Final Project_Week2_Morgenstern

July 3, 2019

1 Final project

Using the Breast Cancer Wisconsin (Diagnostic) Data Set, I am aiming to predict whether the cancer is benign or malignant.

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image. n the 3-dimensional space is that described in: [K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming Discrimination of Two Linearly Inseparable Sets", Optimization Methods and Software 1, 1992, 23-34].

The data set was downloaded from Kaggle: https://www.kaggle.com/uciml/breast-cancer-wisconsin-data#data.csv

Attribute Information:

1) ID number 2) Diagnosis (M = malignant, B = benign) 3-32)

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

a) radius (mean of distances from center to points on the perimeter) b) texture (standard deviation of gray-scale values) c) perimeter d) area e) smoothness (local variation in radius lengths) f) compactness (perimeter^2 / area - 1.0) g) concavity (severity of concave portions of the contour) h) concave points (number of concave portions of the contour) i) symmetry j) 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.

Class distribution: 357 benign, 212 malignant

1.1 Step 1 - Loading and cleaning of data

```
In [18]: # import dataset downloaded from Kaggle and display first rows
         import pandas as pd
         df = pd.read_csv('data.csv')
         df.head()
```

```
Out[18]:         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

   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

   ...  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

   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

   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 rows x 33 columns]
```

In [19]:
```
# display type of data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):
id                         569 non-null int64
diagnosis                  569 non-null object
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
Unnamed: 32                0 non-null float64
dtypes: float64(31), int64(1), object(1)
memory usage: 146.8+ KB
```

In [20]:
```
# check for missing values in data
print df.isnull().sum()
```

```
id                         0
diagnosis                  0
radius_mean                0
texture_mean               0
perimeter_mean             0
area_mean                  0
smoothness_mean            0
compactness_mean           0
concavity_mean             0
concave points_mean        0
symmetry_mean              0
fractal_dimension_mean     0
radius_se                  0
texture_se                 0
perimeter_se               0
area_se                    0
```

```
smoothness_se              0
compactness_se             0
concavity_se               0
concave points_se          0
symmetry_se                0
fractal_dimension_se       0
radius_worst               0
texture_worst              0
perimeter_worst            0
area_worst                 0
smoothness_worst           0
compactness_worst          0
concavity_worst            0
concave points_worst       0
symmetry_worst             0
fractal_dimension_worst    0
Unnamed: 32              569
dtype: int64
```

In [21]:
```
# drop column 32 because of missing values
df1 = df.drop('Unnamed: 32', axis=1)
df1.head()
```

Out[21]:
```
         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

   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

   ...  radius_worst  texture_worst  perimeter_worst  area_worst  \
0  ...         25.38          17.33           184.60      2019.0
1  ...         24.99          23.41           158.80      1956.0
2  ...         23.57          25.53           152.50      1709.0
3  ...         14.91          26.50            98.87       567.7
4  ...         22.54          16.67           152.20      1575.0

   smoothness_worst  compactness_worst  concavity_worst  concave points_worst  \
0            0.1622             0.6656           0.7119                0.2654
1            0.1238             0.1866           0.2416                0.1860
```

```
2            0.1444             0.4245           0.4504                  0.2430
3            0.2098             0.8663           0.6869                  0.2575
4            0.1374             0.2050           0.4000                  0.1625

   symmetry_worst  fractal_dimension_worst
0          0.4601                  0.11890
1          0.2750                  0.08902
2          0.3613                  0.08758
3          0.6638                  0.17300
4          0.2364                  0.07678

[5 rows x 32 columns]
```

In [22]:
```
# display column names
df1.columns
```

Out[22]:
```
Index([u'id', u'diagnosis', u'radius_mean', u'texture_mean', u'perimeter_mean',
       u'area_mean', u'smoothness_mean', u'compactness_mean',
       u'concavity_mean', u'concave points_mean', u'symmetry_mean',
       u'fractal_dimension_mean', u'radius_se', u'texture_se', u'perimeter_se',
       u'area_se', u'smoothness_se', u'compactness_se', u'concavity_se',
       u'concave points_se', u'symmetry_se', u'fractal_dimension_se',
       u'radius_worst', u'texture_worst', u'perimeter_worst', u'area_worst',
       u'smoothness_worst', u'compactness_worst', u'concavity_worst',
       u'concave points_worst', u'symmetry_worst', u'fractal_dimension_worst'],
      dtype='object')
```

In [23]:
```
# drop id column because it is of no use for analysis
df2 = df1.drop('id', axis=1)
df2.columns
```

Out[23]:
```
Index([u'diagnosis', u'radius_mean', u'texture_mean', u'perimeter_mean',
       u'area_mean', u'smoothness_mean', u'compactness_mean',
       u'concavity_mean', u'concave points_mean', u'symmetry_mean',
       u'fractal_dimension_mean', u'radius_se', u'texture_se', u'perimeter_se',
       u'area_se', u'smoothness_se', u'compactness_se', u'concavity_se',
       u'concave points_se', u'symmetry_se', u'fractal_dimension_se',
       u'radius_worst', u'texture_worst', u'perimeter_worst', u'area_worst',
       u'smoothness_worst', u'compactness_worst', u'concavity_worst',
       u'concave points_worst', u'symmetry_worst', u'fractal_dimension_worst'],
      dtype='object')
```

In [32]:
```
# get descriptive statistics of dataset
df2.describe()
```

Out[32]:
```
       radius_mean  texture_mean  perimeter_mean   area_mean  \
count   569.000000    569.000000      569.000000  569.000000
mean     14.127292     19.289649       91.969033  654.889104
std       3.524049      4.301036       24.298981  351.914129
```

```
min       6.981000     9.710000      43.790000   143.500000
25%      11.700000    16.170000      75.170000   420.300000
50%      13.370000    18.840000      86.240000   551.100000
75%      15.780000    21.800000     104.100000   782.700000
max      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  fractal_dimension_mean  ...  radius_worst  \
count     569.000000              569.000000  ...    569.000000
mean        0.181162                0.062798  ...     16.269190
std         0.027414                0.007060  ...      4.833242
min         0.106000                0.049960  ...      7.930000
25%         0.161900                0.057700  ...     13.010000
50%         0.179200                0.061540  ...     14.970000
75%         0.195700                0.066120  ...     18.790000
max         0.304000                0.097440  ...     36.040000

       texture_worst  perimeter_worst   area_worst  smoothness_worst  \
count     569.000000       569.000000   569.000000        569.000000
mean       25.677223       107.261213   880.583128          0.132369
std         6.146258        33.602542   569.356993          0.022832
min        12.020000        50.410000   185.200000          0.071170
25%        21.080000        84.110000   515.300000          0.116600
50%        25.410000        97.660000   686.500000          0.131300
75%        29.720000       125.400000  1084.000000          0.146000
max        49.540000       251.200000  4254.000000          0.222600

       compactness_worst  concavity_worst  concave points_worst  \
count         569.000000       569.000000            569.000000
mean            0.254265         0.272188              0.114606
std             0.157336         0.208624              0.065732
min             0.027290         0.000000              0.000000
25%             0.147200         0.114500              0.064930
50%             0.211900         0.226700              0.099930
75%             0.339100         0.382900              0.161400
max             1.058000         1.252000              0.291000

       symmetry_worst  fractal_dimension_worst
count      569.000000               569.000000
```

```
mean         0.290076                 0.083946
std          0.061867                 0.018061
min          0.156500                 0.055040
25%          0.250400                 0.071460
50%          0.282200                 0.080040
75%          0.317900                 0.092080
max          0.663800                 0.207500

[8 rows x 30 columns]
```

In [24]:
```python
# transform class labels from original string representation ('M' for malignant and '
from sklearn.preprocessing import LabelEncoder

class_le = LabelEncoder()
y = class_le.fit_transform(df2['diagnosis'].values)
y
```

Out[24]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1,
       0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1,
       1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1,
       1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1,
       1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0])
```

In [95]:
```python
X.shape
```

Out[95]:
```
(569, 30)
```

In [96]:
```python
y.shape
```

Out[96]: (569,)

In [31]:
```
# perform one-hot encoding
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

ohe = OneHotEncoder(categorical_features=[0])
ohe.fit_transform(X).toarray()
```

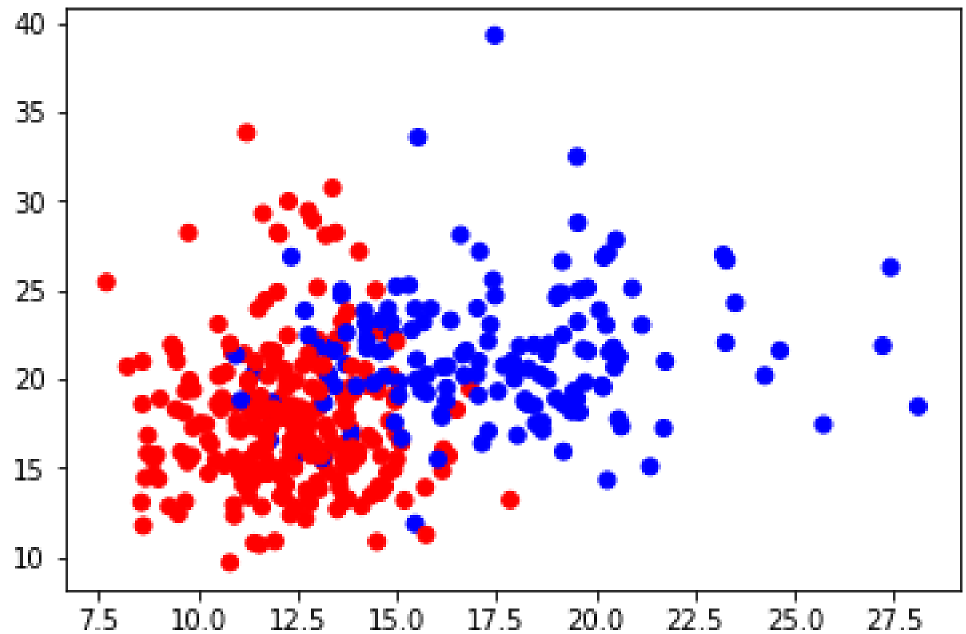
```
/Applications/anaconda2/lib/python2.7/site-packages/sklearn/preprocessing/_encoders.py:392: Dep
  "use the ColumnTransformer instead.", DeprecationWarning)
```

Out[31]:
```
array([[0.     , 0.     , 0.     , ..., 0.2654 , 0.4601 , 0.1189 ],
       [0.     , 0.     , 0.     , ..., 0.186  , 0.275  , 0.08902],
       [0.     , 0.     , 0.     , ..., 0.243  , 0.3613 , 0.08758],
       ...,
       [0.     , 0.     , 0.     , ..., 0.1418 , 0.2218 , 0.0782 ],
       [0.     , 0.     , 0.     , ..., 0.265  , 0.4087 , 0.124  ],
       [0.     , 1.     , 0.     , ..., 0.     , 0.2871 , 0.07039]])
```

In [34]:
```
# split data into training (80% of data) and test set (20% of data)
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, stratify=y,
```

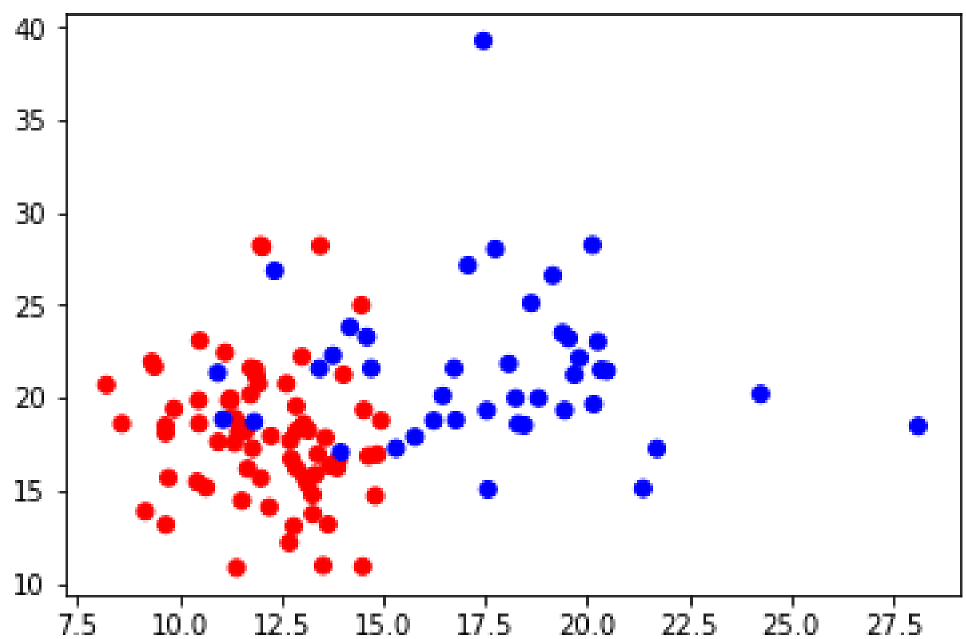
In [84]:
```
# plot the training set
%matplotlib inline
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap

cm_bright = ListedColormap(['#FF0000', '#0000FF'])

plt.scatter(X_train[:,0],X_train[:,1],c=y_train,cmap=cm_bright)
```

Out[84]:
```
<matplotlib.collections.PathCollection at 0x1a304fd510>
```




```
In [24]: # plot the testing set
         plt.scatter(X_test[:,0],X_test[:,1],c=y_test,cmap=cm_bright)
```

```
Out[24]: <matplotlib.collections.PathCollection at 0x1a2ea4c310>
```



In [37]:
```
# standardize data (data centered around 0 with standard deviation of 1)
from sklearn import preprocessing
stdscaler = preprocessing.StandardScaler().fit(X_train)
#print "Means of columns: ", stdscaler.mean_, "\nStandard deviation of columns:", std

X_scaled  = stdscaler.transform(X)
X_train_scaled = stdscaler.transform(X_train)
X_test_scaled = stdscaler.transform(X_test)

print "Training set samples: ", len(X_train)
print "Testing set samples: ", len(X_test)
```

```
Training set samples:  455
Testing set samples:  114
```

In [90]:
```
# normalize numerical columns
from sklearn.preprocessing import MinMaxScaler
mms = MinMaxScaler()
X_train_norm = mms.fit_transform(X_train_scaled)
X_test_norm = mms.transform(X_test_scaled)
```

In [97]:
```
X_train_norm
```

Out[97]:
```
array([[0.29008269, 0.2746888 , 0.27070086, ..., 0.28298969, 0.28760103,
        0.09477896],
       [0.34585841, 0.72365145, 0.3325414 , ..., 0.36013746, 0.13502858,
        0.18476978],
       [0.33705171, 0.4560166 , 0.32129131, ..., 0.23522337, 0.13483146,
        0.19598583],
       ...,
       [0.35662214, 0.53278008, 0.34924184, ..., 0.46804124, 0.22333925,
        0.1867375 ],
       [0.61397329, 0.94439834, 0.58842848, ..., 0.55841924, 0.22629608,
        0.13537977],
       [0.28910416, 0.24854772, 0.28153169, ..., 0.34948454, 0.08555096,
        0.10645415]])
```

1.2 Step 2 - Apply machine learning algorithms to dataset

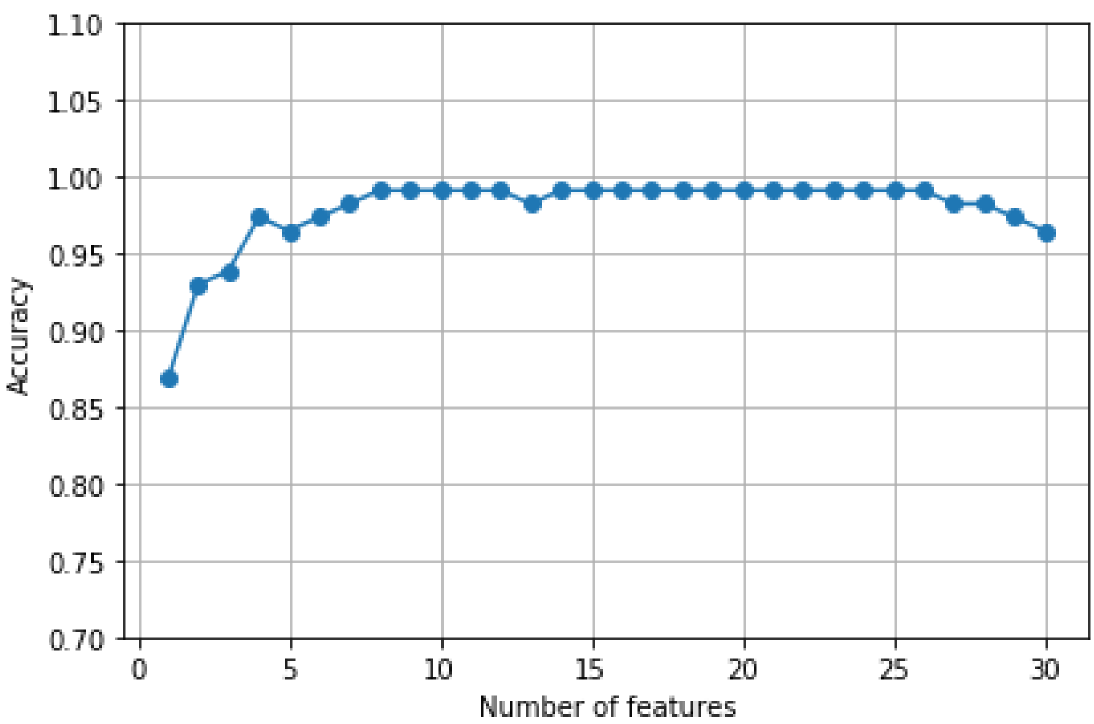
1.2.1 1. Sequential backward selection (SBS) and KNN classifier

In [51]:
```
# sequential feature selection
from sklearn.base import clone
from itertools import combinations
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

```python
class SBS():
    def __init__(self, estimator, k_features, scoring=accuracy_score,
                 test_size=0.25, random_state=1):
        self.scoring = scoring
        self.estimator = clone(estimator)
        self.k_features = k_features
        self.test_size = test_size
        self.random_state = random_state

    def fit(self, X, y):

        X_train, X_test, y_train, y_test = \
            train_test_split(X, y, test_size=self.test_size,
                             random_state=self.random_state)

        dim = X_train.shape[1]
        self.indices_ = tuple(range(dim))
        self.subsets_ = [self.indices_]
        score = self._calc_score(X_train, y_train,
                                 X_test, y_test, self.indices_)
        self.scores_ = [score]

        while dim > self.k_features:
            scores = []
            subsets = []

            for p in combinations(self.indices_, r=dim - 1):
                score = self._calc_score(X_train, y_train,
                                         X_test, y_test, p)
                scores.append(score)
                subsets.append(p)

            best = np.argmax(scores)
            self.indices_ = subsets[best]
            self.subsets_.append(self.indices_)
            dim -= 1

            self.scores_.append(scores[best])
        self.k_score_ = self.scores_[-1]

        return self

    def transform(self, X):
        return X[:, self.indices_]

    def _calc_score(self, X_train, y_train, X_test, y_test, indices):
        self.estimator.fit(X_train[:, indices], y_train)
        y_pred = self.estimator.predict(X_test[:, indices])
```

```
            score = self.scoring(y_test, y_pred)
            return score
```

In [45]:
```
%matplotlib inline
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=5)

# selecting features
sbs = SBS(knn, k_features=1)
sbs.fit(X_train_scaled, y_train)

# plotting performance of feature subsets
k_feat = [len(k) for k in sbs.subsets_]

plt.plot(k_feat, sbs.scores_, marker='o')
plt.ylim([0.7, 1.1])
plt.ylabel('Accuracy')
plt.xlabel('Number of features')
plt.grid()
plt.tight_layout()
# plt.savefig('./sbs.png', dpi=300)
plt.show()
```



```
In [61]: # 8 features are suffiecient to yield almost 100% accuracy
         k8 = list(sbs.subsets_[22])
         print(df2.columns[1:][k8])
```

```
Index([u'radius_mean', u'texture_mean', u'smoothness_mean', u'concavity_mean',
       u'symmetry_mean', u'radius_se', u'concavity_se', u'concavity_worst'],
      dtype='object')
```

```
In [63]: # evaluate performance of KNN classifier on original test set
         knn.fit(X_train_scaled, y_train)
         print('Training accuracy:', knn.score(X_train_scaled, y_train))
         print('Test accuracy:', knn.score(X_test_scaled, y_test))
```

```
('Training accuracy:', 0.978021978021978)
('Test accuracy:', 0.9649122807017544)
```

```
In [64]: # evaluate performance of KNN classifier on 8-feature subset
         knn.fit(X_train_scaled[:, k8], y_train)
         print('Training accuracy:', knn.score(X_train_scaled[:, k8], y_train))
         print('Test accuracy:', knn.score(X_test_scaled[:, k8], y_test))
```

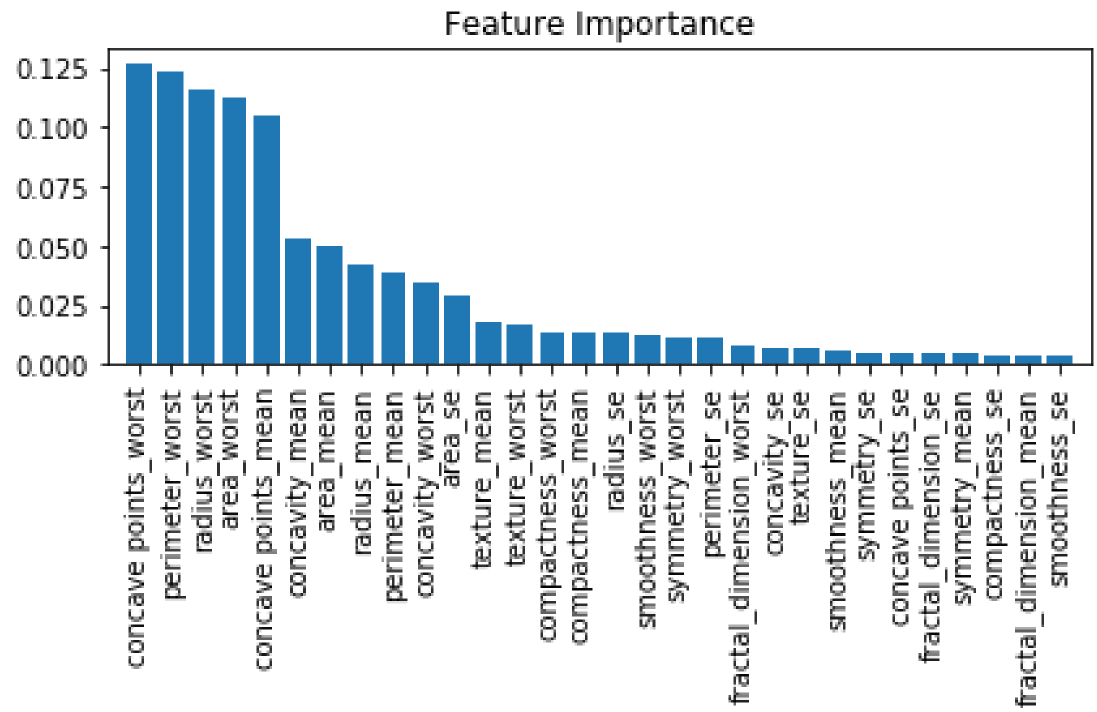
```
('Training accuracy:', 0.9692307692307692)
('Test accuracy:', 0.9649122807017544)
```

1.2.2 2. Assessing feature importance with random forests and applying random forest classifier

```
In [71]: from sklearn.ensemble import RandomForestClassifier

         feat_labels = df2.columns[1:]
         forest = RandomForestClassifier(n_estimators=500, random_state=1)

         # dont't need standardized or normalize features
         forest.fit(X_train, y_train)
         importances = forest.feature_importances_

         indices = np.argsort(importances) [::-1]

         for f in range(X_train.shape[1]):
             print("%2d) %-*s%f" % (f + 1, 30,
                                    feat_labels[indices[f]],
                                    importances[indices[f]]))

         plt.title('Feature Importance')
         plt.bar(range(X_train.shape[1]),
                 importances[indices],
```

```
            align='center')

    plt.xticks(range(X_train.shape[1]),
               feat_labels[indices], rotation=90)

    plt.xlim([-1, X_train.shape[1]])
    plt.tight_layout()
    plt.show()
```

```
 1) concave points_worst          0.126481
 2) perimeter_worst               0.123369
 3) radius_worst                  0.116148
 4) area_worst                    0.112531
 5) concave points_mean           0.105041
 6) concavity_mean                0.053160
 7) area_mean                     0.049476
 8) radius_mean                   0.042389
 9) perimeter_mean                0.039387
10) concavity_worst               0.034959
11) area_se                       0.028942
12) texture_mean                  0.017524
13) texture_worst                 0.016851
14) compactness_worst             0.013924
15) compactness_mean              0.013916
16) radius_se                     0.013411
17) smoothness_worst              0.012795
18) symmetry_worst                0.011638
19) perimeter_se                  0.011281
20) fractal_dimension_worst       0.007911
21) concavity_se                  0.006688
22) texture_se                    0.006551
23) smoothness_mean               0.006161
24) symmetry_se                   0.004866
25) concave points_se             0.004611
26) fractal_dimension_se          0.004452
27) symmetry_mean                 0.004310
28) compactness_se                0.003783
29) fractal_dimension_mean        0.003727
30) smoothness_se                 0.003715
```



In [75]:
```
# Random forest on original data set
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score,confusion_matrix
from sklearn.metrics import accuracy_score

# split data train 70 % and test 30 %
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=

#random forest classifier with n_estimators=10 (default)
clf_rf = RandomForestClassifier(random_state=43)
clr_rf = clf_rf.fit(X_train,y_train)

ac = accuracy_score(y_test,clf_rf.predict(X_test))
print('Accuracy is: ',ac)
cm = confusion_matrix(y_test,clf_rf.predict(X_test))
cm
```

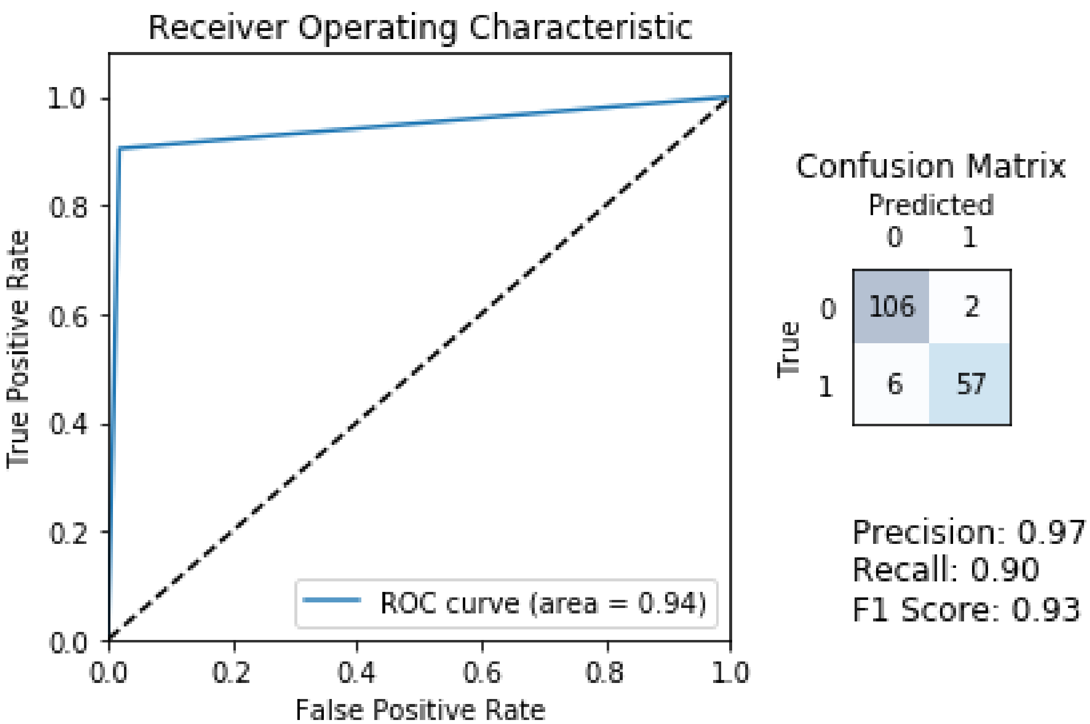
```
('Accuracy is: ', 0.9473684210526315)
```

```
/Applications/anaconda2/lib/python2.7/site-packages/sklearn/ensemble/forest.py:246: FutureWarn
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
Out[75]: array([[104,   4],
                [  5,  58]])
```

1.2.3 3. Linear Discriminant analysis

```
In [110]: # Linear discriminant analysis on original data
          from mlclass2 import simplemetrics, plot_decision_2d_lda
          from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

          lda = LinearDiscriminantAnalysis()
          lda.fit(X_train, y_train)
          predicted = lda.predict(X_test)
          simplemetrics(y_test,predicted)
          plot_decision_2d_lda(lda,X_train,y_train,padding=-0.2,discriminant=False,title="Full
          plot_decision_2d_lda(lda,X_train,y_train,padding=5,discriminant=True,title="Full Data
```




```
---------------------------------------------------------------------------

ValueError                                Traceback (most recent call last)

<ipython-input-110-e9d0d546105e> in <module>()
  8 predicted = lda.predict(X_test)
  9 simplemetrics(y_test,predicted)
```

```
---> 10 plot_decision_2d_lda(lda,X_train,y_train,padding=-0.2,discriminant=False,title="Ful
     11 plot_decision_2d_lda(lda,X_train,y_train,padding=5,discriminant=True,title="Full Da


    /Users/Christina/01_Files/19_Master studies/02_Course work/04_Machine Learning/Final Pr
     28                         np.arange(y_min, y_max, h))
     29
---> 30     Z = lda.predict_proba(np.c_[xx.ravel(), yy.ravel()])
     31     Z = Z[:, 1].reshape(xx.shape)
     32     plt.pcolormesh(xx, yy, Z, cmap='red_blue_classes',


    /Applications/anaconda2/lib/python2.7/site-packages/sklearn/discriminant_analysis.pyc i
    512                 Estimated probabilities.
    513             """
--> 514             prob = self.decision_function(X)
    515             prob *= -1
    516             np.exp(prob, prob)


    /Applications/anaconda2/lib/python2.7/site-packages/sklearn/linear_model/base.pyc in de
    260             if X.shape[1] != n_features:
    261                 raise ValueError("X has %d features per sample; expecting %d"
--> 262                                  % (X.shape[1], n_features))
    263
    264             scores = safe_sparse_dot(X, self.coef_.T,


    ValueError: X has 2 features per sample; expecting 30
```

1.2.4 4. Support vector machine

In [78]:
```
# Support vector machine
from sklearn.svm import SVC, LinearSVC
from sklearn.metrics import hinge_loss
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix

svc = SVC(kernel='linear', C=1, probability=True)
svc.fit(X_train, y_train)
predicted = svc.predict(X_test)
print classification_report(y_test,predicted)
print "Hinge loss", hinge_loss(y_test,predicted)
plot_decision_2d_lda(svc,X_train,y_train)
```

```
     precision    recall  f1-score   support

  0       0.96      0.98      0.97       108
```

```
          1       0.97      0.94      0.95        63

   micro avg       0.96      0.96      0.96       171
   macro avg       0.97      0.96      0.96       171
weighted avg       0.96      0.96      0.96       171

Hinge loss 0.6666666666666666
```

```
    ---------------------------------------------------------------------------

    ValueError                                Traceback (most recent call last)

    <ipython-input-78-c874d1892155> in <module>()
      9 print classification_report(y_test,predicted)
     10 print "Hinge loss", hinge_loss(y_test,predicted)
---> 11 plot_decision_2d_lda(svc,X_train,y_train)


    /Users/Christina/01_Files/19_Master studies/02_Course work/04_Machine Learning/Final Pi
     28                          np.arange(y_min, y_max, h))
     29
---> 30     Z = lda.predict_proba(np.c_[xx.ravel(), yy.ravel()])
     31     Z = Z[:, 1].reshape(xx.shape)
     32     plt.pcolormesh(xx, yy, Z, cmap='red_blue_classes',


    /Applications/anaconda2/lib/python2.7/site-packages/sklearn/svm/base.pyc in _predict_pi
    620
    621     def _predict_proba(self, X):
--> 622         X = self._validate_for_predict(X)
    623         if self.probA_.size == 0 or self.probB_.size == 0:
    624             raise NotFittedError("predict_proba is not available when fitted "


    /Applications/anaconda2/lib/python2.7/site-packages/sklearn/svm/base.pyc in _validate_i
    476             raise ValueError("X.shape[1] = %d should be equal to %d, "
    477                              "the number of features at training time" %
--> 478                              (n_features, self.shape_fit_[1]))
    479         return X
    480


    ValueError: X.shape[1] = 2 should be equal to 30, the number of features at training ti
```