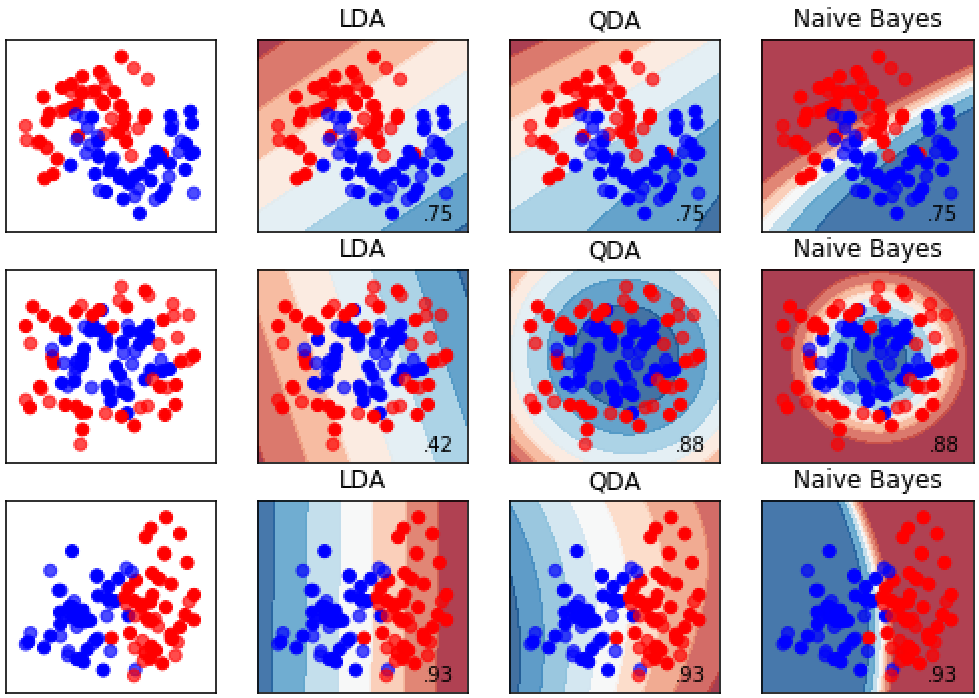
A comparative study of linear models for classification: Logistic L2, Logistic L1, naive Bayes, LDA and QDA

Devika Subramanian, ML Bootcamp, (c) 2019.

In [1]:
```
import pandas as pd
import random
import numpy as np
import matplotlib.pyplot as plt

# This is a bit of magic to make matplotlib figures appear inline in the noteb
ook
# rather than in a new window.
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# Some more magic so that the notebook will reload external python modules;
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipyt
hon
%load_ext autoreload
%autoreload 2
```

In [2]:
```
from matplotlib import colors
from matplotlib.colors import ListedColormap

def plot_datasets(X,y,X_train,y_train,X_test,y_test,i):

    h = 0.02
    x_min, x_max = X[:, 0].min() - .5, X[:, 0].max() + .5
    y_min, y_max = X[:, 1].min() - .5, X[:, 1].max() + .5
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                         np.arange(y_min, y_max, h))

    # just plot the dataset first
    cm = plt.cm.RdBu
    cm_bright = ListedColormap(['#FF0000', '#0000FF'])
    ax = plt.subplot(3, 4, i)
    # Plot the training points
    ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=cm_bright)
    # and testing points
    ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cm_bright, alpha=0.7
)
    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set_xticks(())
    ax.set_yticks(())
    return  xx, yy

def plot_decision_boundary_classifier(name,model,xx,yy,X_train,y_train,X_test,
y_test,score,i):
    # Plot the decision boundary. For that, we will assign a color to each
    # point in the mesh [x_min, m_max]x[y_min, y_max].
    ax = plt.subplot(3, 4, i)

    if hasattr(model, "decision_function"):
       Z = model.decision_function(np.c_[xx.ravel(), yy.ravel()])
    else:
       Z = model.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]

    cm = plt.cm.RdBu
    cm_bright = ListedColormap(['#FF0000', '#0000FF'])

    # Put the result into a color plot
    Z = Z.reshape(xx.shape)
    ax.contourf(xx, yy, Z, cmap=cm, alpha=.8)
    # Plot also the training points
    ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=cm_bright)
    # and testing points
    ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cm_bright,
               alpha=0.7)

    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set_xticks(())
    ax.set_yticks(())
    ax.set_title(name)
    ax.text(xx.max() - .3, yy.min() + .3, ('%.2f' % score).lstrip('0'),
            size=10, horizontalalignment='right')
```

In [3]:
```
# examine LDA and QDA and Naive Bayes on three synthetic data sets

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_moons, make_circles, make_classification
from sklearn.model_selection import train_test_split


X, y = make_classification(n_features=2, n_redundant=0, n_informative=2,
                           random_state=1, n_clusters_per_class=1)
rng = np.random.RandomState(2)
X += 2 * rng.uniform(size=X.shape)
linearly_separable = (X, y)

datasets = [make_moons(noise=0.3, random_state=0),
            make_circles(noise=0.2, factor=0.5, random_state=1),
            linearly_separable
            ]
names = ["LDA","QDA", "Naive Bayes"]
models = [LinearDiscriminantAnalysis(), QuadraticDiscriminantAnalysis(),Gaussi
anNB()]

figure = plt.figure(figsize=(7,6))

i = 1
for ds in datasets:
# preprocess dataset, split into training and test part
    X, y = ds
    X = StandardScaler().fit_transform(X)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.4)
    xx,yy = plot_datasets(X,y,X_train,y_train,X_test,y_test,i)
    i = i + 1
    for (name,model) in zip(names,models):
        model.fit(X_train, y_train)
        score = model.score(X_test, y_test)
        plot_decision_boundary_classifier(name,model,xx,yy,X_train,y_train,X_t
est,y_test,score,i)
        i = i + 1
figure.subplots_adjust(left=.02, right=.98)
```

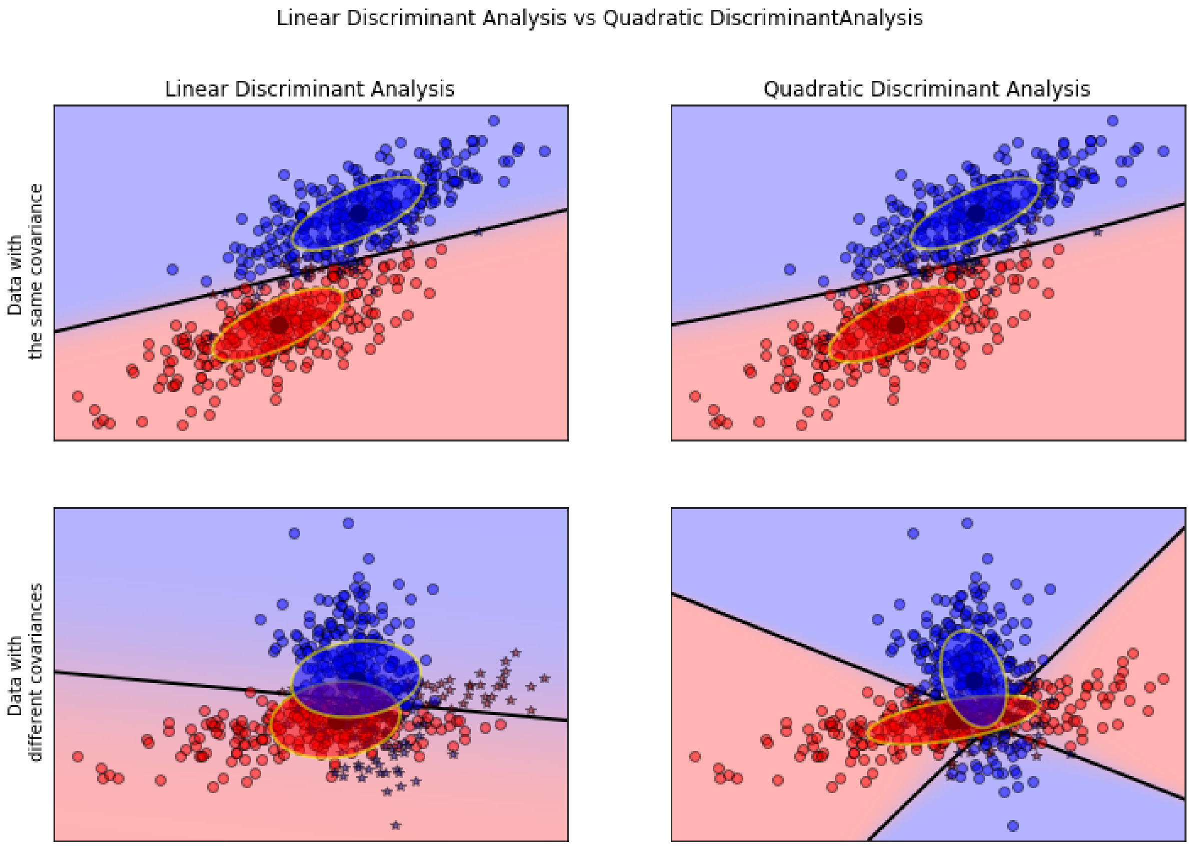

LDA
QDA
Naive Bayes
.75
.75
.75
LDA
QDA
Naive Bayes
.42
.88
.88
LDA
QDA
Naive Bayes
.93
.93
.93

In [4]:
```
from scipy import linalg
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl
from matplotlib import colors

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis

# ###########################################################################
#
# Colormap
cmap = colors.LinearSegmentedColormap(
    'red_blue_classes',
    {'red': [(0, 1, 1), (1, 0.7, 0.7)],
     'green': [(0, 0.7, 0.7), (1, 0.7, 0.7)],
     'blue': [(0, 0.7, 0.7), (1, 1, 1)]})
plt.cm.register_cmap(cmap=cmap)


# ###########################################################################
#
# Generate datasets
def dataset_fixed_cov():
    '''Generate 2 Gaussians samples with the same covariance matrix'''
    n, dim = 300, 2
    np.random.seed(0)
    C = np.array([[0., -0.23], [0.83, .23]])
    X = np.r_[np.dot(np.random.randn(n, dim), C),
              np.dot(np.random.randn(n, dim), C) + np.array([1, 1])]
    y = np.hstack((np.zeros(n), np.ones(n)))
    return X, y


def dataset_cov():
    '''Generate 2 Gaussians samples with different covariance matrices'''
    n, dim = 300, 2
    np.random.seed(0)
    C = np.array([[0., -1.], [2.5, .7]]) * 2.
    X = np.r_[np.dot(np.random.randn(n, dim), C),
              np.dot(np.random.randn(n, dim), C.T) + np.array([1, 4])]
    y = np.hstack((np.zeros(n), np.ones(n)))
    return X, y


# ###########################################################################
#
# Plot functions
def plot_data(lda, X, y, y_pred, fig_index):
    splot = plt.subplot(2, 2, fig_index)
    if fig_index == 1:
        plt.title('Linear Discriminant Analysis')
        plt.ylabel('Data with\n the same covariance')
    elif fig_index == 2:
        plt.title('Quadratic Discriminant Analysis')
    elif fig_index == 3:
```

```
        plt.ylabel('Data with\n different covariances')

    tp = (y == y_pred)  # True Positive
    tp0, tp1 = tp[y == 0], tp[y == 1]
    X0, X1 = X[y == 0], X[y == 1]
    X0_tp, X0_fp = X0[tp0], X0[~tp0]
    X1_tp, X1_fp = X1[tp1], X1[~tp1]

    alpha = 0.5

    # class 0: dots
    plt.plot(X0_tp[:, 0], X0_tp[:, 1], 'o', alpha=alpha,
             color='red', markeredgecolor='k')
    plt.plot(X0_fp[:, 0], X0_fp[:, 1], '*', alpha=alpha,
             color='#990000', markeredgecolor='k')  # dark red

    # class 1: dots
    plt.plot(X1_tp[:, 0], X1_tp[:, 1], 'o', alpha=alpha,
             color='blue', markeredgecolor='k')
    plt.plot(X1_fp[:, 0], X1_fp[:, 1], '*', alpha=alpha,
             color='#000099', markeredgecolor='k')  # dark blue

    # class 0 and 1 : areas
    nx, ny = 200, 100
    x_min, x_max = plt.xlim()
    y_min, y_max = plt.ylim()
    xx, yy = np.meshgrid(np.linspace(x_min, x_max, nx),
                         np.linspace(y_min, y_max, ny))
    Z = lda.predict_proba(np.c_[xx.ravel(), yy.ravel()])
    Z = Z[:, 1].reshape(xx.shape)
    plt.pcolormesh(xx, yy, Z, cmap='red_blue_classes',
                   norm=colors.Normalize(0., 1.))
    plt.contour(xx, yy, Z, [0.5], linewidths=2., colors='k')

    # means
    plt.plot(lda.means_[0][0], lda.means_[0][1],
             'o', color='black', markersize=10, markeredgecolor='k')
    plt.plot(lda.means_[1][0], lda.means_[1][1],
             'o', color='black', markersize=10, markeredgecolor='k')

    return splot


def plot_ellipse(splot, mean, cov, color):
    v, w = linalg.eigh(cov)
    u = w[0] / linalg.norm(w[0])
    angle = np.arctan(u[1] / u[0])
    angle = 180 * angle / np.pi  # convert to degrees
    # filled Gaussian at 2 standard deviation
    ell = mpl.patches.Ellipse(mean, 2 * v[0] ** 0.5, 2 * v[1] ** 0.5,
                              180 + angle, facecolor=color,
                              edgecolor='yellow',
                              linewidth=2, zorder=2)
    ell.set_clip_box(splot.bbox)
    ell.set_alpha(0.5)
    splot.add_artist(ell)
    splot.set_xticks(())
```

```
    splot.set_yticks(())


def plot_lda_cov(lda, splot):
    plot_ellipse(splot, lda.means_[0], lda.covariance_, 'red')
    plot_ellipse(splot, lda.means_[1], lda.covariance_, 'blue')


def plot_qda_cov(qda, splot):
    plot_ellipse(splot, qda.means_[0], qda.covariance_[0], 'red')
    plot_ellipse(splot, qda.means_[1], qda.covariance_[1], 'blue')

plt.figure(figsize=(12,8))
for i, (X, y) in enumerate([dataset_fixed_cov(), dataset_cov()]):
    # Linear Discriminant Analysis
    lda = LinearDiscriminantAnalysis(solver="svd", store_covariance=True)
    y_pred = lda.fit(X, y).predict(X)
    splot = plot_data(lda, X, y, y_pred, fig_index=2 * i + 1)
    plot_lda_cov(lda, splot)
    plt.axis('tight')

    # Quadratic Discriminant Analysis
    qda = QuadraticDiscriminantAnalysis(store_covariance=True)
    y_pred = qda.fit(X, y).predict(X)
    splot = plot_data(qda, X, y, y_pred, fig_index=2 * i + 2)
    plot_qda_cov(qda, splot)
    plt.axis('tight')

plt.suptitle('Linear Discriminant Analysis vs Quadratic Discriminant'
             'Analysis')
```

Out[4]:
```
Text(0.5, 0.98, 'Linear Discriminant Analysis vs Quadratic DiscriminantAnalys
is')
```



In [ ]: