theAwesome_PredModel

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1 Prediction Model

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Dataset from Breast Cancer UCI Machine Learning Repo
Attribute Information:

1. ID number
2. Diagnosis (M = malignant, B = benign)

3-32: Ten real-valued features are computed for each cell nucleus:

- radius (mean of distances from center to points on the perimeter)
- texture (standard deviation of gray-scale values)
- perimeter
- area
- smoothness (local variation in radius lengths)
- compactness (perimeter^2 / area - 1.0)
- concavity (severity of concave portions of the contour)
- concave points (number of concave portions of the contour)
- symmetry
- fractal dimension ("coastline approximation" - 1)

The mean, standard error and "worst" or largest (mean of the three largest values) of these features were computed for each image, resulting in 30 features. For instance, field 3 is Mean Radius, field 13 is Radius SE, field 23 is Worst Radius.

All feature values are recoded with four significant digits.
Missing attribute values: none
Class distribution: 357 benign, 212 malignant

1.1 Step 0: Data Preparation and Cleaning

```
In [19]: import pandas as pd
```

```
In [20]: # Read CSV data into df
         df = pd.read_csv('./theAwesome_PredModel.csv')
         # delete id column no need
```

```
df.drop('id',axis=1,inplace=True)
# delete unnamed colum at the end
df.drop('Unnamed: 32',axis=1,inplace=True)
df.head()
```

Out[20]:

```
  diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0         M        17.99         10.38          122.80     1001.0
1         M        20.57         17.77          132.90     1326.0
2         M        19.69         21.25          130.00     1203.0
3         M        11.42         20.38           77.58      386.1
4         M        20.29         14.34          135.10     1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
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

   symmetry_mean           ...              radius_worst  texture_worst  \
0         0.2419           ...                     25.38          17.33
1         0.1812           ...                     24.99          23.41
2         0.2069           ...                     23.57          25.53
3         0.2597           ...                     14.91          26.50
4         0.1809           ...                     22.54          16.67

   perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
0           184.60      2019.0            0.1622             0.6656
1           158.80      1956.0            0.1238             0.1866
2           152.50      1709.0            0.1444             0.4245
3            98.87       567.7            0.2098             0.8663
4           152.20      1575.0            0.1374             0.2050

   concavity_worst  concave points_worst  symmetry_worst  \
0           0.7119                0.2654          0.4601
1           0.2416                0.1860          0.2750
2           0.4504                0.2430          0.3613
3           0.6869                0.2575          0.6638
4           0.4000                0.1625          0.2364

   fractal_dimension_worst
0                  0.11890
1                  0.08902
2                  0.08758
3                  0.17300
4                  0.07678

[5 rows x 31 columns]
```

```
In [8]: # Learn the unique values in diagnosis column
        df.diagnosis.unique()
        # M: Malign (Yes Cancer)
        # B: Benign (No Cancer)

        # I can also map M and B as 1 and 0 for more numerical
        #  approach
        df['diagnosis'] = df['diagnosis'].map({'M':1,'B':0})
```

1.2 Step 1: Data Information and Descriptive Statistics

Generate the information about your dataset: number of columns and rows, names and data types of the columns, memory usage of the dataset.

> Hint: Pandas data frame info() function.

Generate descriptive statistics of all columns (input and output) of your dataset. Descriptive statistics for numerical columns include: count, mean, std, min, 25 percentile (Q1), 50 percentile (Q2, median), 75 percentile (Q3), max values of the columns. For categorical columns, determine distinct values and their frequency in each categorical column.

> Hint: Pandas, data frame describe() function.

```
In [9]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
diagnosis                  569 non-null int64
radius_mean                569 non-null float64
texture_mean               569 non-null float64
perimeter_mean             569 non-null float64
area_mean                  569 non-null float64
smoothness_mean            569 non-null float64
compactness_mean           569 non-null float64
concavity_mean             569 non-null float64
concave points_mean        569 non-null float64
symmetry_mean              569 non-null float64
fractal_dimension_mean     569 non-null float64
radius_se                  569 non-null float64
texture_se                 569 non-null float64
perimeter_se               569 non-null float64
area_se                    569 non-null float64
smoothness_se              569 non-null float64
compactness_se             569 non-null float64
concavity_se               569 non-null float64
concave points_se          569 non-null float64
symmetry_se                569 non-null float64
fractal_dimension_se       569 non-null float64
```

```
radius_worst               569 non-null float64
texture_worst              569 non-null float64
perimeter_worst            569 non-null float64
area_worst                 569 non-null float64
smoothness_worst           569 non-null float64
compactness_worst          569 non-null float64
concavity_worst            569 non-null float64
concave points_worst       569 non-null float64
symmetry_worst             569 non-null float64
fractal_dimension_worst    569 non-null float64
dtypes: float64(30), int64(1)
memory usage: 137.9 KB
```

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

```
Out[10]:         diagnosis  radius_mean  texture_mean  perimeter_mean    area_mean  \
         count  569.000000   569.000000    569.000000      569.000000   569.000000
         mean     0.372583    14.127292     19.289649       91.969033   654.889104
         std      0.483918     3.524049      4.301036       24.298981   351.914129
         min      0.000000     6.981000      9.710000       43.790000   143.500000
         25%      0.000000    11.700000     16.170000       75.170000   420.300000
         50%      0.000000    13.370000     18.840000       86.240000   551.100000
         75%      1.000000    15.780000     21.800000      104.100000   782.700000
         max      1.000000    28.110000     39.280000      188.500000  2501.000000

                smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
         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

                symmetry_mean           ...             radius_worst  texture_worst  \
         count     569.000000           ...               569.000000     569.000000
         mean        0.181162           ...                16.269190      25.677223
         std         0.027414           ...                 4.833242       6.146258
         min         0.106000           ...                 7.930000      12.020000
         25%         0.161900           ...                13.010000      21.080000
         50%         0.179200           ...                14.970000      25.410000
         75%         0.195700           ...                18.790000      29.720000
         max         0.304000           ...                36.040000      49.540000

                perimeter_worst   area_worst  smoothness_worst  compactness_worst  \
         count       569.000000   569.000000        569.000000         569.000000
```

```
mean        107.261213   880.583128          0.132369            0.254265
std          33.602542   569.356993          0.022832            0.157336
min          50.410000   185.200000          0.071170            0.027290
25%          84.110000   515.300000          0.116600            0.147200
50%          97.660000   686.500000          0.131300            0.211900
75%         125.400000  1084.000000          0.146000            0.339100
max         251.200000  4254.000000          0.222600            1.058000

       concavity_worst  concave points_worst  symmetry_worst  \
count       569.000000            569.000000      569.000000
mean          0.272188              0.114606        0.290076
std           0.208624              0.065732        0.061867
min           0.000000              0.000000        0.156500
25%           0.114500              0.064930        0.250400
50%           0.226700              0.099930        0.282200
75%           0.382900              0.161400        0.317900
max           1.252000              0.291000        0.663800

       fractal_dimension_worst
count               569.000000
mean                  0.083946
std                   0.018061
min                   0.055040
25%                   0.071460
50%                   0.080040
75%                   0.092080
max                   0.207500

[8 rows x 31 columns]
```

1.3 Step 2: Train Test Split

Split your data into Training and Test data set by randomly selecting; use 70% for training and 30 % for testing. Generate descriptive statistics of all columns (input and output) of Training and Test datasets. Review the descriptive statistics of input output columns in Train, Test and original Full (before the splitting operation) datasets and compare them to each other. Are they similar or not? Do you think Train and Test dataset are representative of the Full datasets ? why ?

Hint: Scikit learn, data train_test_split(), stratified function.

```
In [11]: df["diagnosis"].value_counts(df["diagnosis"].unique()[0])
```

```
Out[11]: 0    0.627417
         1    0.372583
         Name: diagnosis, dtype: float64
```

```
In [12]: # Splitting train and test data
         # .7 and .3
         import numpy as np # Linear algebra and numerical apps
```

```
msk = np.random.rand(len(df)) < 0.7
train_df = df[msk]
test_df = df[~msk]
```

```
In [15]: train_df.describe()
```

```
Out[15]:          diagnosis  radius_mean  texture_mean  perimeter_mean    area_mean  \
         count  422.000000   422.000000    422.000000      422.000000   422.000000
         mean     0.383886    14.184332     19.225924       92.302227   663.239100
         std      0.486908     3.650024      4.335877       25.114122   365.713579
         min      0.000000     6.981000      9.710000       43.790000   143.500000
         25%      0.000000    11.602500     16.162500       74.262500   412.550000
         50%      0.000000    13.415000     18.760000       86.210000   555.900000
         75%      1.000000    16.167500     21.575000      106.525000   812.200000
         max      1.000000    28.110000     39.280000      188.500000  2501.000000

                smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
         count       422.000000        422.000000      422.000000           422.000000
         mean          0.096341          0.103223        0.086774             0.048537
         std           0.013840          0.051327        0.076341             0.038415
         min           0.052630          0.019380        0.000000             0.000000
         25%           0.086688          0.062370        0.028973             0.020195
         50%           0.096530          0.091705        0.061745             0.033285
         75%           0.105375          0.130200        0.123275             0.073580
         max           0.163400          0.345400        0.426800             0.201200

                symmetry_mean           ...            radius_worst  texture_worst  \
         count     422.000000           ...              422.000000     422.000000
         mean        0.180788           ...               16.405773      25.683531
         std         0.027480           ...                5.027512       6.185842
         min         0.120300           ...                7.930000      12.020000
         25%         0.161900           ...               12.842500      20.992500
         50%         0.178750           ...               14.975000      25.465000
         75%         0.195225           ...               19.792500      30.100000
         max         0.304000           ...               36.040000      47.160000

                perimeter_worst   area_worst  smoothness_worst  compactness_worst  \
         count       422.000000   422.000000        422.000000         422.000000
         mean        108.022346   900.204976          0.132793           0.252230
         std          34.791385   594.827452          0.022765           0.155543
         min          50.410000   185.200000          0.071170           0.027290
         25%          83.535000   507.425000          0.117275           0.144425
         50%          98.115000   685.550000          0.132650           0.211750
         75%         129.075000  1216.000000          0.146075           0.341175
         max         251.200000  4254.000000          0.222600           0.937900

                concavity_worst  concave points_worst  symmetry_worst  \
         count       422.000000            422.000000      422.000000
         mean           0.268960               0.114119        0.290083
         std            0.205858               0.065442        0.062144
         min            0.000000               0.000000        0.164800
         25%            0.108950               0.064945        0.250250
         50%            0.229800               0.098330        0.280600
         75%            0.385300               0.162725        0.316875
         max            1.252000               0.286700        0.663800

                fractal_dimension_worst
         count               422.000000
         mean                  0.083759
         std                   0.017556
         min                   0.055210
         25%                   0.071572
         50%                   0.079460
         75%                   0.092082
         max                   0.173000

         [8 rows x 31 columns]
```

1.4 Step 3: Analysis of the Output Column

Analyze the output columns in Train and Test dataset. If the output column is numerical then calculate the IQR (inter quartile range, Q3-Q1) and Range (difference between max and min value). If your output column is categorical then determine if the column is nominal or ordinal, why?. Is there a class imbalance problem? (check if there is big difference between the number of distinct values in your categorical output column)

```
In [13]: print(train_df["diagnosis"].value_counts(train_df["diagnosis"].unique()[0]))
         print(len(train_df))
         train_df.describe()
```

```
0    0.616114
1    0.383886
Name: diagnosis, dtype: float64
422
```

```
Out[13]:         diagnosis  radius_mean  texture_mean  perimeter_mean    area_mean  \
         count  422.000000   422.000000    422.000000      422.000000   422.000000
         mean     0.383886    14.184332     19.225924       92.302227   663.239100
         std      0.486908     3.650024      4.335877       25.114122   365.713579
         min      0.000000     6.981000      9.710000       43.790000   143.500000
         25%      0.000000    11.602500     16.162500       74.262500   412.550000
         50%      0.000000    13.415000     18.760000       86.210000   555.900000
         75%      1.000000    16.167500     21.575000      106.525000   812.200000
         max      1.000000    28.110000     39.280000      188.500000  2501.000000

                smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
count       422.000000        422.000000      422.000000           422.000000
mean          0.096341          0.103223        0.086774             0.048537
std           0.013840          0.051327        0.076341             0.038415
min           0.052630          0.019380        0.000000             0.000000
25%           0.086688          0.062370        0.028973             0.020195
50%           0.096530          0.091705        0.061745             0.033285
75%           0.105375          0.130200        0.123275             0.073580
max           0.163400          0.345400        0.426800             0.201200

       symmetry_mean           ...              radius_worst  texture_worst  \
count     422.000000           ...                422.000000     422.000000
mean        0.180788           ...                 16.405773      25.683531
std         0.027480           ...                  5.027512       6.185842
min         0.120300           ...                  7.930000      12.020000
25%         0.161900           ...                 12.842500      20.992500
50%         0.178750           ...                 14.975000      25.465000
75%         0.195225           ...                 19.792500      30.100000
max         0.304000           ...                 36.040000      47.160000

       perimeter_worst   area_worst  smoothness_worst  compactness_worst  \
count       422.000000   422.000000        422.000000         422.000000
mean        108.022346   900.204976          0.132793           0.252230
std          34.791385   594.827452          0.022765           0.155543
min          50.410000   185.200000          0.071170           0.027290
25%          83.535000   507.425000          0.117275           0.144425
50%          98.115000   685.550000          0.132650           0.211750
75%         129.075000  1216.000000          0.146075           0.341175
max         251.200000  4254.000000          0.222600           0.937900

       concavity_worst  concave points_worst  symmetry_worst  \
count       422.000000            422.000000      422.000000
mean          0.268960              0.114119        0.290083
std           0.205858              0.065442        0.062144
min           0.000000              0.000000        0.164800
25%           0.108950              0.064945        0.250250
50%           0.229800              0.098330        0.280600
75%           0.385300              0.162725        0.316875
max           1.252000              0.286700        0.663800

       fractal_dimension_worst
count               422.000000
mean                  0.083759
std                   0.017556
min                   0.055210
25%                   0.071572
50%                   0.079460
75%                   0.092082
max                   0.173000
```

```
         [8 rows x 31 columns]
```

```
In [14]: print(test_df["diagnosis"].value_counts(test_df["diagnosis"].unique()[0]))
         print(len(test_df))
         test_df.describe()
```

```
0    0.659864
1    0.340136
Name: diagnosis, dtype: float64
147
```

```
Out[14]:        diagnosis  radius_mean  texture_mean  perimeter_mean    area_mean  \
         count  147.000000   147.000000    147.000000      147.000000   147.000000
         mean     0.340136    13.963544     19.472585       91.012517   630.918367
         std      0.475374     3.140310      4.208618       21.842541   308.798010
         min      0.000000     8.950000     10.380000       56.360000   245.200000
         25%      0.000000    11.940000     16.570000       77.080000   439.300000
         50%      0.000000    13.170000     19.220000       86.870000   537.300000
         75%      1.000000    14.995000     22.215000       98.570000   696.250000
         max      1.000000    24.630000     33.560000      165.500000  1841.000000

                smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
         count       147.000000        147.000000      147.000000           147.000000
         mean          0.096415          0.107551        0.094612             0.050017
         std           0.014738          0.056924        0.088731             0.040008
         min           0.064290          0.026750        0.000000             0.000000
         25%           0.085130          0.067720        0.032380             0.022085
         50%           0.094620          0.095090        0.060150             0.035280
         75%           0.105100          0.130900        0.133350             0.074435
         max           0.139800          0.311400        0.426400             0.182300

                symmetry_mean            ...             radius_worst  texture_worst  \
         count     147.000000            ...               147.000000     147.000000
         mean        0.182235            ...                15.877095      25.659116
         std         0.027291            ...                 4.217536       6.052036
         min         0.106000            ...                 9.414000      14.100000
         25%         0.162050            ...                13.220000      21.380000
         50%         0.181300            ...                14.960000      25.210000
         75%         0.196850            ...                17.375000      29.125000
         max         0.255600            ...                31.010000      49.540000

                perimeter_worst   area_worst  smoothness_worst  compactness_worst  \
         count       147.000000   147.000000        147.000000         147.000000
         mean        105.076190   824.253741          0.131149           0.260109
         std          29.931954   486.390633          0.023061           0.162776
         min          60.900000   270.000000          0.085670           0.050360
```

```
25%          86.160000   532.000000           0.114150            0.152400
50%          97.170000   686.500000           0.130100            0.216400
75%         115.800000   926.950000           0.144050            0.327600
max         206.800000  2944.000000           0.190900            1.058000

       concavity_worst  concave points_worst  symmetry_worst  \
count       147.000000            147.000000      147.000000
mean          0.281458              0.116004        0.290055
std           0.216822              0.066766        0.061277
min           0.000000              0.000000        0.156500
25%           0.131700              0.064410        0.251350
50%           0.224100              0.101500        0.292900
75%           0.379200              0.153000        0.320400
max           1.105000              0.291000        0.488200

       fractal_dimension_worst
count               147.000000
mean                  0.084481
std                   0.019493
min                   0.055040
25%                   0.071370
50%                   0.081130
75%                   0.091870
max                   0.207500

[8 rows x 31 columns]
```

Our output/classification label is diagnosis(M(1)/B(0)), which is nominal categorical data.

The ratios between Benign and Malignant outputs in train and test are pretty similar to what we had in the full data.

1.5 Step 4: Scale Training and Test Dataset

Using one of the scaling method (max, min-max, standard or robust), create a scaler object and scale the numerical input columns of the Training dataset. Using the same scaler object, scale the numerical input columns of the Test set. Generate the descriptive statistics of the scaled input columns of Training and Test set.

If some of the input columns are categorical then convert them to binary columns using onehotencoder() function (scikit learn) or dummy() function (Pandas data frame).

Hint: http://scikit-learn.org/stable/modules/preprocessing.html#preprocessing

```
In [13]: # I am going to apply min-max scaling for my data.
         from sklearn import preprocessing
         # Fitting the minmax scaled version for training data
         minmax_scale = preprocessing.MinMaxScaler().fit(train_df.iloc[:, 1:])
         # Now actually scale train and test data
         train_df.iloc[:, 1:] = minmax_scale.transform(train_df.iloc[:, 1:])
         test_df.iloc[:, 1:] = minmax_scale.transform(test_df.iloc[:, 1:])
```

```
/Users/eneskemalergin/anaconda3/lib/python3.5/site-packages/pandas/core/indexing.py:477: Setting
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self.obj[item] = s
```

```
In [11]: train_df.head()
```

```
Out[11]:    diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
         1          1     0.643144      0.272574        0.615783   0.501591
         2          1     0.601496      0.390260        0.595743   0.449417
         3          1     0.210090      0.360839        0.233501   0.102906
         5          1     0.258839      0.202570        0.267984   0.141506
         8          1     0.284869      0.409537        0.302052   0.159618

            smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
         1         0.277910          0.181768        0.203799             0.366806
         2         0.588699          0.431017        0.462946             0.668583
         3         1.000000          0.811361        0.566135             0.549922
         5         0.816227          0.461996        0.370075             0.422844
         8         0.809976          0.533157        0.435976             0.488918

            symmetry_mean           ...             radius_worst  texture_worst  \
         1       0.407367           ...                 0.606901       0.324132
         2       0.546587           ...                 0.556386       0.384462
         3       0.832611           ...                 0.248310       0.412066
         5       0.556338           ...                 0.268232       0.333808
         8       0.698808           ...                 0.268943       0.532442

            perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
         1         0.539818    0.435214          0.301026           0.148757
         2         0.508442    0.374508          0.446763           0.381154
         3         0.241347    0.094008          0.909445           0.812734
         5         0.263908    0.136748          0.692253           0.479232
         8         0.277852    0.136183          0.629996           0.494080

            concavity_worst  concave points_worst  symmetry_worst  \
         1         0.192971              0.639175        0.233590
         2         0.359744              0.835052        0.403706
         3         0.548642              0.884880        1.000000
         5         0.427716              0.598282        0.477035
         8         0.430511              0.707904        0.554504

            fractal_dimension_worst
         1                 0.222878
         2                 0.213433
```

```
3                 0.773711
5                 0.454939
8                 0.342123

[5 rows x 31 columns]
```

```
In [12]: test_df.head()
```

```
Out[12]:    diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
         0           1     0.521037      0.022658        0.545989   0.363733
         4           1     0.629893      0.156578        0.630986   0.489290
         6           1     0.533343      0.347311        0.523875   0.380276
         7           1     0.318472      0.376057        0.320710   0.184263
         17          1     0.433007      0.370984        0.444406   0.277964

             smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
         0          0.698712          0.792037        0.703799             0.768949
         4          0.472434          0.347893        0.464353             0.545217
         6          0.401550          0.274891        0.264306             0.386827
         7          0.704963          0.445126        0.219653             0.312859
         17         0.681210          0.560763        0.403846             0.537376

             symmetry_mean           ...             radius_worst  texture_worst  \
         0        0.736186           ...                 0.620776       0.151110
         4        0.405742           ...                 0.519744       0.132328
         6        0.397616           ...                 0.531839       0.445077
         7        0.615385           ...                 0.324795       0.458736
         17       0.598050           ...                 0.463536       0.553785

             perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
         0          0.668310    0.450698          0.572692           0.616677
         4          0.506948    0.341575          0.397241           0.166732
         6          0.511928    0.349194          0.445348           0.218115
         7          0.299766    0.174941          0.595331           0.326157
         17         0.430251    0.277674          0.690838           0.379982

             concavity_worst  concave points_worst  symmetry_worst  \
         0          0.568610              0.912027        0.598462
         4          0.319489              0.558419        0.157500
         6          0.302236              0.663918        0.295289
         7          0.213898              0.534708        0.321506
         17         0.382109              0.712371        0.422038

             fractal_dimension_worst
         0                  0.418864
         4                  0.142595
         6                  0.187853
         7                  0.393939
```

```
17                   0.388036

[5 rows x 31 columns]
```

1.6 Step 5: Build Predictive Model

Using one of the methods (K-Nearest Neighbor, Naïve Bayes, Neural Network, Support Vector Machines, Decision Tree), build your predictive model using the scaled input columns of Training set. You can use any value for the model parameters, or use the default values. In building your model, use k-fold crossvalidation.

> Hint: - http://scikit-learn.org/stable/supervised_learning.html#supervised-learning , - http://scikit-learn.org/stable/modules/cross_validation.html

```
In [15]: # Input and Output
         inp_train = train_df.iloc[:, 1:]
         out_train = train_df["diagnosis"]
         inp_test = test_df.iloc[:, 1:]
         out_test = test_df["diagnosis"]
```

```
In [16]: # Naive Bayes:
         from sklearn.naive_bayes import GaussianNB
         from sklearn.model_selection import cross_val_score
         nb_model = GaussianNB()
         nb_model.fit(inp_train, out_train)

         # Cross validation score of my model
         nb_model_scores = cross_val_score(nb_model, inp_train, out_train, cv=10, scoring='accur
         print(nb_model_scores)
```

```
[ 0.95        0.875       0.9         0.9         0.925       0.925       0.95
  0.925       0.94871795  0.94736842]
```

1.7 Step 6. Model Predictions on Training Dataset

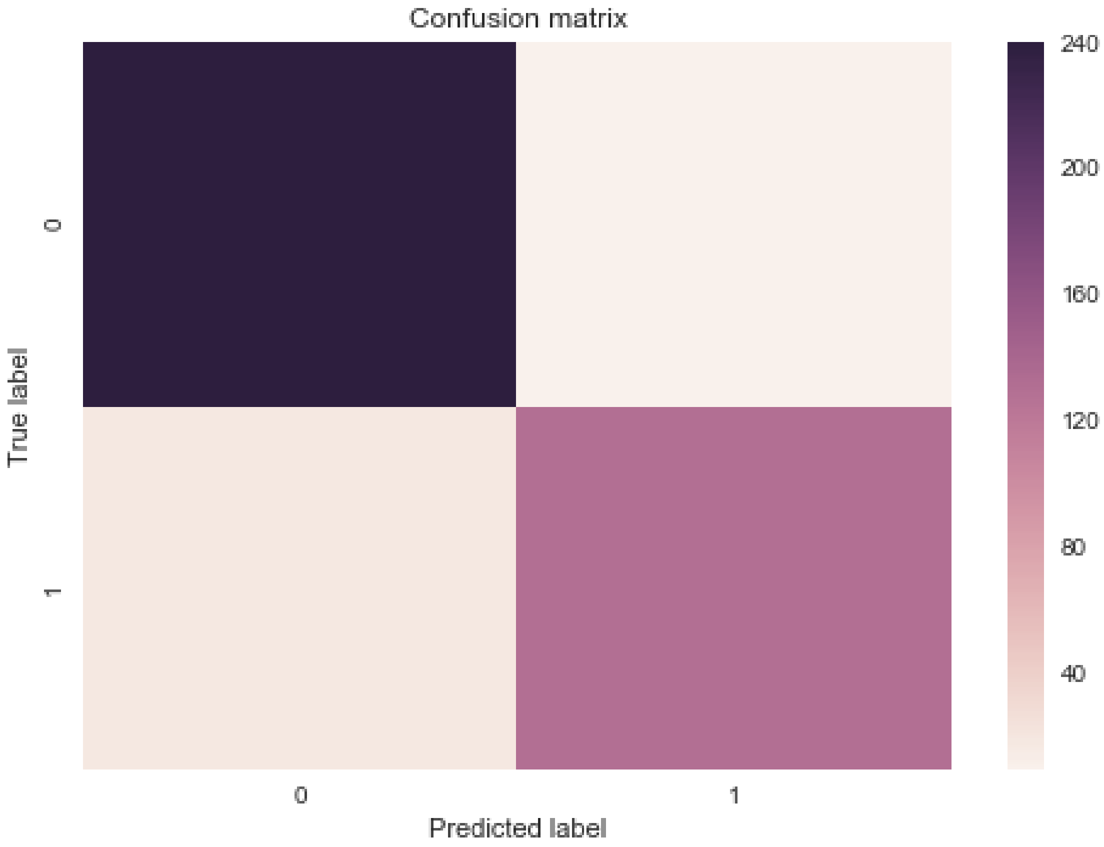
Apply your model to input (scaled) columns of Training dataset to obtain the predicted output for Training dataset. If your model is regression then plot actual output versus predicted output column of Training dataset. If your model is classification then generate confusion matrix on actual and predicted columns of Training dataset.

> Hint: Matplotlip, Seaborn, Bokeh scatter(), plot() functions - http://scikit-learn.org/0.15/auto_examples/plot_confusion_matrix.html - http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html

```
In [17]: # importing libraries for plotting
         # Importing library for confusion matrix
         from sklearn.metrics import confusion_matrix
         import matplotlib.pyplot as plt
         import seaborn as sns
         sns.set(style='darkgrid')
```

```
In [18]: # train prediction for train data
         out_train_pred = nb_model.predict(inp_train)
         # Compute confusion matrix for prediction of train
         cm = confusion_matrix(out_train, out_train_pred)
         print(cm)
         # Show confusion matrix in a separate window
         sns.heatmap(cm)
         plt.title('Confusion matrix')
         plt.ylabel('True label')
         plt.xlabel('Predicted label')
         plt.show()
```

```
[[240   9]
 [ 18 130]]
```



1.8 Step 7. Model Predictions on Test Dataset

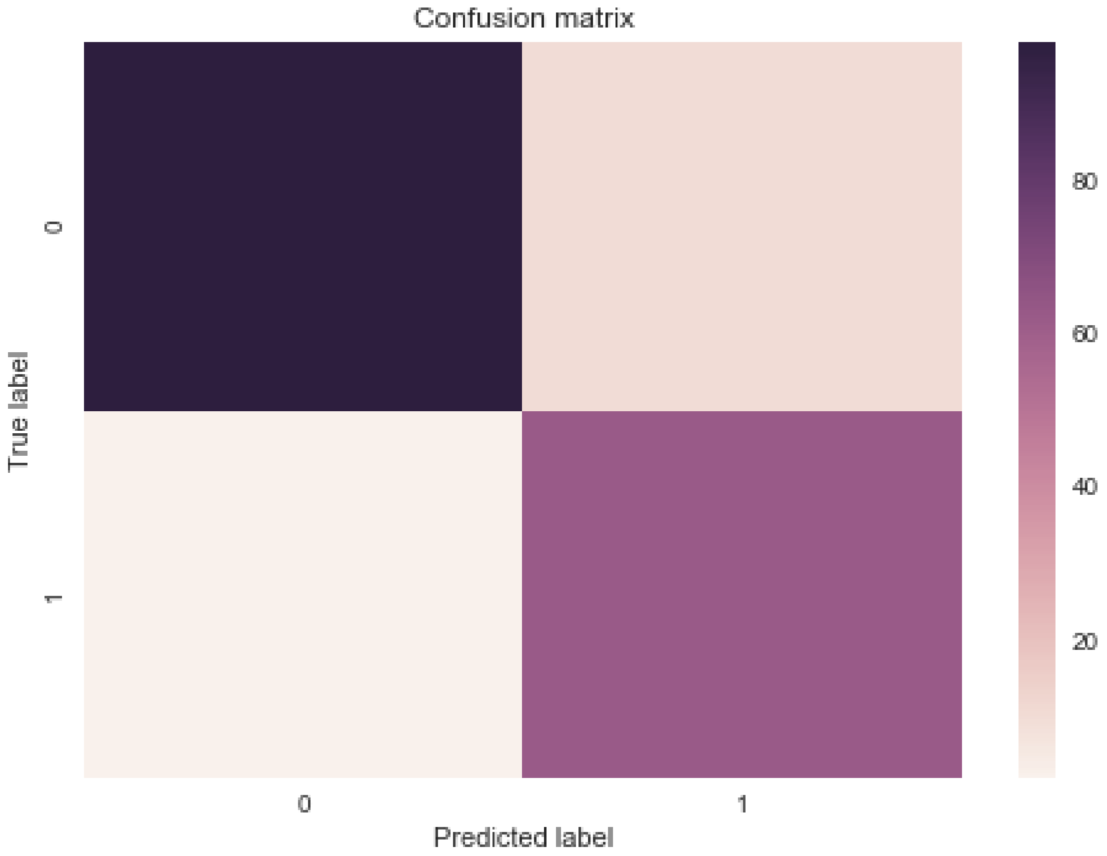
Apply your model to input (scaled) columns of Test dataset to obtain the predicted output for Test dataset. If your model is regression then plot actual output versus predicted output column of

Test dataset. If your model is classification then generate confusion matrix on actual and predicted columns of Test dataset.

> Hint: Matplotlip, Seaborn, Bokeh scatter(), plot() functions - http://scikit-learn.org/0.15/auto_examples/plot_confusion_matrix.html - http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html

```
In [19]: # train prediction for train data
         out_test_pred = nb_model.predict(inp_test)
         # Compute confusion matrix for prediction of train
         cm = confusion_matrix(out_test, out_test_pred)
         print(cm)
         # Show confusion matrix in a separate window
         sns.heatmap(cm)
         plt.title('Confusion matrix')
         plt.ylabel('True label')
         plt.xlabel('Predicted label')
         plt.show()
```

```
[[98 10]
 [ 2 62]]
```



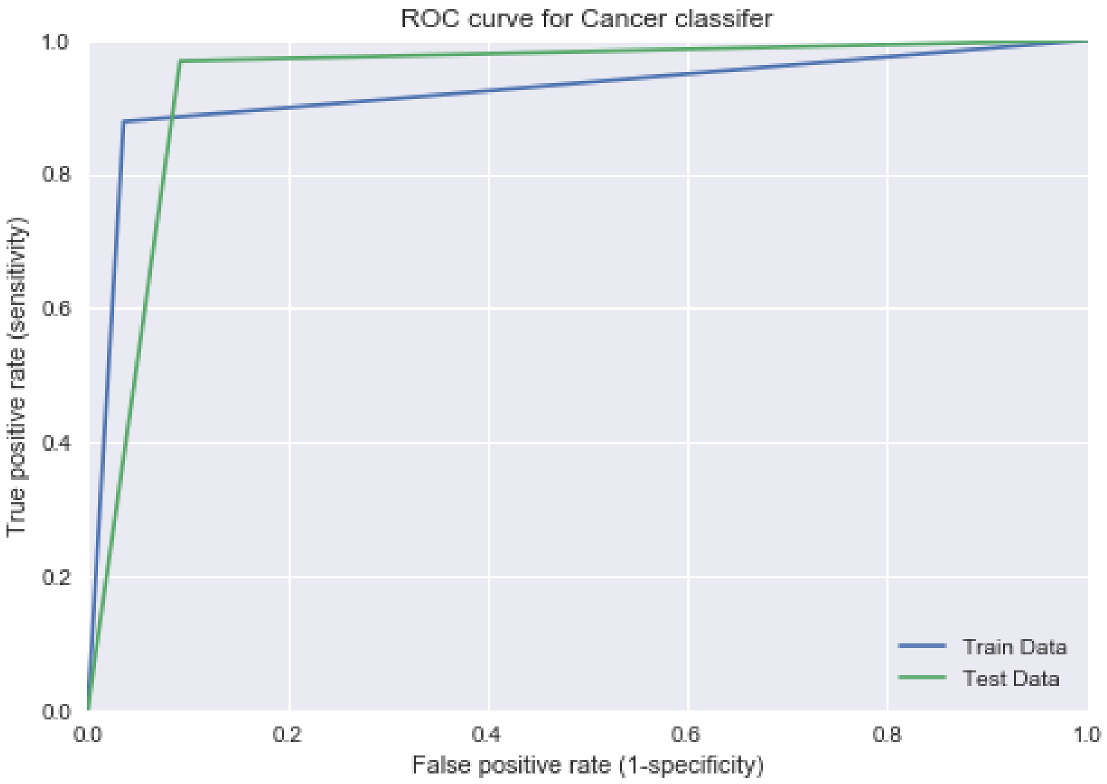
1.9 Step 8. Model Performance

Using one of the error (evaluation) metrics (classification or regression), calculate the performance of the model on Training set and Test set. Compare the performance of the model on Training and Test set. Which one (Training or Testing performance) is better, is there an overfitting case, why ?. Would you deploy (Productionize) this model for using in actual usage in your business system? why ?

Classification Metrics: Accuracy, Precision, Recall, F-score, Recall, AUC, ROC etc Regression Metrics: RMSE, MSE, MAE, R2 etc

- http://scikit-learn.org/stable/model_selection.html#model-selection
- http://scikit-learn.org/stable/modules/model_evaluation.html#classification-report

```
In [20]: # I would like to use ROC
         # Area under ROC Curve (or AUC for short) is
         #  a performance metric for binary classification problems.
         from sklearn.metrics import roc_curve
         # ROC curve for train data
         fpr,tpr,thresholds = roc_curve(out_train, out_train_pred)
         # plot the curve
         plt.plot(fpr, tpr, label="Train Data")
         # ROC curve for test data
         fpr, tpr, thresholds = roc_curve(out_test, out_test_pred)
         # Plotting the curves
         plt.plot(fpr, tpr, label="Test Data")
         plt.xlim([0.0,1.0])
         plt.ylim([0.0,1.0])
         plt.title('ROC curve for Cancer classifer')
         plt.xlabel('False positive rate (1-specificity)')
         plt.ylabel('True positive rate (sensitivity)')
         plt.legend(loc=4,)
         plt.show()
```



As it seems clear in the plot we created, the Test data is better than the Train data. Which is not expected. **I do not see the traces of overfitting since the test data is also performing well.**

But there is also another chance that Test data is also overfitting… ??

Naive bayes on this particular data set works really good. It might be good for fast prototyping and usage.

1.10 Step 9. Update the Model

Go back to Step5, and choose different values of the model parameters and re-train the model. Repeat Steps: 6 and 7. Using the same error metric, generate the accuracy of the model on Training and Test dataset. Did you get a better performance on Training or Test set? Explain why the new model performs better or worse than the former model.

Let's try to calibrate the GaussianNB(); I will be using isotonic, sigmoid calibration for Gaussian Naive Bayes:

```
In [19]: # For Training Data:
         # Let's remember we have GaussianNB model with
         #  no calibration called out_train_pred
         from sklearn.calibration import CalibratedClassifierCV
         # Gaussian Naive-Bayes with isotonic calibration
         nb_model_isotonic = CalibratedClassifierCV(nb_model, cv=2, method='isotonic')
         nb_model_isotonic.fit(inp_train, out_train)
         out_train_isotonic = nb_model_isotonic.predict_proba(inp_train)[:, 1]
         out_test_isotonic = nb_model_isotonic.predict_proba(inp_test)[:, 1]
```

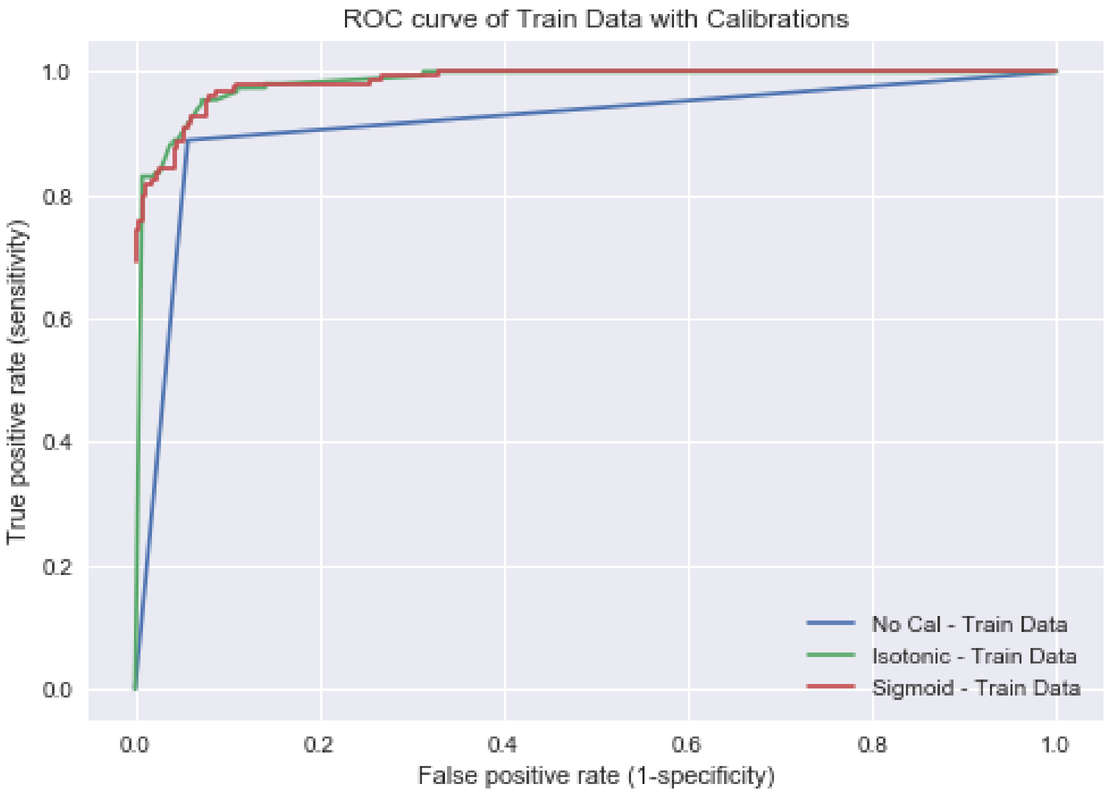
```
In [20]: # Gaussian Naive-Bayes with sigmoid calibration
         nb_model_sigmoid = CalibratedClassifierCV(nb_model, cv=2, method='sigmoid')
         nb_model_sigmoid.fit(inp_train, out_train)
         out_train_sigmoid = nb_model_sigmoid.predict_proba(inp_train)[:, 1]
         out_test_sigmoid = nb_model_sigmoid.predict_proba(inp_test)[:, 1]
```

```
In [21]: ## Plotting the comparison of train Data roc_curves
         # ROC curve for train data no calibration
         fpr,tpr,thresholds = roc_curve(out_train, out_train_pred)
         # plot the curve
         plt.plot(fpr, tpr, label="No Cal - Train Data")

         # ROC curve for train data isotonic calibration
         fpr,tpr,thresholds = roc_curve(out_train, out_train_isotonic)
         # plot the curve
         plt.plot(fpr, tpr, label="Isotonic - Train Data")

         # ROC curve for train data sigmoid calibration
         fpr,tpr,thresholds = roc_curve(out_train, out_train_sigmoid)
         # plot the curve
         plt.plot(fpr, tpr, label="Sigmoid - Train Data")

         plt.xlim([-0.05,1.05])
         plt.ylim([-0.05,1.05])
         plt.title('ROC curve of Train Data with Calibrations')
         plt.xlabel('False positive rate (1-specificity)')
         plt.ylabel('True positive rate (sensitivity)')
         plt.legend(loc=4,)
         plt.show()
```

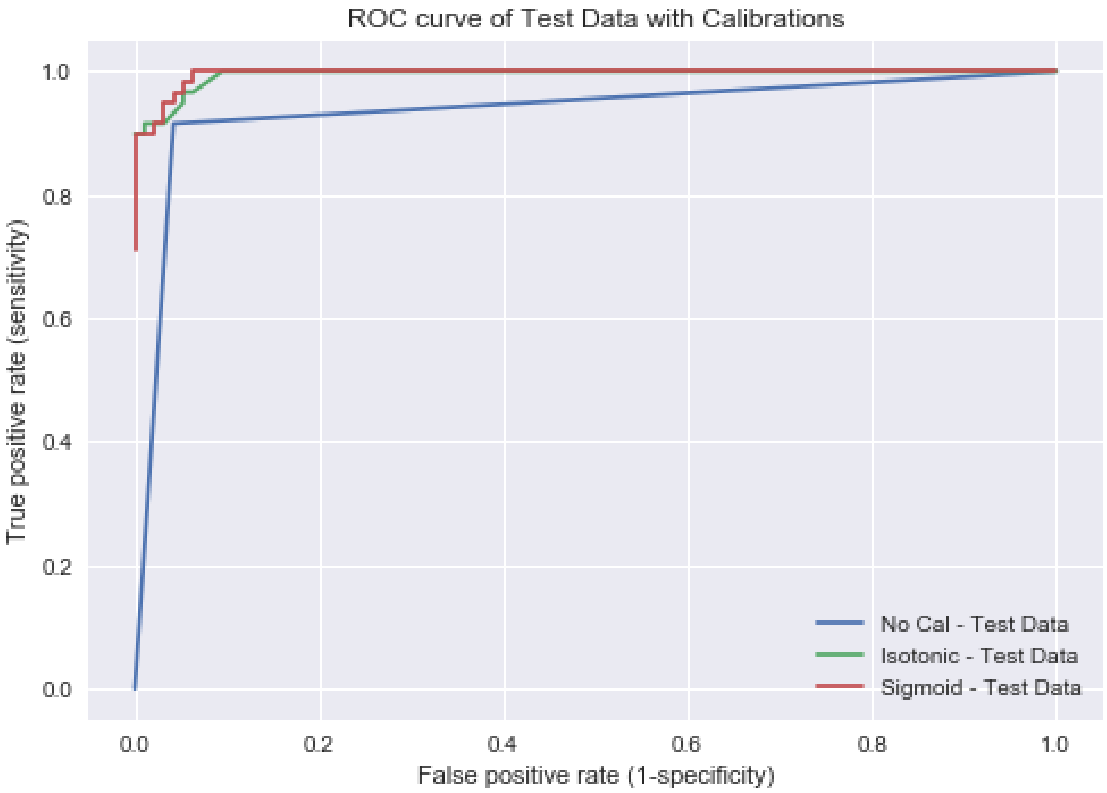


```
In [22]: # ROC curve for test data no calibration
         fpr, tpr, thresholds = roc_curve(out_test, out_test_pred)
         # Plotting the curves
         plt.plot(fpr, tpr, label="No Cal - Test Data")

         # ROC curve for test data isotonic calibration
         fpr,tpr,thresholds = roc_curve(out_test, out_test_isotonic)
         # plot the curve
         plt.plot(fpr, tpr, label="Isotonic - Test Data")

         # ROC curve for test data sigmoid calibration
         fpr,tpr,thresholds = roc_curve(out_test, out_test_sigmoid)
         # plot the curve
         plt.plot(fpr, tpr, label="Sigmoid - Test Data")

         plt.xlim([-0.05,1.05])
         plt.ylim([-0.05,1.05])
         plt.title('ROC curve of Test Data with Calibrations')
         plt.xlabel('False positive rate (1-specificity)')
         plt.ylabel('True positive rate (sensitivity)')
         plt.legend(loc=4,)
         plt.show()
```



Extra calibration which add one more layer above the GaussianNB() works better than no calibration. Isotonic and Sigmoid calibrations are performed better than the initial no calibration version.

1.11 Step 10. Change the Error Metric

Choose another error metric other than you used in Step 8 and evaluate the performance of the model on Training and Test dataset by generating the accuracy of the model based on the new metric. Compare the results and explain which error metric is better for your modeling and why?

```
In [23]: # Checking the error metric to Brier scores
         from sklearn.metrics import brier_score_loss

         # Checking for only test data predictions

         print("Brier scores: (the smaller the better)")
         mdl_score = brier_score_loss(out_test, out_test_pred)
         print("No calibration: %1.3f" % mdl_score)
         mdl_isotonic_score = brier_score_loss(out_test, out_test_isotonic)
         print("With isotonic calibration: %1.3f" % mdl_isotonic_score)
         mdl_sigmoid_score = brier_score_loss(out_test, out_test_sigmoid)
         print("With sigmoid calibration: %1.3f" % mdl_sigmoid_score)
```

```
Brier scores: (the smaller the better)
No calibration: 0.058
With isotonic calibration: 0.026
With sigmoid calibration: 0.037
```

```
In [24]: # Applying other metrics
         from sklearn import metrics
         print("Printing the different metric results for Not calibrated test data")
         print("-"*60)
         print("Precision score: %1.3f" %
               metrics.precision_score(out_test, out_test_pred))
         print("Recall score on: %1.3f" %
               metrics.recall_score(out_test, out_test_pred))
         print("F1 score on: %1.3f" %
               metrics.f1_score(out_test, out_test_pred) )
         print("Fbeta score with b=0.5 on: %1.3f" %
               metrics.fbeta_score(out_test, out_test_pred, beta=0.5))
         print("Fbeta score with b=1.0 on: %1.3f" %
               metrics.fbeta_score(out_test, out_test_pred, beta=1))
         print("Fbeta score with b=2.0 on: %1.3f" %
               metrics.fbeta_score(out_test, out_test_pred, beta=2))
```

```
Printing the different metric results for Not calibrated test data
------------------------------------------------------------
Precision score: 0.931
Recall score on: 0.915
F1 score on: 0.923
Fbeta score with b=0.5 on: 0.928
Fbeta score with b=1.0 on: 0.923
Fbeta score with b=2.0 on: 0.918
```

When it comes to selecting a way to show how well my models are working I always use both error and accuracy together. In this specific task I had an opportunity to try different metrics available in scikit-learn. In terms of showing a better results, for this model, I would go with Recall score. However I usually go with precision_score.

As the ending remarks for the project I would like to emphasize that Naive Bayes is working suprisingly good for this particular dataset (Breast Cancer from UCI ML website). I am suspecting that my model overfitted because for both test and train data is produced ~92-98% precision, which is quite impossible with ~30 or so features and 500 data points.

I could use more data and selected features to get more real results. For the Final project I am planning to use some techniques that will allow me to select features and only work with them.

-Enes K. Ergin-