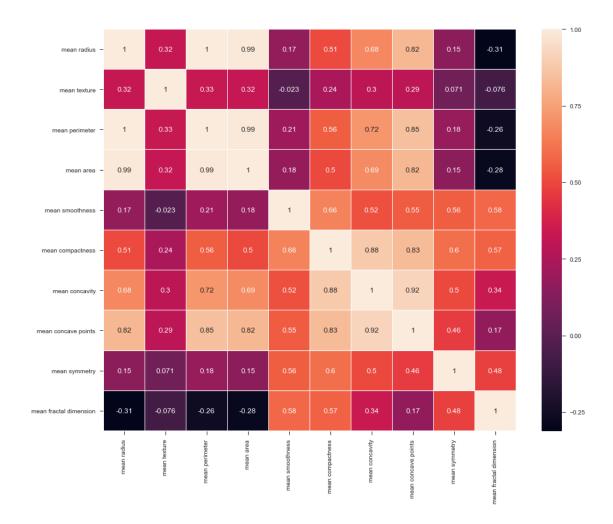
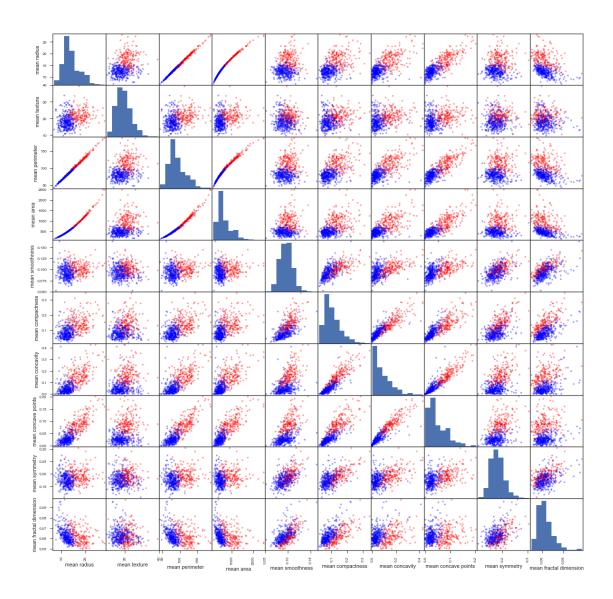
# Breast\_Cancer

#### December 5, 2018

```
In [1]: import matplotlib.pyplot as plt
        import numpy as np
        import pandas as pd
        import seaborn as sns
        from sklearn.datasets import load_breast_cancer
        from sklearn.metrics import classification_report, confusion_matrix
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import StandardScaler
        from sklearn import metrics
        %matplotlib inline
In [2]: breast_cancer = load_breast_cancer()
       X = breast_cancer.data
        y = breast_cancer.target
        labels = ["WDBC-Malignant", "WDBC-Benign"]
       df = pd.DataFrame(data=breast_cancer.data, columns=breast_cancer.feature_names)
In [3]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=
In [4]: # Normalize data
        scaler = StandardScaler()
        scaler.fit(X_train)
       X_train = scaler.transform(X_train)
        X_test = scaler.transform(X_test)
0.1 Visualization
In [5]: sns.set(style='ticks', color_codes=True)
        plt.figure(figsize=(15, 12))
        sns.heatmap(df.loc[:,:'mean fractal dimension'].corr(), linewidths=0.1, annot=True,)
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x10ef8e748>
```





## 0.2 Using Decision Tree Classifier

In [9]: print(classification\_report(y\_test, y\_pred=y\_pred, target\_names=labels))

	precision	recall	f1-score	support
WDBC-Malignant	0.89	0.92	0.90	61
WDBC-Benign	0.95	0.94	0.94	110
avg / total	0.93	0.93	0.93	171

### 0.3 Using Logistic Regression

In [12]: print(classification\_report(y\_test, y\_pred, target\_names=labels))

	precision	recall	f1-score	support
WDBC-Malignant WDBC-Benign	0.98 0.98	0.97 0.99	0.98 0.99	61 110
avg / total	0.98	0.98	0.98	171

### 0.4 Using Support Vector Machine

```
y_pred = clf.predict(X_test)
         clf.best_estimator_
Out[13]: SVC(C=10.0, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma=0.01, kernel='rbf',
           max_iter=-1, probability=False, random_state=0, shrinking=True,
           tol=0.001, verbose=False)
In [14]: print(confusion_matrix(y_test, y_pred))
[[ 59
        2]
 [ 1 109]]
In [15]: print(classification_report(y_test, y_pred, target_names=labels))
                precision
                             recall f1-score
                                                support
WDBC-Malignant
                     0.98
                               0.97
                                         0.98
                                                     61
  WDBC-Benign
                     0.98
                               0.99
                                         0.99
                                                    110
  avg / total
                     0.98
                               0.98
                                         0.98
                                                    171
0.5 Using Multi-Layer Perceptron Classifier (Neural Network)
In [16]: from sklearn.neural_network import MLPClassifier
         mlp = MLPClassifier(hidden_layer_sizes=(20, 10, 30), random_state=0)
         mlp.fit(X_train, y_train)
Out[16]: MLPClassifier(activation='relu', alpha=0.0001, batch size='auto', beta 1=0.9,
                beta_2=0.999, early_stopping=False, epsilon=1e-08,
                hidden layer sizes=(20, 10, 30), learning rate='constant',
                learning_rate_init=0.001, max_iter=200, momentum=0.9,
                nesterovs_momentum=True, power_t=0.5, random_state=0, shuffle=True,
                solver='adam', tol=0.0001, validation_fraction=0.1, verbose=False,
                warm_start=False)
In [17]: y_pred = mlp.predict(X_test)
In [18]: print(confusion_matrix(y_test, y_pred))
[[ 59
        21
```

clf.fit(X\_train, y\_train)

[ 0 110]]

In [19]: print(classification\_report(y\_test, y\_pred))

	precision	recall	f1-score	support
0	1.00	0.97	0.98	61
1	0.98	1.00	0.99	110
avg / total	0.99	0.99	0.99	171