Support Vector Machines - Breast Cancer Project

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- Predicting if the cancer diagnosis is benign or malignant based on several observations/features
- 30 features are used, examples:
 - 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)
- Datasets are linearly separable using all 30 input features
- Number of Instances: 569
- Class Distribution: 212 Malignant, 357 Benign

array(['malignant', 'benign'], dtype='<U9')</pre>

Target class:

Out[5]:

- Malignant
- Benign

Import Needed Libraries

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

Load Data - Will be using a built in scikit-learn dataset called breast_cancer

```
# if you need to get a full description of this dataset
        # print(cancer['DESCR'])
        # create a dataframe out of this dataset
In [7]:
        df = pd.DataFrame( np.c [cancer['data'], cancer['target']], columns= np.append(cancer['
        df.head()
In [8]:
Out[8]:
                                                                                            mean
                                                                         mean
           mean
                  mean
                            mean mean
                                             mean
                                                         mean
                                                                 mean
                                                                                   mean
                                                                                            fractal ...
                                                                        concave
           radius texture perimeter
                                   area smoothness compactness concavity
                                                                               symmetry
                                                                                         dimension
                                                                         points
           17.99
                   10.38
                           122.80 1001.0
        0
                                           0.11840
                                                       0.27760
                                                                 0.3001
                                                                        0.14710
                                                                                  0.2419
                                                                                           0.07871
            20.57
                   17.77
                           132.90 1326.0
                                           0.08474
                                                       0.07864
                                                                        0.07017
                                                                 0.0869
                                                                                  0.1812
                                                                                           0.05667
        2
           19.69
                   21.25
                           130.00 1203.0
                                           0.10960
                                                       0.15990
                                                                 0.1974
                                                                       0.12790
                                                                                  0.2069
                                                                                           0.05999
                   20.38
                            77.58
                                  386.1
                                           0.14250
                                                       0.28390
                                                                 0.2414
                                                                        0.10520
                                                                                  0.2597
                                                                                           0.09744
        3
           11.42
           20.29
                   14.34
                           135.10 1297.0
                                           0.10030
                                                       0.13280
                                                                 0.1980 0.10430
                                                                                  0.1809
                                                                                           0.05883
       5 rows × 31 columns
In [9]: df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 569 entries, 0 to 568
        Data columns (total 31 columns):
            Column
                                       Non-Null Count Dtype
        ____
                                        _____
            mean radius
         \cap
                                       569 non-null float64
         1
           mean texture
                                      569 non-null float64
                                      569 non-null float64
         2
           mean perimeter
                                                      float64
         3
            mean area
                                       569 non-null
                                      569 non-null float64
         4
            mean smoothness
                                      569 non-null float64
         5
           mean compactness
                                      569 non-null float64
         6
            mean concavity
```

```
569 non-null float64
569 non-null float64
  mean concave points
7
  mean symmetry
8
9
   mean fractal dimension 569 non-null float64
                           569 non-null float64
10 radius error
                          569 non-null float64
11 texture error
12 perimeter error
                          569 non-null float64
13 area error
                          569 non-null float64
                          569 non-null
14 smoothness error
                                         float64
15 compactness error
                          569 non-null float64
                          569 non-null float64
16 concavity error
                         569 non-null float64
17 concave points error
                                        float64
18 symmetry error
                           569 non-null
19 fractal dimension error 569 non-null float64
20 worst radius
                          569 non-null float64
                          569 non-null
21 worst texture
                                         float64
                          569 non-null float64
22 worst perimeter
23 worst area
                          569 non-null float64
                         569 non-null float64
569 non-null float64
24 worst smoothness
25 worst compactness26 worst concavity
                                         float64
                          569 non-null
worst concave points 569 non-null float64 worst symmetry 569 non-null float64
29 worst fractal dimension 569 non-null
                                          float64
```

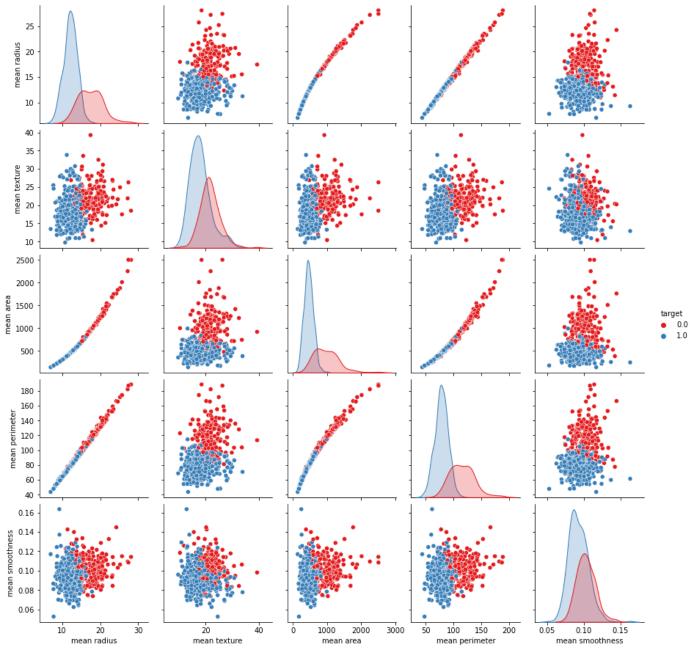
569 non-null

float64

30 target

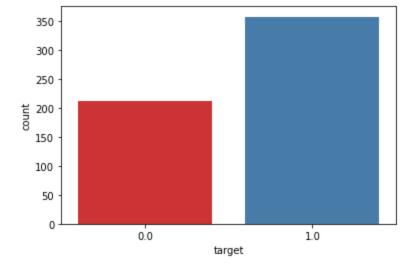
dtypes: float64(31)
memory usage: 137.9 KB

EDA



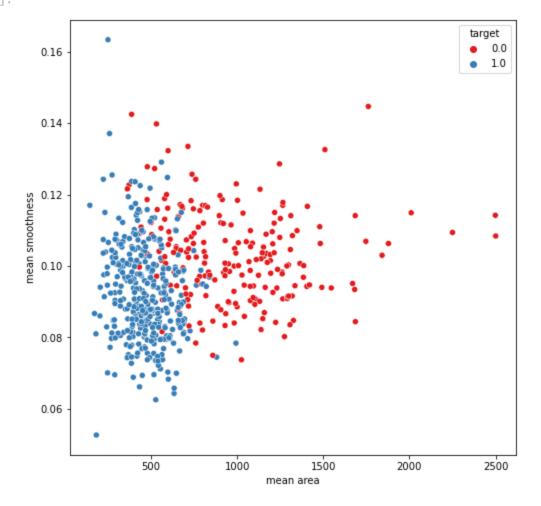
```
In [11]: # let's count numver of benign and malignent cases
    sns.countplot( x = df['target'], palette= 'Set1')
# Class Distribution: 212 - Malignant, 357 - Benign
```

Out[11]: <AxesSubplot:xlabel='target', ylabel='count'>



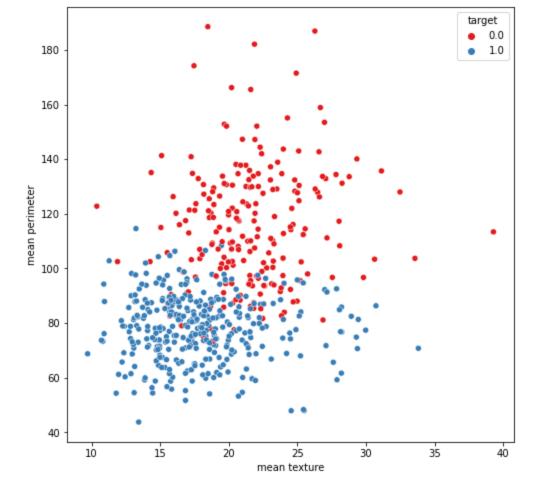
```
In [12]: plt.figure(figsize=(8,8))
    sns.scatterplot( data= df, x = df['mean area'], y = df['mean smoothness'], hue = df['tar
```

Out[12]: <AxesSubplot:xlabel='mean area', ylabel='mean smoothness'>



```
In [13]: plt.figure(figsize=(8,8))
    sns.scatterplot( data= df, x = df['mean texture'], y = df['mean perimeter'], hue = df['t
```

Out[13]: <AxesSubplot:xlabel='mean texture', ylabel='mean perimeter'>

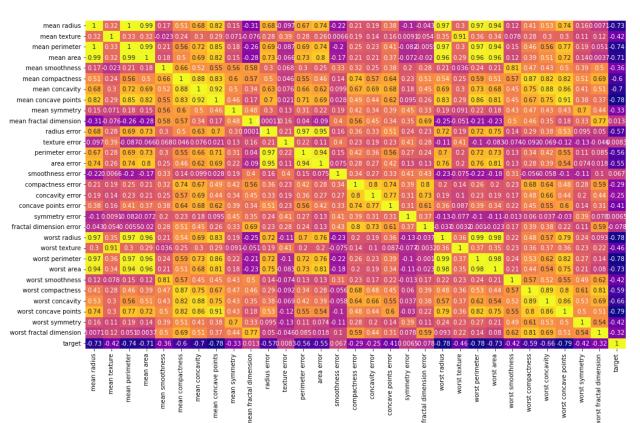


- 0.8

- 0.2

-0.2

Out[15]: <AxesSubplot:>



Train The SVM Model

```
In [16]: # recall that the df has all features -- no target
      X = df.drop(['target'], axis=1)
      y = df['target']
In [17]: from sklearn.model_selection import train test split
In [31]: X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=1
In [32]: # grab the Support Vector classifier
      from sklearn.svm import SVC
      classifier = SVC()
In [33]: # now fit/train the model to the training set (X train, y train)
      classifier.fit(X train, y train)
Out[33]:
      ▼ SVC
      SVC()
In [34]: # test/get pridections of the SVC model
      predictions = classifier.predict(X test)
In [35]: # let's import the classification report and confusion matrix
      from sklearn.metrics import classification report, confusion matrix
print(classification report(y test, predictions))
      print(confusion matrix(y test, predictions))
      precision recall f1-score support
                1.00 0.86 0.92
                                             42
             0.0
             1.0
                    0.92
                            1.00
                                   0.96
                                             72
                                    0.95
         accuracy
                                         114
                                   0.94
        macro avg
                   0.96 0.93
                                            114
                                            114
      weighted avg
                    0.95
                           0.95
                                   0.95
      [[36 6]
       [ 0 72]]
```

The confusion matrix shows:

False Positives(Type I Error)= 6 False Negatives(Type II Error)= 0

```
In [38]: cm = confusion_matrix(y_test, predictions)
    sns.heatmap(cm, annot = True, fmt = "d", cmap ='Blues')
```

Out[38]: <AxesSubplot:>

