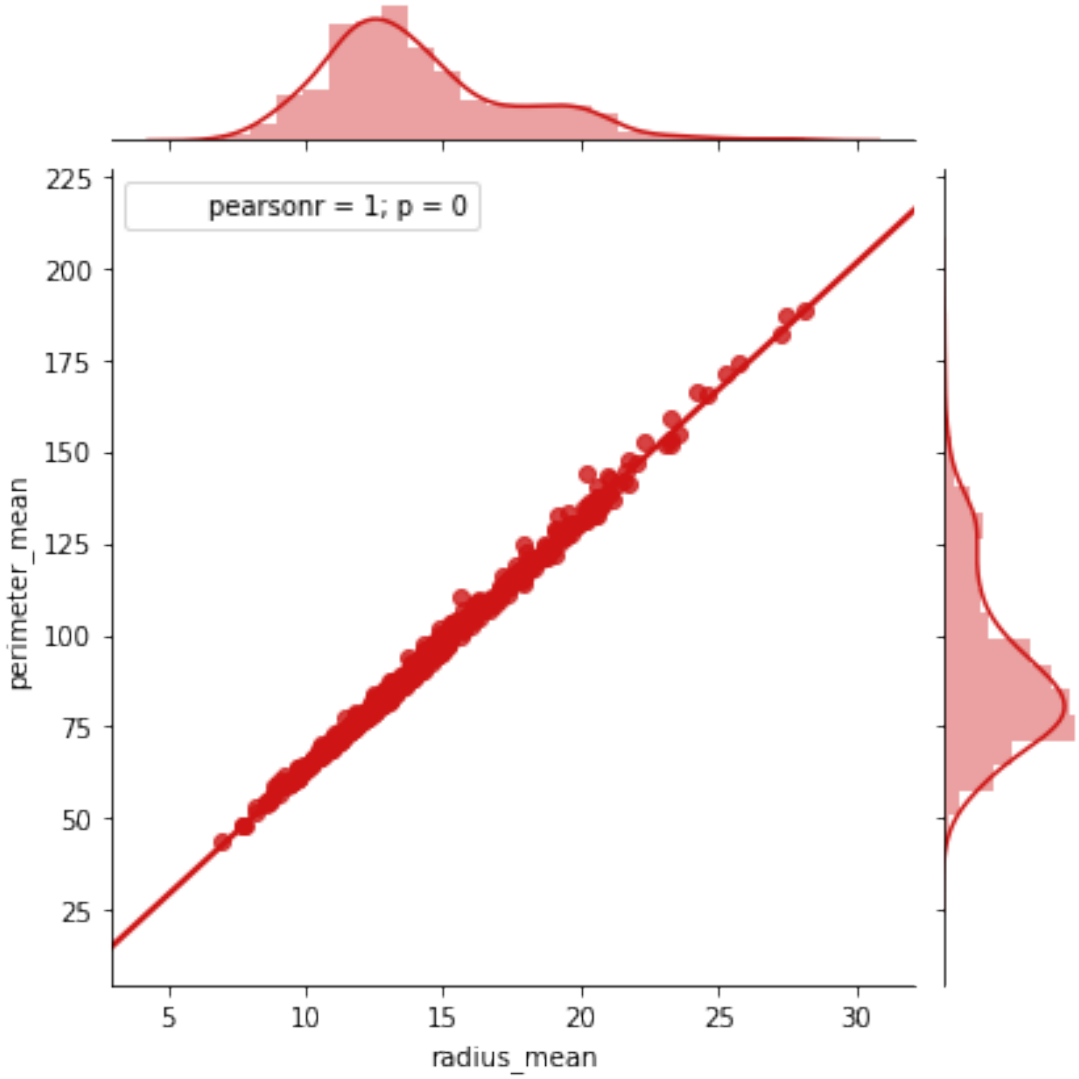

```
In [89]: sns.jointplot(x.loc[:,'radius_mean'], x.loc[:,'area_mean'], kind="regg", color="#ce1414
```

```
Out[89]: <seaborn.axisgrid.JointGrid at 0x1a17c2c390>
```



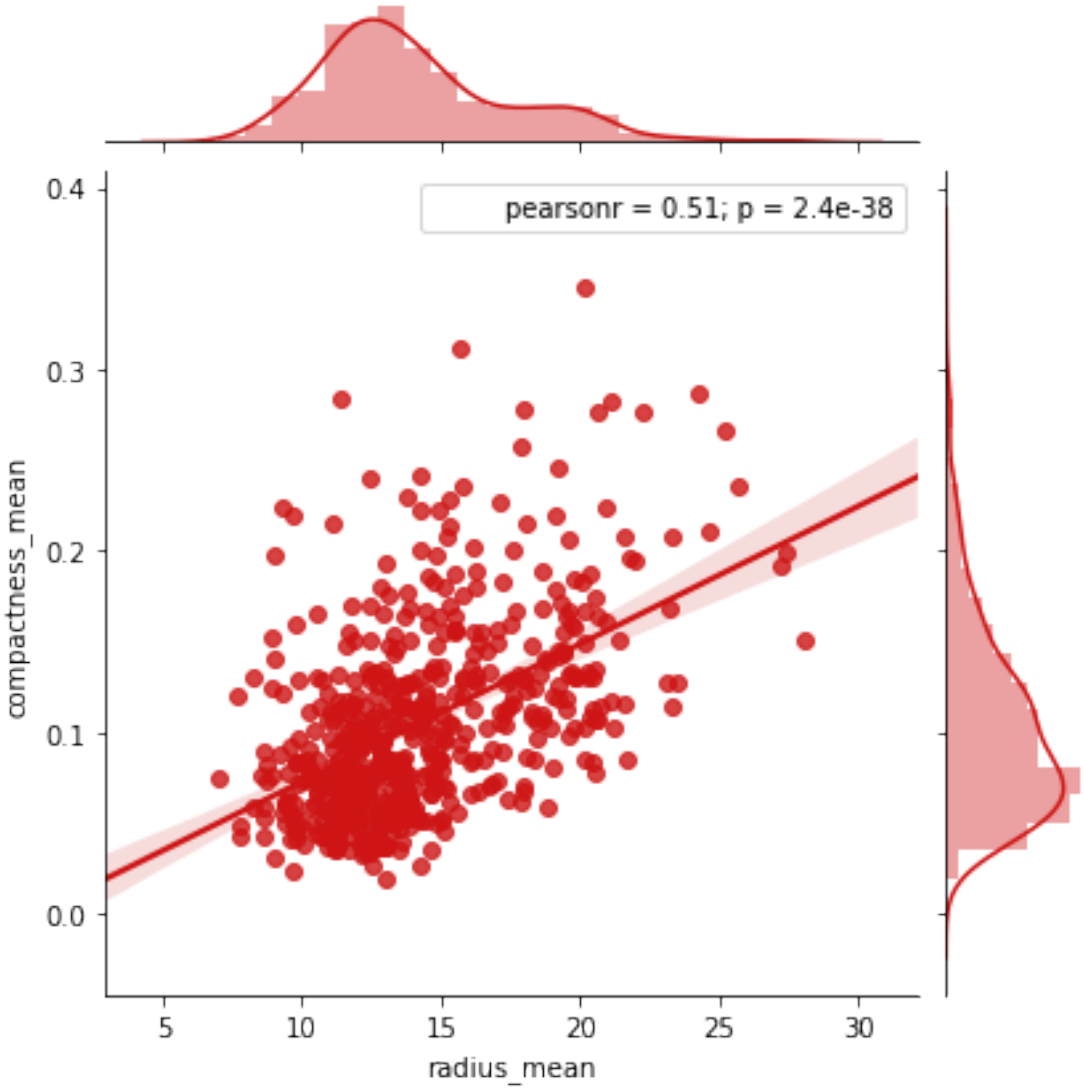

```
In [90]: sns.jointplot(x.loc[:,'radius_mean'], x.loc[:,'perimeter_mean'], kind="regg", color="#c
```

```
Out[90]: <seaborn.axisgrid.JointGrid at 0x1a17cb6bd0>
```



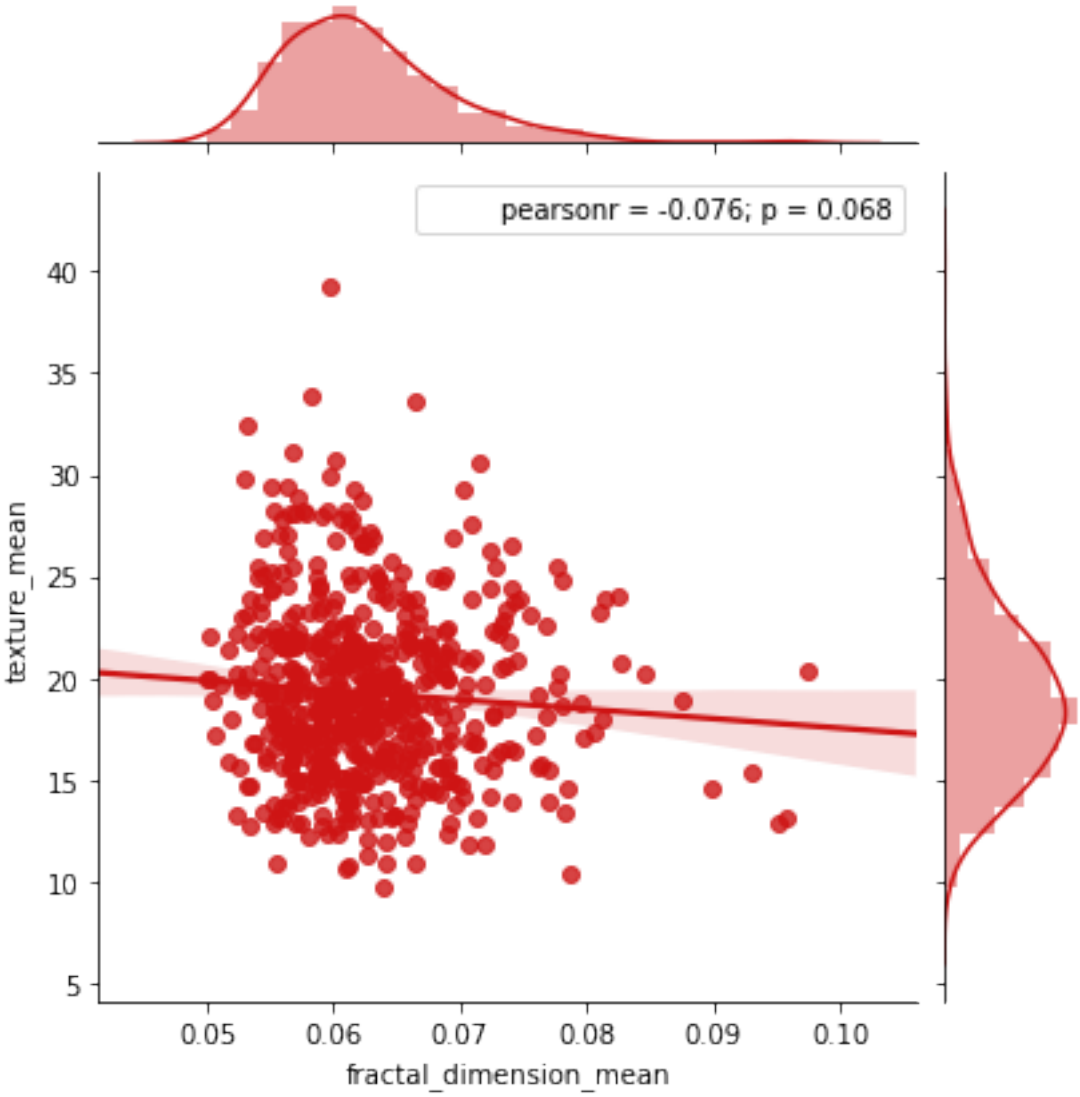

```
In [91]: sns.jointplot(x.loc[:,'radius_mean'], x.loc[:,'compactness_mean'], kind="regg", color="
```

```
Out[91]: <seaborn.axisgrid.JointGrid at 0x1a16ee9490>
```



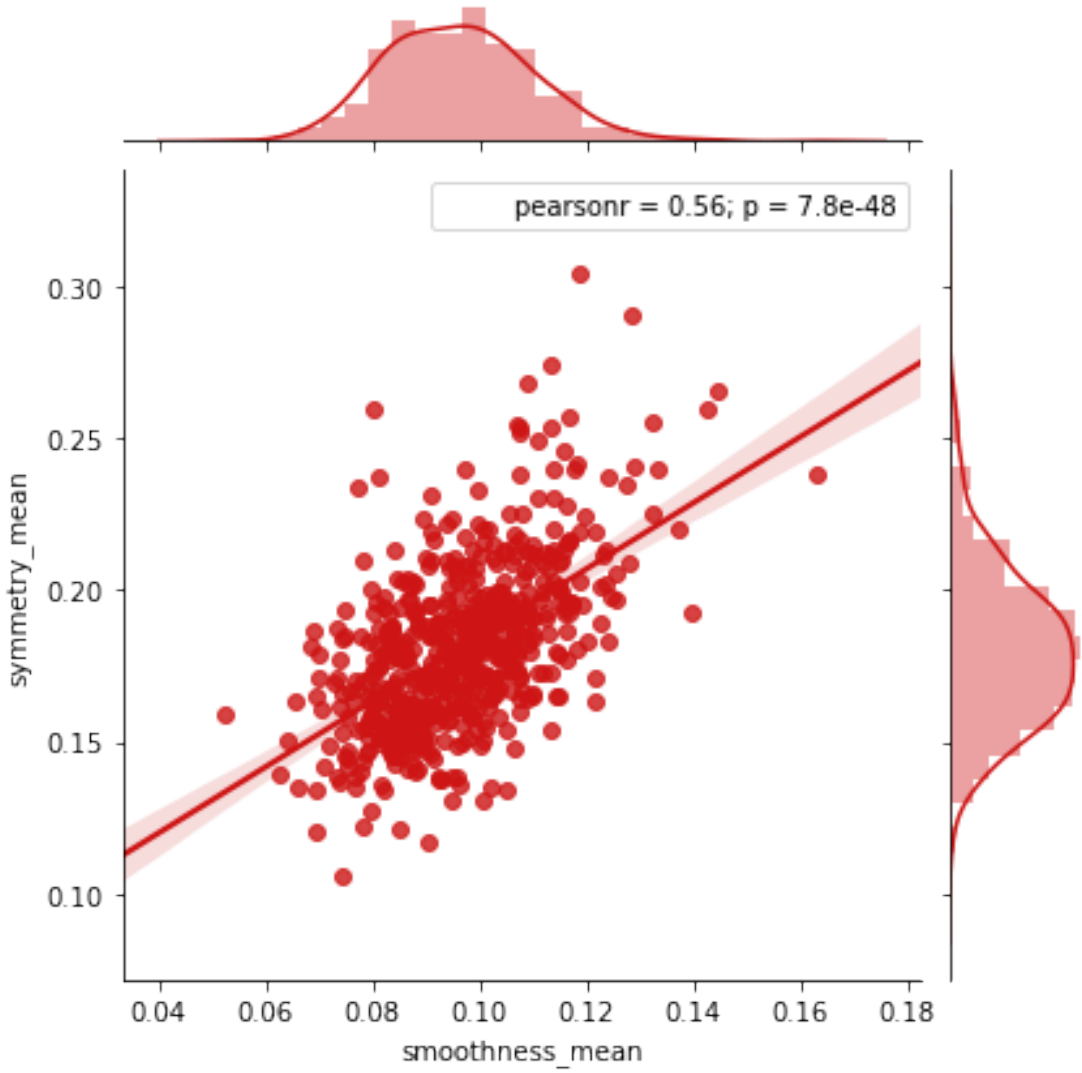

```
In [92]: sns.jointplot(x.loc[:,'fractal_dimension_mean'], x.loc[:,'texture_mean'], kind="regg",
```

```
Out[92]: <seaborn.axisgrid.JointGrid at 0x1a16cec250>
```



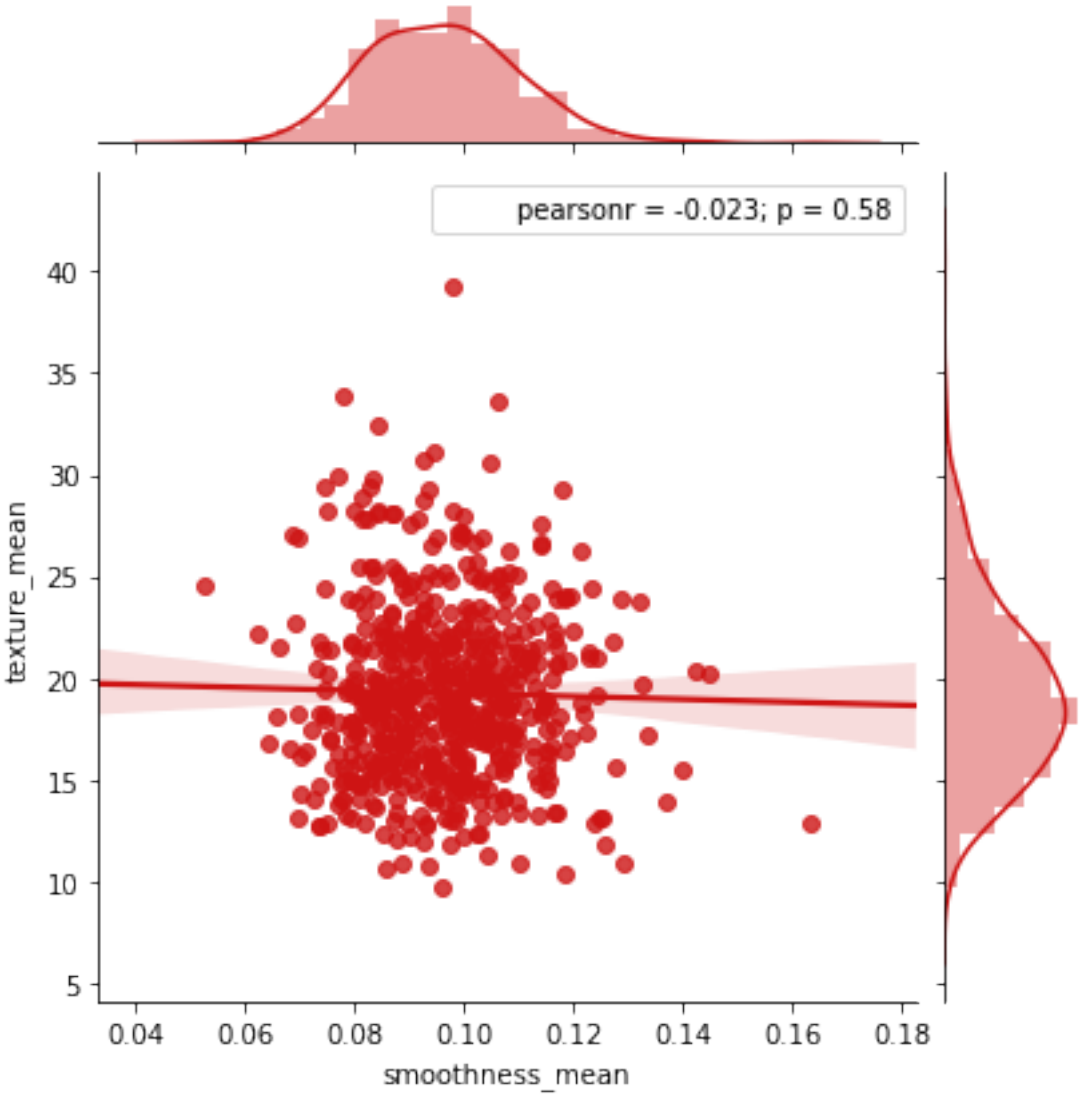

```
In [93]: sns.jointplot(x.loc[:,'smoothness_mean'], x.loc[:,'symmetry_mean'], kind="regg", color=
```

```
Out[93]: <seaborn.axisgrid.JointGrid at 0x1a1790cb50>
```

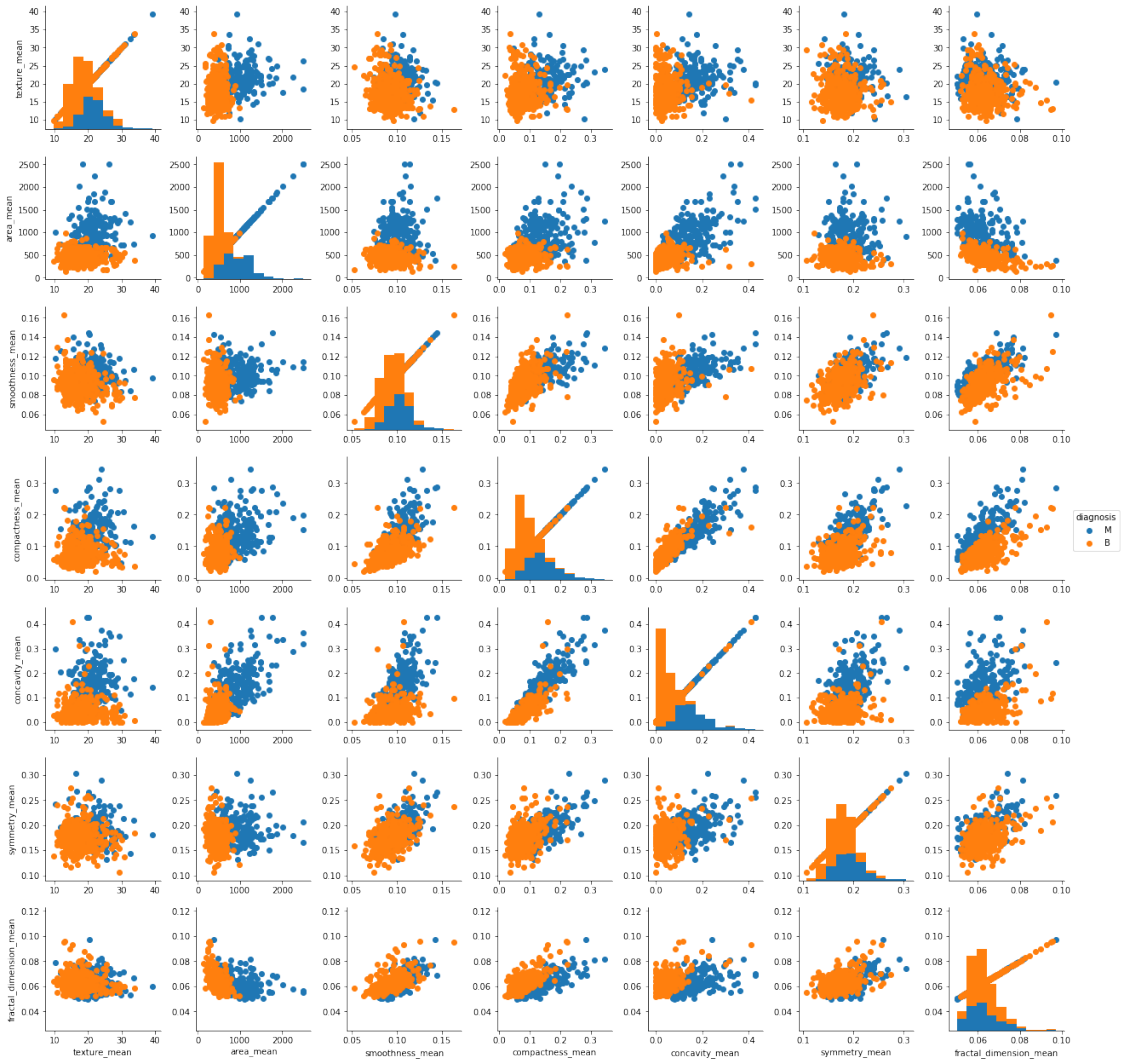



```
In [94]: sns.jointplot(x.loc[:,'smoothness_mean'], x.loc[:,'texture_mean'], kind="regg", color="
```

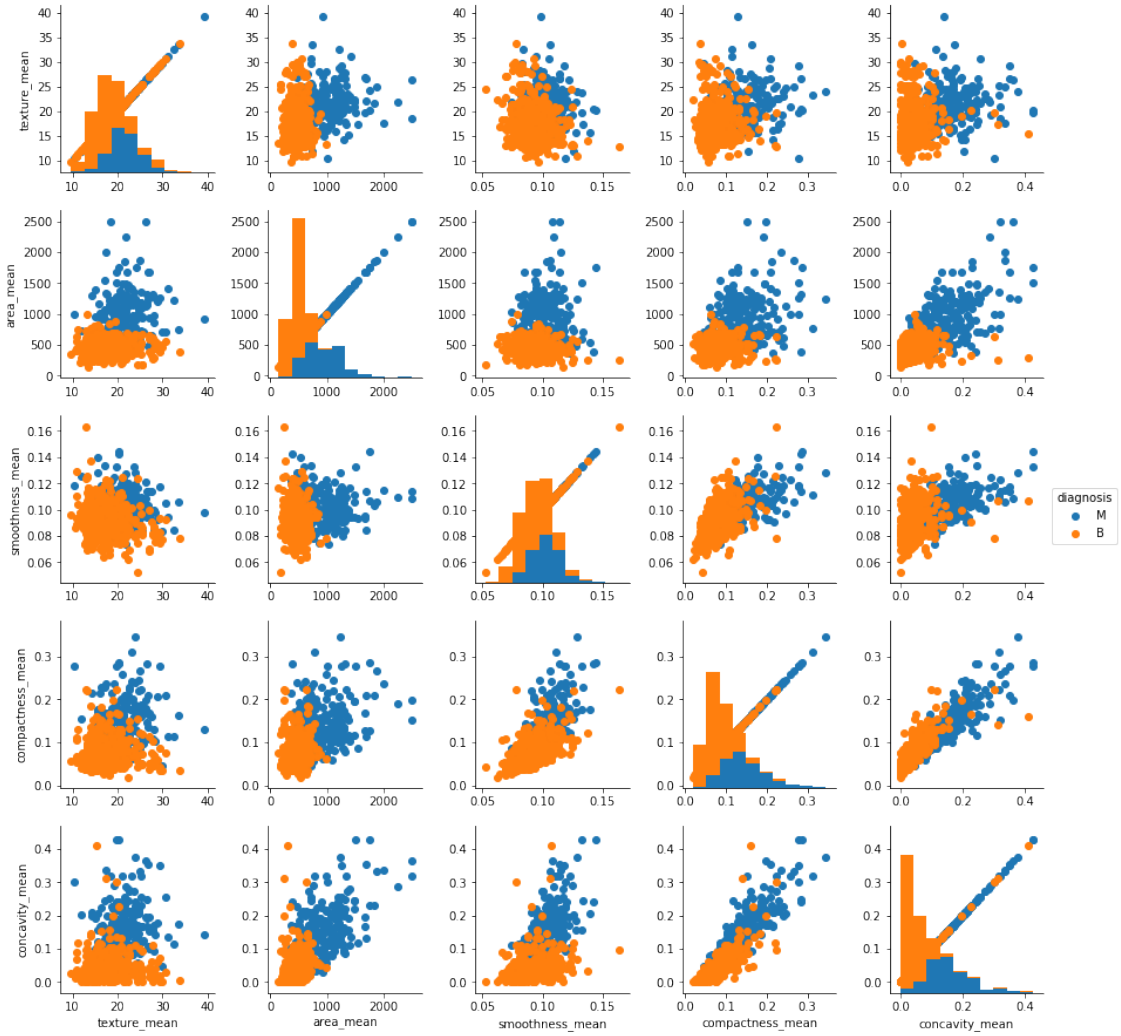
```
Out[94]: <seaborn.axisgrid.JointGrid at 0x1a17f2c590>
```



In [95]:
```
a = data.drop(['Unnamed: 32','id','radius_se','texture_se','perimeter_se','area_se','sm
g = sns.PairGrid(a, hue='diagnosis')
g = g.map_diag(plt.hist)
g = g.map(plt.scatter)
g = g.add_legend()
```




```
In [96]: a = data.drop(['Unnamed: 32','id','radius_se','texture_se','perimeter_se','area_se','sm
         g = sns.PairGrid(a, hue='diagnosis')
         g = g.map_diag(plt.hist)
         g = g.map(plt.scatter)
         g = g.add_legend()
```


texture_mean
area_mean
smoothness_mean
compactness_mean
concavity_mean
texture_mean
area_mean
smoothness_mean
compactness_mean
concavity_mean
diagnosis
M
B