In [2]:
```
import sklearn

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn
```

Homework 6: Support Vector Machines

Conceptual exercises

Non-linear separation

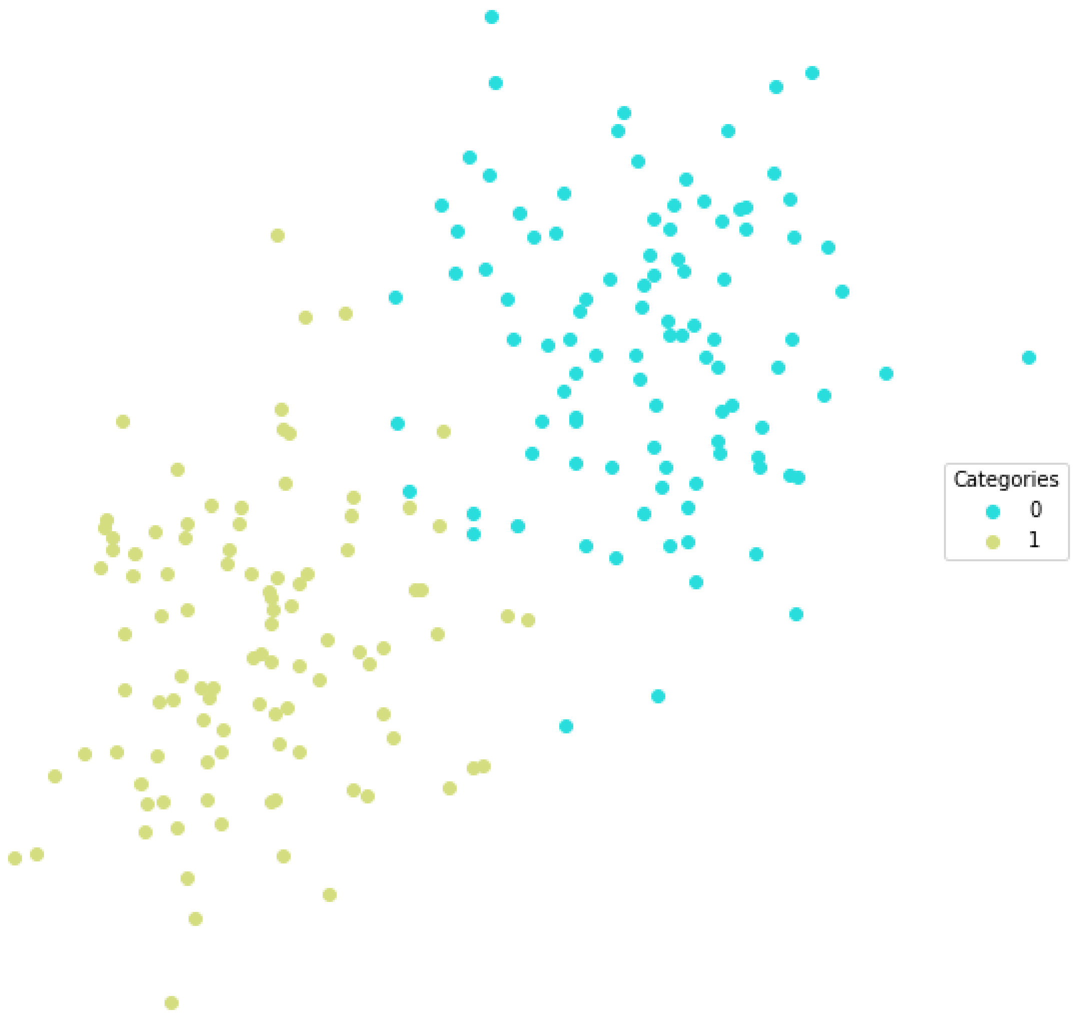
1. (15 points) Generate a simulated two-class data set with 100 observations and two features in which there is a visible (clear) but still non-linear separation between the two classes. Show that in this setting, a support vector machine with a radial kernel will outperform a support vector classifier (a linear kernel) on the training data. Which technique performs best on the test data? Make plots and report training and test error rates in order to support your conclusions.

In [532]:
```
from sklearn.datasets import make_blobs

def multiBlobs(noise = 0, numPerCategory = 100, centers = 2):
    if isinstance(centers, int):
        n_samples = numPerCategory * centers
    else:
        n_samples = numPerCategory * len(centers)
    X, y = sklearn.datasets.make_blobs(n_samples=n_samples, centers=cent
ers, cluster_std = (.6 * (noise * 6)))
    datDict = {
        'vect' : list(X),
        'category' : y,
    }
    return pd.DataFrame(datDict)
```

In [624]:
```
from sklearn.model_selection import train_test_split

noise = 0.8
data = multiBlobs(noise)
dfTrain, dfTest = train_test_split(data)
```

In [625]:
```python
def plotter(df):
    fig, ax = plt.subplots(figsize = (10,10))
    pallet = seaborn.color_palette(palette='rainbow', n_colors= len(set(
df['category'])))
    for i, cat in enumerate(set(df['category'])):
        a = np.stack(df[df['category'] == cat]['vect'])
        ax.scatter(a[:,0], a[:, 1], c = pallet[i], label = cat)
    ax.legend(loc = 'center right', title = 'Categories')
    ax.axis('off')
    plt.show()
    plt.close()

plotter(data)
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
```



In [555]:
```
from sklearn.svm import SVC, LinearSVC
```

In [626]:
```
svc = SVC(kernel = 'linear')
```

In [627]:
```
X_train = np.stack(dfTrain['vect'], axis=0)
svc.fit(X_train, dfTrain['category'])
```

Out[627]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='linear', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
```

In [628]:
```
from sklearn.metrics import accuracy_score
accuracy_score(svc.predict(X_train), dfTrain['category'])
```

Out[628]:
```
0.9733333333333334
```

In [629]:
```
svm = SVC(kernel = 'rbf', gamma='scale')
svm.fit(X_train, dfTrain['category'])
```

Out[629]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rb
f',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

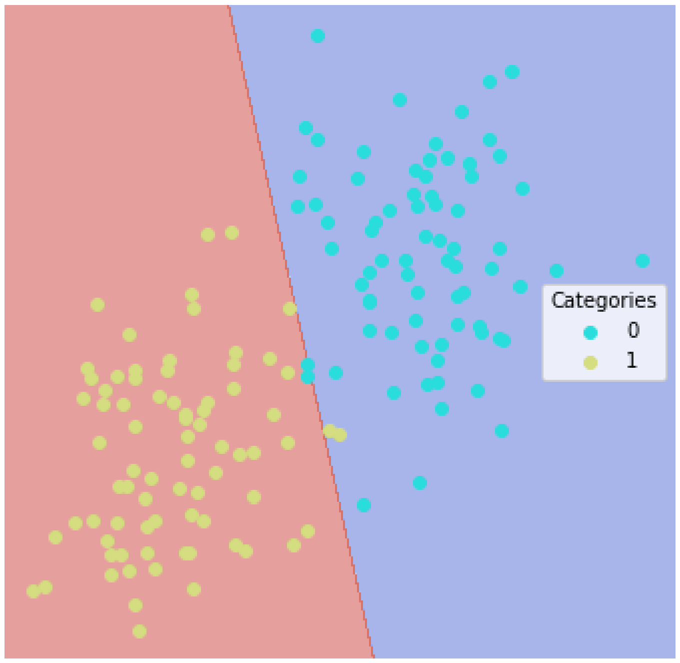
In [630]:
```
accuracy_score(svm.predict(X_train), dfTrain['category'])
```

Out[630]:
```
0.9866666666666667
```

```
In [632]: def plotregions(clf, df, h = .01):

              transformedDF = df
              catsMap = {c : i for i, c in enumerate(np.unique(df['category']))}

              fig, ax = plt.subplots(figsize = (6,6))
              ax.axis('off')
              pallet = seaborn.color_palette(palette='rainbow', n_colors = len(set
          (transformedDF['category'])))

              if np.random.choice(df['vect']).shape[0] > 2:
                  xx, yy = np.meshgrid(np.arange(1.1 * reduced_data[:,0].min(),
                          1.1 * reduced_data[:,0].max(), h),
                      np.arange(1.1 * reduced_data[:,1].min(),
                          1.1 * reduced_data[:,1].max(), h))
                  Z = clf.predict(pca.inverse_transform(np.c_[xx.ravel(), yy.ravel
          ()]))
              else:
                  reduced_data = np.stack(df['vect'], axis=0)
                  xx, yy = np.meshgrid(np.arange(1.1 * reduced_data[:,0].min(),
                          1.1 * reduced_data[:,0].max(), h),
                      np.arange(1.1 * reduced_data[:,1].min(),
                          1.1 * reduced_data[:,1].max(), h))

                  Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
              Z = np.vectorize(lambda x: catsMap[x])(Z)
              Z = Z.reshape(xx.shape)
              plt.contourf(xx, yy, Z, alpha=0.5, cmap=plt.cm.coolwarm)
              for i, cat in enumerate(set(df['category'])):
                  a = np.stack(transformedDF[transformedDF['category'] == cat]['ve
          ct'])
                  ax.scatter(a[:,0], a[:, 1], c = pallet[catsMap[cat]], label = ca
          t)
              ax.legend(loc = 'center right', title = 'Categories')
              plt.show()
              plt.close()
```

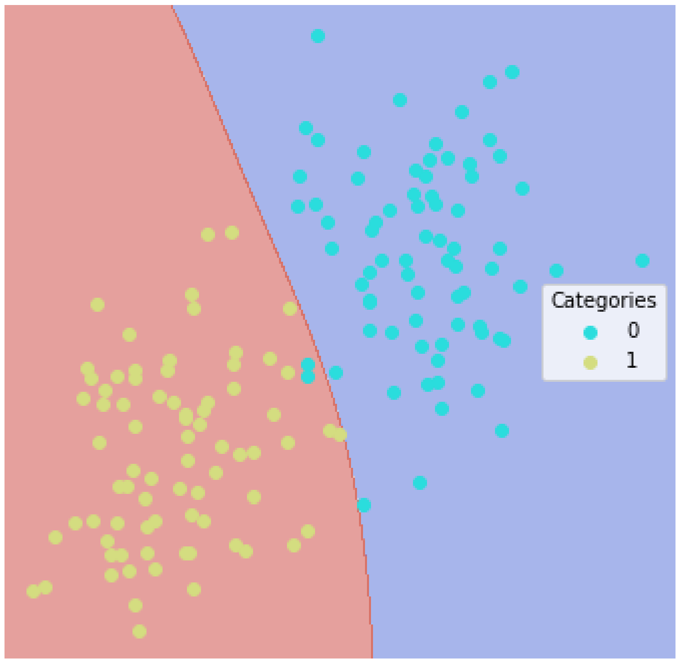
```
In [633]: plotregions(svc, dfTrain)
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
```



In [634]:
```
plotregions(svm, dfTrain)
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
```



In [635]:
```
X_test = np.stack(dfTest['vect'], axis=0)
print('svm', accuracy_score(svm.predict(X_test), dfTest['category']))
print('svc', accuracy_score(svc.predict(X_test), dfTest['category']))
```

```
svm 0.94
svc 0.94
```

Because of the non-linear separation between the two classes, the linear SVC did not performa as well as the the radial kernel SVM on the training. Both models, however, did equally well on the testing dataset.

SVM vs. logistic regression

We have seen that we can fit an SVM with a non-linear kernel in order to perform classification using a non-linear decision boundary. We will now see that we can also obtain a non-linear decision boundary by performing logistic regression using non-linear transformations of the features. Your goal here is to compare different approaches to estimating non-linear decision boundaries, and thus assess the benefits and drawbacks of each.

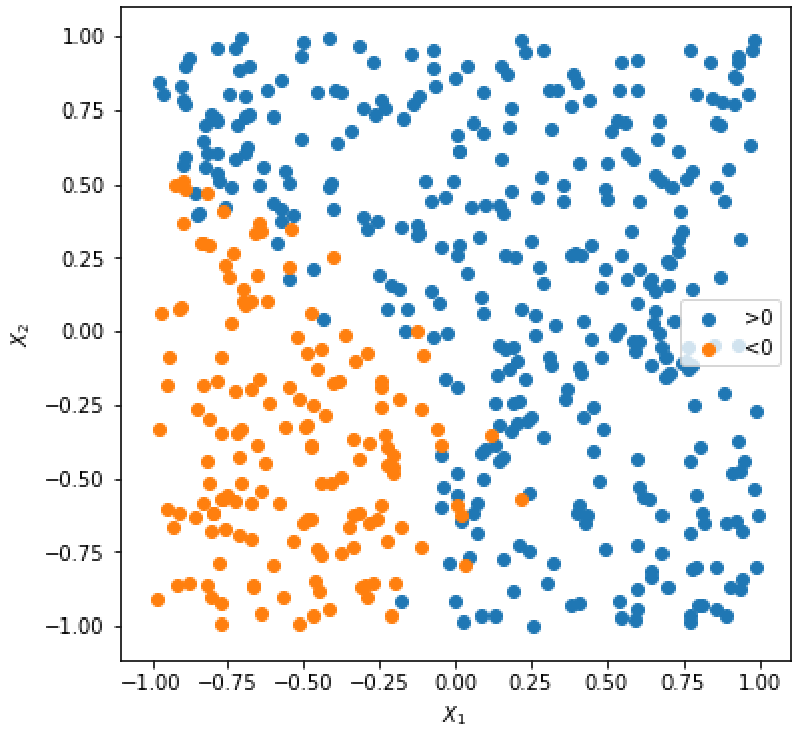
1. (5 points) Generate a data set with $n = 500$ and $p = 2$, such that the observations belong to two classes with some overlapping, non-linear boundary between them.

In [774]:
```python
#set X1 and X2

x1 = np.random.uniform(-1,1, 500)
x2 = np.random.uniform(-1,1, 500)
```

In [775]:
```python
# generate data
epsilon = np.random.uniform(0,0.5, 500)
y = x1 + x2 + x2**2 + epsilon
```

1. (5 points) Plot the observations with colors according to their class labels ($y$). Your plot should display $X_1$ on the $x$-axis and $X_2$ on the $y$-axis.

In [776]:
```python
fig, ax = plt.subplots(figsize = (6,6))
pallet = seaborn.color_palette(palette='rainbow', n_colors= 2)
ax.scatter(x1[y >= 0],x2[y >= 0])
ax.scatter(x1[y <= 0],x2[y <= 0])
ax.legend(['>0','<0'], loc = 'center right')
ax.axis('on')
plt.xlabel('$X_1$')
plt.ylabel('$X_2$')
plt.show()
plt.close()
```



1. (5 points) Fit a logistic regression model to the data, using $X_1$ and $X_2$ as predictors.

In [777]:
```python
# have to stack x1 and x2 for log reg
linear_prep = np.stack((x1, x2), axis=1)
```

In [778]:
```
from sklearn.linear_model import LogisticRegression
log_reg = (sklearn.linear_model.LogisticRegression())

log_reg.fit(linear_prep, y >= 0)
```

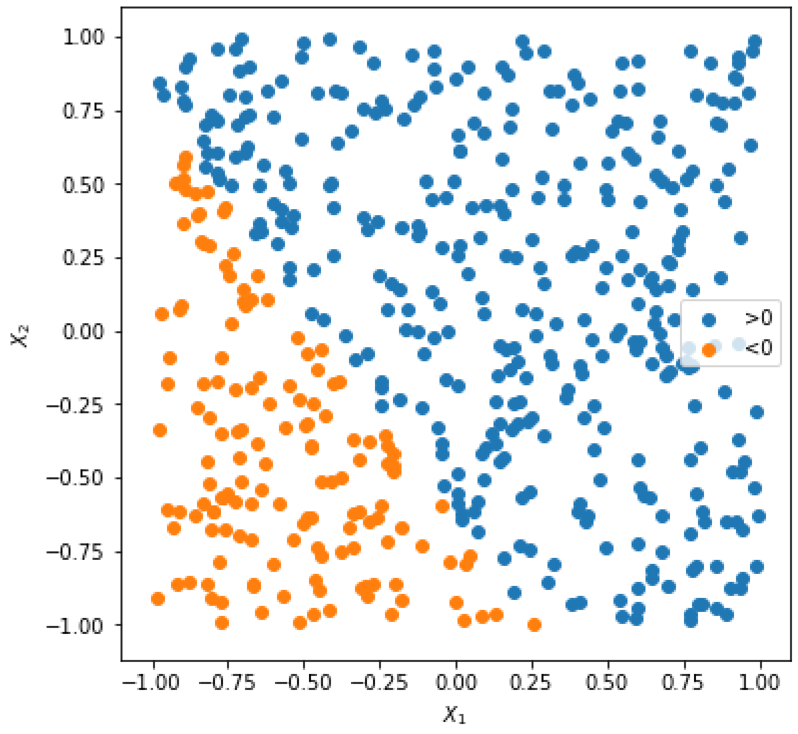
```
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/line
ar_model/logistic.py:432: FutureWarning: Default solver will be changed
to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[778]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=
True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbos
e=0,
                   warm_start=False)
```

1. (5 points) Obtain a predicted class label for each observation based on the logistic model previously fit. Plot the observations, colored according to the predicted class labels (the predicted decision boundary should look linear).

In [779]:
```
#predict classes
pred_log = log_reg.predict(linear_prep)
```

In [780]:
```
#plot classes
fig, ax = plt.subplots(figsize = (6,6))
pallet = seaborn.color_palette(palette='rainbow', n_colors= 2)
plt.scatter(x1[pred_log],x2[pred_log])
plt.scatter(x1[~pred_log],x2[~pred_log])
ax.legend(['>0','<0'], loc = 'center right')
ax.axis('on')
plt.xlabel('$X_1$')
plt.ylabel('$X_2$')
plt.show()
plt.close()
```



6. (5 points) Now fit a logistic regression model to the data, but this time using some non-linear function of both $X_1$ and $X_2$ as predictors (e.g. $X_1^2, X_1 \times X_2, \log(X_2)$, and so on).

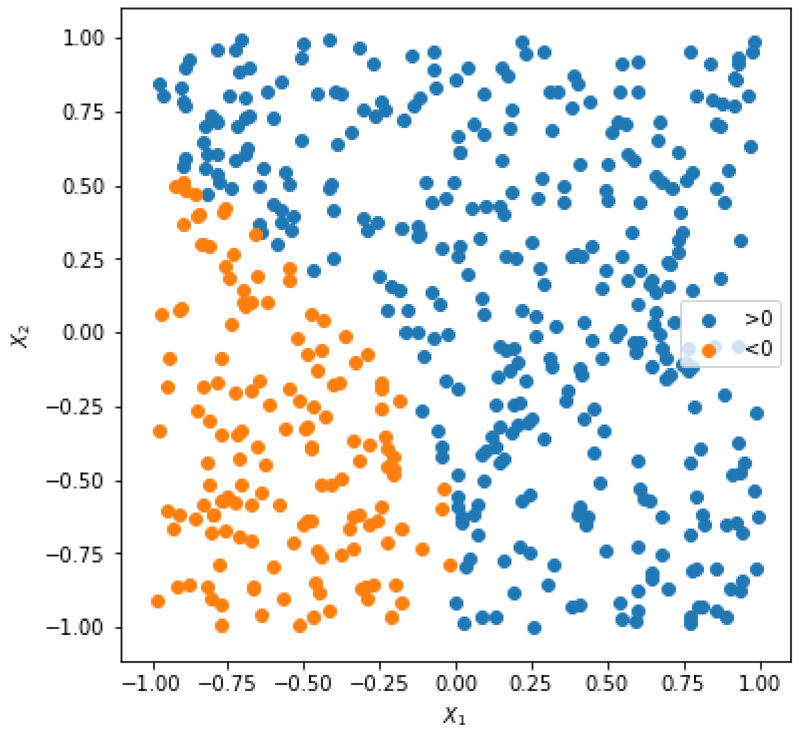
In [781]:
```
import math
# variable x1 times x2

nonlinear_func = np.stack((x1, x2,(x1**2),(x2**2)), axis=1)
output = y >=0
#logistic regression
non_lr = LogisticRegression().fit(nonlinear_func, output )
```

```
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/line
ar_model/logistic.py:432: FutureWarning: Default solver will be changed
to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

7. (5 points) Now, obtain a predicted class label for each observation based on the fitted model with non-linear transformations of the X features in the previous question. Plot the observations, colored according to the new predicted class labels from the non-linear model (the decision boundary should now be obviously non-linear). If it is not, then repeat earlier steps until you come up with an example in which the predicted class labels and the resultant decision boundary are clearly non-linear.

```
In [782]: pred_non_lr = non_lr.predict(nonlinear_func)
```

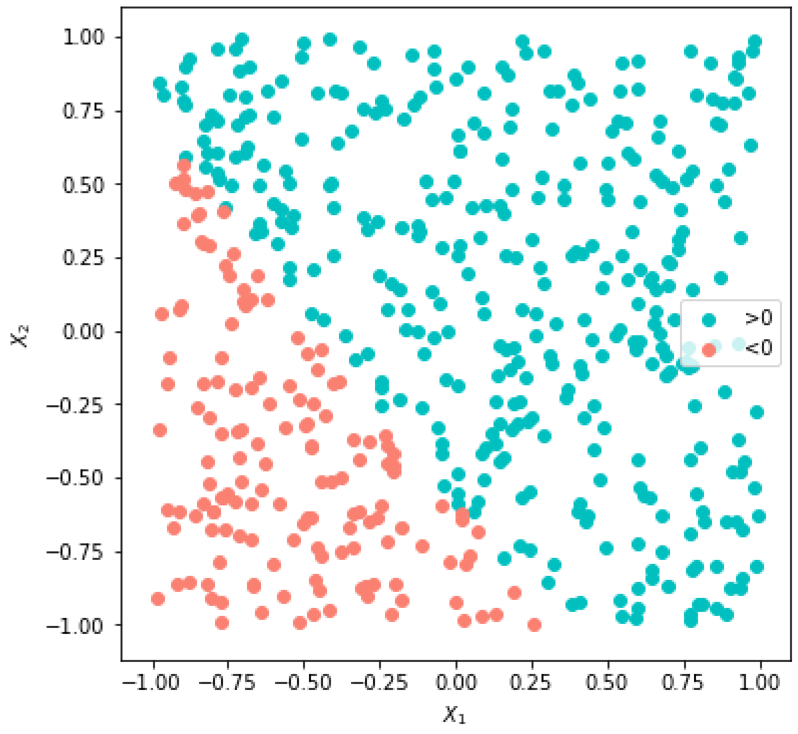
```
In [783]: # predictions with nonlinear
          fig, ax = plt.subplots(figsize = (6,6))
          pallet = seaborn.color_palette(palette='rainbow', n_colors= 2)
          plt.scatter(x1[pred_non_lr],x2[pred_non_lr])
          plt.scatter(x1[~pred_non_lr],x2[~pred_non_lr])
          ax.legend(['>0','<0'], loc = 'center right')
          ax.axis('on')
          plt.xlabel('$X_1$')
          plt.ylabel('$X_2$')
          plt.show()
          plt.close()
```



8. (5 points) Now, fit a support vector classifier (linear kernel) to the data with original X_1 and X_2 as predictors. Obtain a class prediction for each observation. Plot the observations, colored according to the predicted class labels.

```
In [784]: svc = SVC(kernel='linear').fit(linear_prep, output)
          svc_pred = svc.predict(linear_prep)
```

In [785]:
```
# predictions with svc
fig, ax = plt.subplots(figsize = (6,6))
#pallet = seaborn.color_palette(palette='rainbow', n_colors= 3)
plt.scatter(x1[svc_pred],x2[svc_pred], color = 'c')
plt.scatter(x1[~svc_pred],x2[~svc_pred], color = 'salmon')
ax.legend(['>0','<0'], loc = 'center right')
ax.axis('on')
plt.xlabel('$X_1$')
plt.ylabel('$X_2$')
plt.show()
plt.close()
```

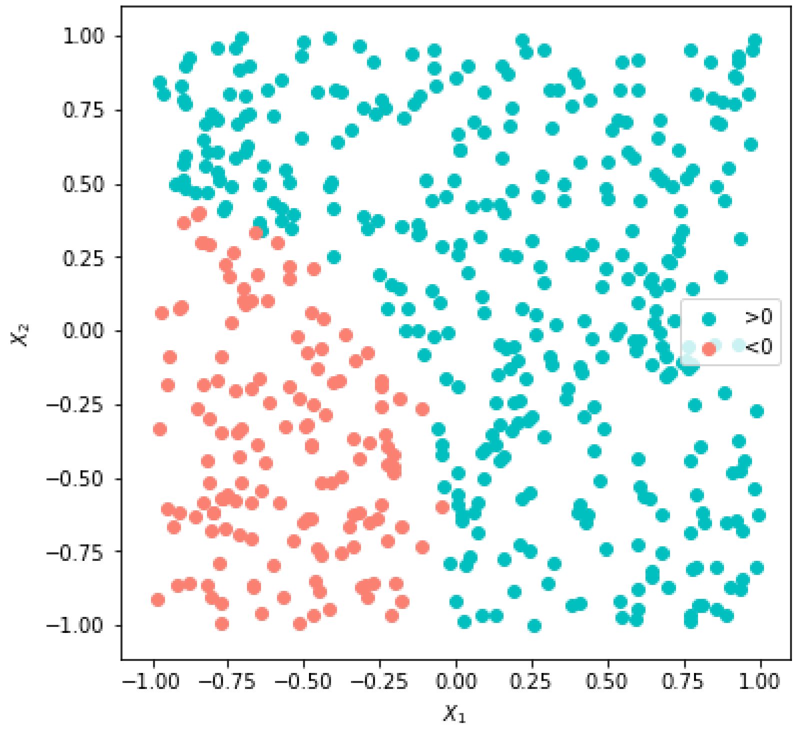


9. (5 points) Fit a SVM using a non-linear kernel to the data. Obtain a class prediction for each observation. Plot the observations, colored according to the predicted class labels.

In [786]:
```
#svm classifier
svm.fit(linear_prep, output)
svm_pred = svm.predict(linear_prep)
```

```
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/svm/
base.py:193: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled featur
es. Set gamma explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

```
In [788]: #plot svm
          fig, ax = plt.subplots(figsize = (6,6))
          #pallet = seaborn.color_palette(palette='rainbow', n_colors= 3)
          plt.scatter(x1[svm_pred],x2[svm_pred], color = 'c')
          plt.scatter(x1[~svm_pred],x2[~svm_pred], color = 'salmon')
          ax.legend(['>0','<0'], loc = 'center right')
          ax.axis('on')
          plt.xlabel('$X_1$')
          plt.ylabel('$X_2$')
          plt.show()
          plt.close()
```



10. (5 points) Discuss your results and specifically the tradeoffs between estimating non-linear decision boundaries using these two different approaches.

```
In [790]: print(accuracy_score(pred_log, output))
          print(accuracy_score(pred_non_lr, output))
          print(accuracy_score(svc_pred, output))
          print(accuracy_score(svm_pred, output))
```

```
0.924
0.95
0.924
0.948
```

Between the different boundary types, we see that the prediction accuracy from the logistic regression using a non-inear function actually performs the best out all the models. This is probably due to the fact that the non-linear function was similar to the base data generation function. However, using SVM was a close second in accuracy and did quite well in estimating the non-linear decision boundary.

Tuning cost

In class we learned that in the case of data that is just barely linearly separable, a support vector classifier with a small value of cost that misclassifies a couple of training observations may perform better on test data than one with a huge value of cost that does not misclassify any training observations. You will now investigate that claim.

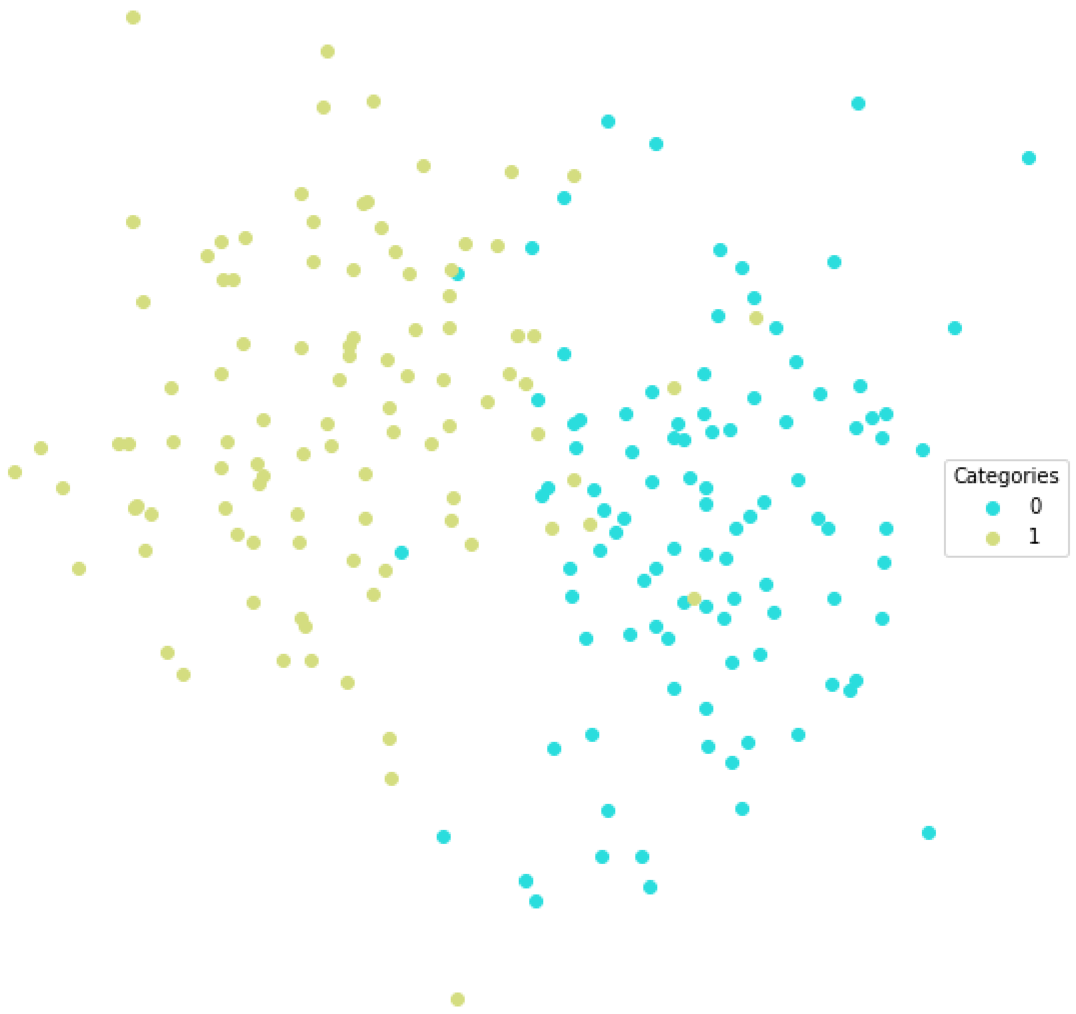
11. (5 points) Generate two-class data with $p=2$ in such a way that the classes are just barely linearly separable.

In [305]:
```
def multiBlobs(noise = 0, numPerCategory = 100, centers = 2):
    if isinstance(centers, int):
        n_samples = numPerCategory * centers
    else:
        n_samples = numPerCategory * len(centers)
    X, y = sklearn.datasets.make_blobs(n_samples=n_samples, centers=cent
ers, cluster_std = (.6 * (noise * 6)))
    datDict = {
        'vect' : list(X),
        'category' : y,
    }
    return pd.DataFrame(datDict)
```

In [314]:
```
noise = 0.6
data_2 = multiBlobs(noise)
dfTrain, dfTest = train_test_split(data_2)
```

```
In [315]: plotter(data_2)
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
```



12. (5 points) Compute the cross-validation error rates for support vector classifiers with a range of cost values. How many training errors are made for each value of cost considered, and how does this relate to the cross-validation errors obtained?

In [792]:
```
costs = np.arange(0.5, 3, 0.5)

X_train = np.stack(dfTrain['vect'], axis =0)
y_train = dfTrain['category']

for cost in costs:
    svc_linear = SVC(C=cost, kernel = 'linear')
    print('cv error for C = {}'.format(cost))
    accu = cross_val_score(svc_linear, X_train,
                           y_train, scoring = 'accuracy', cv = 10)

    print(1-np.mean(accu))
```

```
cv error for C = 0.5
0.045952380952380856
cv error for C = 1.0
0.03928571428571426
cv error for C = 1.5
0.03928571428571426
cv error for C = 2.0
0.045952380952380856
cv error for C = 2.5
0.045952380952380856
```

13. (5 points) Generate an appropriate test data set, and compute the test errors corresponding to each of the values of cost considered. Which value of cost leads to the fewest test errors, and how does this compare to the values of cost that yield the fewest training errors and the fewest cross-validation errors?

In [283]:
```
dfTest.head()
```

Out[283]:

	vect	category
170	[-4.57510217154708, 2.97463383847121]	0
119	[0.03143049528769626, 7.765868041615752]	1
52	[7.128040936041439, 10.61613400100343]	1
93	[-1.3634811022291884, 5.048278794338122]	1
68	[-9.481173211727787, 8.50171624636198]	0

```
In [791]: X_test = np.stack(dfTrain['vect'], axis =0)
          y_test = dfTrain['category']

          for cost in costs:
              svc_linear = SVC(C=cost, kernel = 'linear')
              svc_linear.fit(X_train, y_train)
              preds = svc_linear.predict(X_test)
              print('cv error for C = {}'.format(cost))
              accu = cross_val_score(svc_linear, X_test, y_test)
              print(1 - np.mean(accu))
```

```
cv error for C = 0.5
0.039879951980792305
cv error for C = 1.0
0.039879951980792305
cv error for C = 1.5
0.039879951980792305
cv error for C = 2.0
0.039879951980792305
cv error for C = 2.5
0.039879951980792305

/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/mode
l_selection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence th
is warning.
  warnings.warn(CV_WARNING, FutureWarning)
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/mode
l_selection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence th
is warning.
  warnings.warn(CV_WARNING, FutureWarning)
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/mode
l_selection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence th
is warning.
  warnings.warn(CV_WARNING, FutureWarning)
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/mode
l_selection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence th
is warning.
  warnings.warn(CV_WARNING, FutureWarning)
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/mode
l_selection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence th
is warning.
  warnings.warn(CV_WARNING, FutureWarning)
```

14. (5 points) Discuss your results.

Cross validation error remained in training was lowest with a cost value of 1 and 1.5. For the test error, we saw no change with the different values of cost.

Application: Predicting attitudes towards racist college professors

In this problem set, you are going to return to the GSS question from last week and predict attitudes towards racist college professors. Recall, each respondent was asked "Should a person who believes that Blacks are genetically inferior be allowed to teach in a college or university?" Given the kerfuffle over Richard J. Herrnstein and Charles Murray's The Bell Curve and the ostracization of Nobel laureate James Watson over his controversial views on race and intelligence, this analysis will provide further insight into the public debate over this issue.

gss_*.csv contain a selection of features from the 2012 GSS. The outcome of interest colrac is a binary variable coded as either ALLOWED or NOT ALLOWED, where 1 = the racist professor should be allowed to teach, and 0 = the racist professor should not be allowed to teach. Documentation for the other predictors (if the variable is not clearly coded) can be viewed here. Some data pre-processing has been done in advance for you to ease your model fitting: (1) Missing values have been imputed; (2) Categorical variables with low-frequency classes had those classes collapsed into an "other" category; (3) Nominal variables with more than two classes have been converted to dummy variables; and (4) Remaining categorical variables have been converted to integer values, stripping their original labels.

This week, building on last week's problem set, you will approach this classification problem from an SVM-based framework.

15. (5 points) Fit a support vector classifier to predict colrac as a function of all available predictors, using 10-fold cross-validation to find an optimal value for cost. Report the CV errors associated with different values of cost, and discuss your results.

16. (15 points) Repeat the previous question, but this time using SVMs with radial and polynomial basis kernels, with different values for gamma and degree and cost. Present and discuss your results (e.g., fit, compare kernels, cost, substantive conclusions across fits, etc.).

In [195]:
```
gss_train = pd.read_csv('./data/gss_train.csv')
```

In [197]:
```
gss_train.head()
```

Out[197]:

	age	attend	authoritarianism	black	born	childs	colath	colrac	colcom	colmil	...	partyid_
0	21	0	4	0	0	0	1	1	0	1	...	
1	42	0	4	0	0	2	0	1	1	0	...	
2	70	1	1	1	0	3	0	1	1	0	...	
3	35	3	2	0	0	2	0	1	0	1	...	
4	24	3	6	0	1	3	1	1	0	0	...	

5 rows × 56 columns

In [198]:
```
X_train = gss_train.drop(['colrac'], axis=1)
y_train = gss_train['colrac']
```

```
In [239]: # set costs
          import numpy as np
          costs = np.arange(0.5, 3, 0.5)
```

```
In [240]: from sklearn.model_selection import cross_val_score
          for cost in costs:
              svc_linear = SVC(C=cost, kernel = 'linear')
              #svc_linear.fit(X_train, y_train)
              print('cv error for C = {}'.format(cost))
              accu = cross_val_score(svc_linear, X_train,
                                     y_train, scoring = 'accuracy', cv = 10)

              print(np.mean(accu))
```

```
cv error for C = 0.5
0.7967491186570764
cv error for C = 1.0
0.7940418195212058
cv error for C = 1.5
0.7933615474123623
cv error for C = 2.0
0.7933615474123623
cv error for C = 2.5
0.794037223088038
```

The cross validation error is lowest when the cost is 0.5.

```
In [793]: gammas = ['auto', 'scale']

          for cost in costs:
              for gamma in gammas:
                  svm = SVC(C=cost, kernel = 'rbf', gamma=gamma)
                  svm_score = cross_val_score(svm, X_train,
                                             y_train, scoring = 'accuracy', cv = 10)
                  print('cv error for C = {}'.format(cost))
                  print('and gamma = {}'.format(gamma))
                  print(np.mean(svm_score))
```

```
cv error for C = 0.5
and gamma = auto
0.9875
cv error for C = 0.5
and gamma = scale
0.9674404761904762
cv error for C = 1.0
and gamma = auto
0.9870833333333333
cv error for C = 1.0
and gamma = scale
0.9741071428571428
cv error for C = 1.5
and gamma = auto
0.9870833333333333
cv error for C = 1.5
and gamma = scale
0.9741071428571428
cv error for C = 2.0
and gamma = auto
0.99375
cv error for C = 2.0
and gamma = scale
0.9741071428571428
cv error for C = 2.5
and gamma = auto
0.99375
cv error for C = 2.5
and gamma = scale
0.9678571428571429
```

From a cost of 2.0 to 2.5 and with an auto gamma, the radial kernel performed the best.According to the sklearn documentation, the gamma parameter defines how close or far a sample's radius will be as a support vector.

In [245]:
```
degrees = range(0,5)

for cost in costs:
    for degree in degrees:
        for gamma in gammas:
            svc_poly = SVC(C = cost, kernel = 'poly', degree=degree, gam
ma = gamma)
            svc_poly_score = cross_val_score(svc_poly, X_train,
                                             y_train, scoring = 'accuracy', cv
= 10)
            print('cv error for C = {}'.format(cost), 'and degree = {}'.
format(degree))
            print(np.mean(svc_poly_score))
```

```
cv error for C = 0.5 and degree = 0
0.5253223981411901
cv error for C = 0.5 and degree = 0
0.5253223981411901
cv error for C = 0.5 and degree = 1
0.7940554854265305
cv error for C = 0.5 and degree = 1
0.70500570081107
cv error for C = 0.5 and degree = 2
0.7744192761450671
cv error for C = 0.5 and degree = 2
0.7366674132014497
cv error for C = 0.5 and degree = 3
0.7379461470784577
cv error for C = 0.5 and degree = 3
0.7365988985835583
cv error for C = 0.5 and degree = 4
0.7372794791778492
cv error for C = 0.5 and degree = 4
0.7237650402079931
cv error for C = 1.0 and degree = 0
0.5253223981411901
cv error for C = 1.0 and degree = 0
0.5253223981411901
cv error for C = 1.0 and degree = 1
0.7981096628747635
cv error for C = 1.0 and degree = 1
0.732631498091709
cv error for C = 1.0 and degree = 2
0.7744011988978432
cv error for C = 1.0 and degree = 2
0.7548563630059315
cv error for C = 1.0 and degree = 3
0.7379461470784577
cv error for C = 1.0 and degree = 3
0.745382805761521
cv error for C = 1.0 and degree = 4
0.7372794791778492
cv error for C = 1.0 and degree = 4
0.7507518098841206
cv error for C = 1.5 and degree = 0
0.5253223981411901
cv error for C = 1.5 and degree = 0
0.5253223981411901
cv error for C = 1.5 and degree = 1
0.80013675159888
cv error for C = 1.5 and degree = 1
0.7454605749428377
cv error for C = 1.5 and degree = 2
0.7696988009787626
cv error for C = 1.5 and degree = 2
0.7582074095736608
cv error for C = 1.5 and degree = 3
0.7379461470784577
cv error for C = 1.5 and degree = 3
0.7568558731310409
cv error for C = 1.5 and degree = 4
```

```
0.7372794791778492
cv error for C = 1.5 and degree = 4
0.7608781840325464
cv error for C = 2.0 and degree = 0
0.5253223981411901
cv error for C = 2.0 and degree = 0
0.5253223981411901
cv error for C = 2.0 and degree = 1
0.798776330775372
cv error for C = 2.0 and degree = 1
0.7501584381258398
cv error for C = 2.0 and degree = 2
0.7629555867331514
cv error for C = 2.0 and degree = 2
0.7642886140489209
cv error for C = 2.0 and degree = 3
0.7379461470784577
cv error for C = 2.0 and degree = 3
0.7629372626975695
cv error for C = 2.0 and degree = 4
0.7372794791778492
cv error for C = 2.0 and degree = 4
0.7622204659117411
cv error for C = 2.5 and degree = 0
0.5253223981411901
cv error for C = 2.5 and degree = 0
0.5253223981411901
cv error for C = 2.5 and degree = 1
0.7980960586665286
cv error for C = 2.5 and degree = 1
0.7555776945278383
cv error for C = 2.5 and degree = 2
0.7643069380845028
cv error for C = 2.5 and degree = 2
0.7656445001363507
cv error for C = 2.5 and degree = 3
0.7379461470784577
cv error for C = 2.5 and degree = 3
0.7676489151800754
cv error for C = 2.5 and degree = 4
0.7372794791778492
cv error for C = 2.5 and degree = 4
0.7642520276748466
```

It's difficult to extract strong meaning from the attitudes towards racist college professors in th dataset from this exercise alone. It would seem that the best performing parameters of the polynomial kernel was when the degree was 1 and the cost was 1.5 suggesting that the poly was not the best fit for the data but rather a linear kernel would be a better match.

```
In [ ]:
```