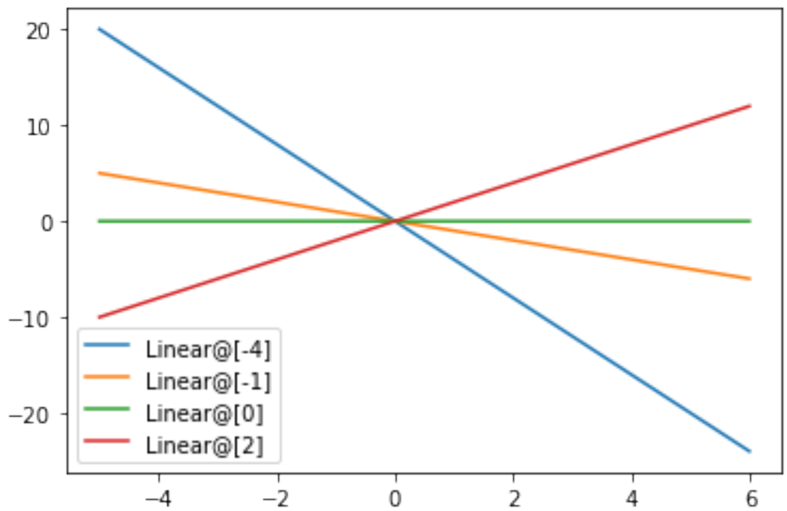
In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import sklearn
import scipy.spatial
import functools

%matplotlib inline
```

Question 21

In [2]:
```
### Kernel function generators
def linear_kernel(X1, X2):
    """
    Computes the linear kernel between two sets of vectors.
    Args:
        X1 - an n1xd matrix with vectors x1_1,...,x1_n1 in the rows
        X2 - an n2xd matrix with vectors x2_1,...,x2_n2 in the rows
    Returns:
        matrix of size n1xn2, with x1_i^T x2_j in position i,j
    """
    return np.dot(X1,np.transpose(X2))

def RBF_kernel(X1,X2,sigma):
    """
    Computes the RBF kernel between two sets of vectors
    Args:
        X1 - an n1xd matrix with vectors x1_1,...,x1_n1 in the rows
        X2 - an n2xd matrix with vectors x2_1,...,x2_n2 in the rows
        sigma - the bandwidth (i.e. standard deviation) for the RBF/Ga
    Returns:
        matrix of size n1xn2, with exp(-||x1_i-x2_j||^2/(2 sigma^2)) i
    """
    #TODO
    mat = scipy.spatial.distance.cdist(X1,X2, metric='sqeuclidean')
    return np.exp(-mat/(2*sigma**2))

def polynomial_kernel(X1, X2, offset, degree):
    """
    Computes the inhomogeneous polynomial kernel between two sets of v
    Args:
        X1 - an n1xd matrix with vectors x1_1,...,x1_n1 in the rows
        X2 - an n2xd matrix with vectors x2_1,...,x2_n2 in the rows
        offset, degree - two parameters for the kernel
    Returns:
        matrix of size n1xn2, with (offset + <x1_i,x2_j>)^degree in po
    """
    return (offset + linear_kernel(X1,X2))**degree
```

Question 22

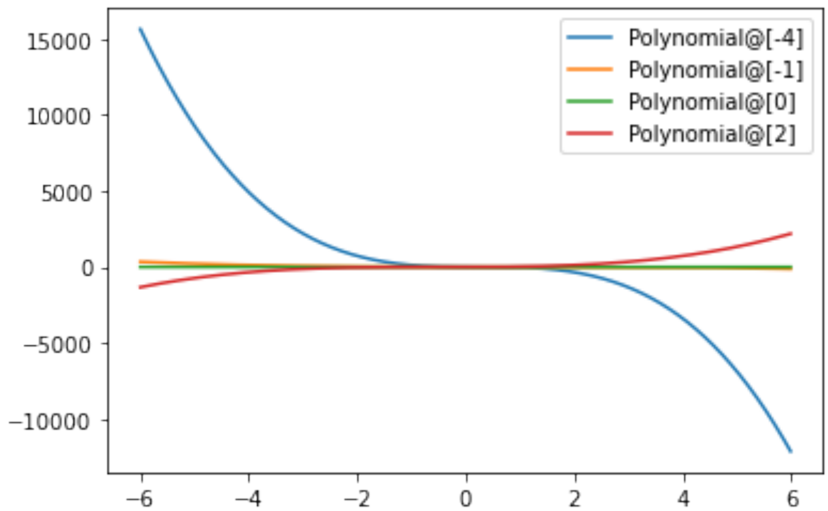
In [3]:
```
# PLot kernel machine functions
plot_step = .01
xpts = np.arange(-5.0, 6, plot_step).reshape(-1,1)
prototypes = np.array([-4,-1,0,2]).reshape(-1,1)

# Linear kernel
y = linear_kernel(prototypes, xpts)
for i in range(len(prototypes)):
    label = "Linear@"+str(prototypes[i,:])
    plt.plot(xpts, y[i,:], label=label)
plt.legend(loc = 'best')
plt.show()
```



Question 23

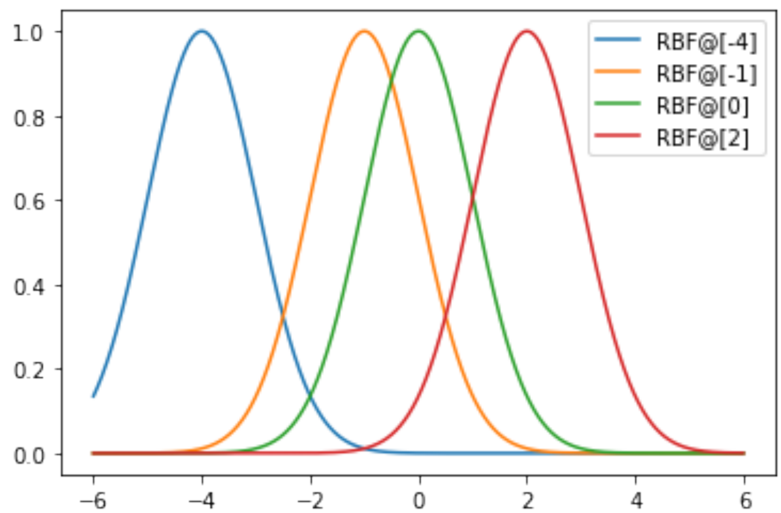
Part a)

In [4]:
```
# PLot kernel machine functions
plot_step = .01
xpts = np.arange(-6.0, 6, plot_step).reshape(-1,1)
prototypes = np.array([-4,-1,0,2]).reshape(-1,1)

# Linear kernel
y = polynomial_kernel(prototypes, xpts,1,3)
for i in range(len(prototypes)):
    label = "Polynomial@"+str(prototypes[i,:])
    plt.plot(xpts, y[i,:], label=label)
plt.legend(loc = 'best')
plt.show()
```



Part b

In [5]:
```
# PLot kernel machine functions
plot_step = .01
xpts = np.arange(-6.0, 6, plot_step).reshape(-1,1)
prototypes = np.array([-4,-1,0,2]).reshape(-1,1)

# Linear kernel
y = RBF_kernel(prototypes, xpts, 1)
for i in range(len(prototypes)):
    label = "RBF@"+str(prototypes[i,:])
    plt.plot(xpts, y[i,:], label=label)
plt.legend(loc = 'best')
plt.show()
```



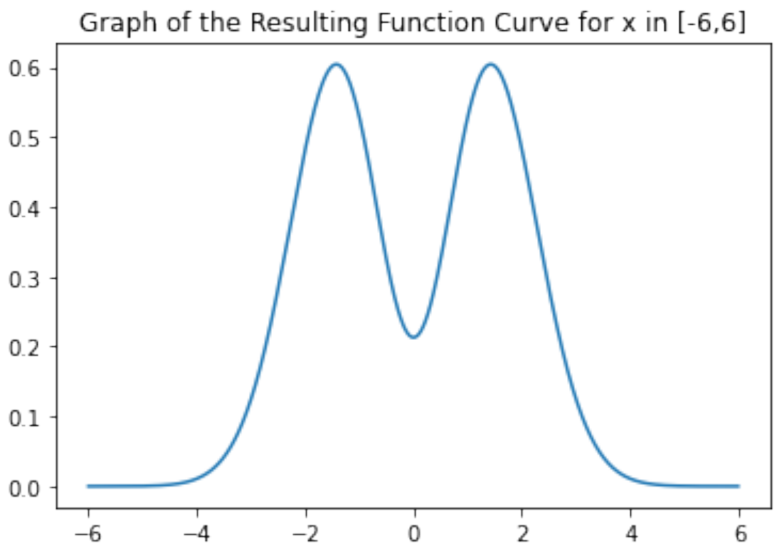
Question 24

In [6]:
```
class Kernel_Machine(object):
    def __init__(self, kernel, training_points, weights):
        """
        Args:
            kernel(X1,X2) - a function return the cross-kernel matrix
            training_points - an nxd matrix with rows x_1,..., x_n
            weights - a vector of length n with entries alpha_1,...,al
        """

        self.kernel = kernel
        self.training_points = training_points
        self.weights = weights

    def predict(self, X):
        """
        Evaluates the kernel machine on the points given by the rows o
        Args:
            X - an nxd matrix with inputs x_1,...,x_n in the rows
        Returns:
            Vector of kernel machine evaluations on the n points in X.
                Sum_{i=1}^R alpha_i k(x_j, mu_i)
        """

        kernel_matrix = self.kernel(X, self.training_points)
        return (kernel_matrix @ self.weights)
```

In [7]:
```
k = functools.partial(RBF_kernel, sigma=1)
train_points = np.array([-1,0,1]).reshape(-1,1)
weights = np.array([1,-1,1]).reshape(-1,1)
X = np.array([-4,-1,0,1]).reshape(-1,1)
test_kernel_object = Kernel_Machine(k, train_points, weights)
test_kernel_object.predict(X)
```

Out[7]:
```
array([[0.01077726],
       [0.52880462],
       [0.21306132],
       [0.52880462]])
```

In [8]:
```
# PLot kernel machine functions
plot_step = .01
xpts = np.arange(-6.0, 6, plot_step).reshape(-1,1)
# Linear kernel
y = test_kernel_object.predict(xpts).reshape(-1,1)

plt.plot(xpts, y)
plt.title('Graph of the Resulting Function Curve for x in [-6,6]')
plt.show()
```

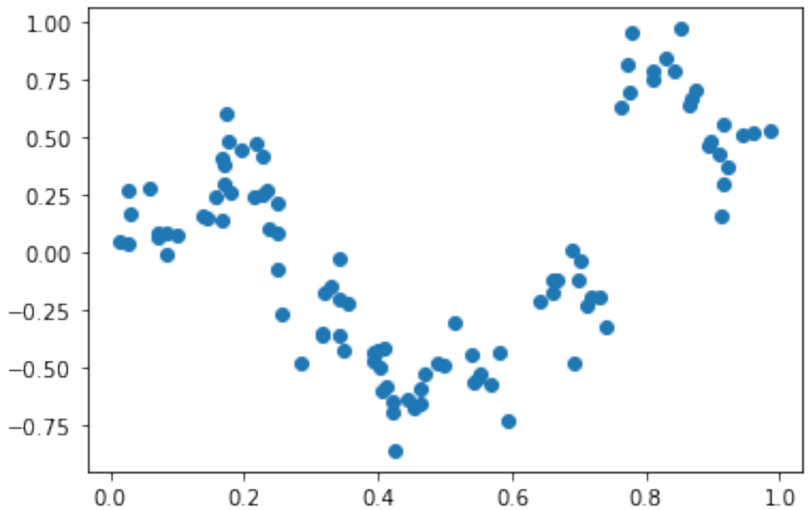


Load train & test data; Convert to column vectors so it generalizes well to data in higher dimensions.

Question 25

In [9]:
```
data_train,data_test = np.loadtxt("krr-train.txt"),np.loadtxt("krr-tes
x_train, y_train = data_train[:,0].reshape(-1,1),data_train[:,1].resha
x_test, y_test = data_test[:,0].reshape(-1,1),data_test[:,1].reshape(-
plt.scatter(x_train,y_train)
```

Out[9]: <matplotlib.collections.PathCollection at 0x7fc8315edf10>



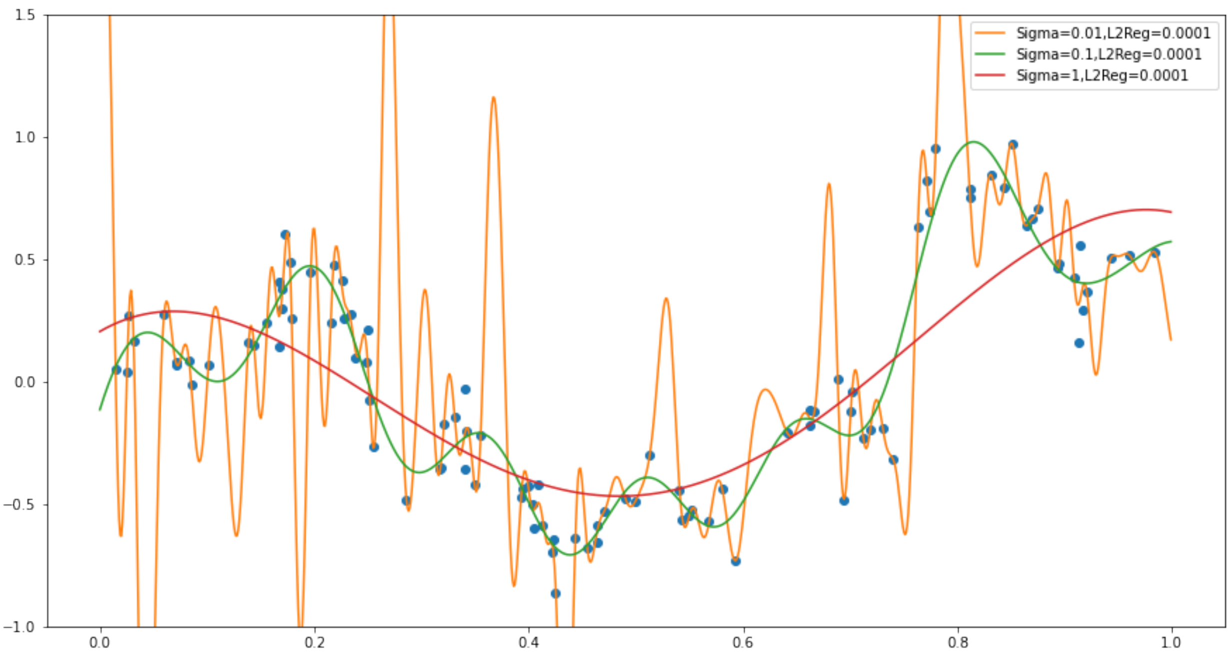
Looks like there is not a linear relationship, but rather a potential polynomial, or sinusoidal relationship, alternatively it could be a uniform + noise distribution.

Question 26

In [10]:
```
def train_kernel_ridge_regression(X, y, kernel, l2reg):
    kernel_matrix = kernel(X,X)
    matrix = ((np.identity(X.shape[0])*l2reg)+kernel_matrix)
    alpha = np.linalg.inv(matrix)@y
    return Kernel_Machine(kernel, X, alpha)
```

Question 27

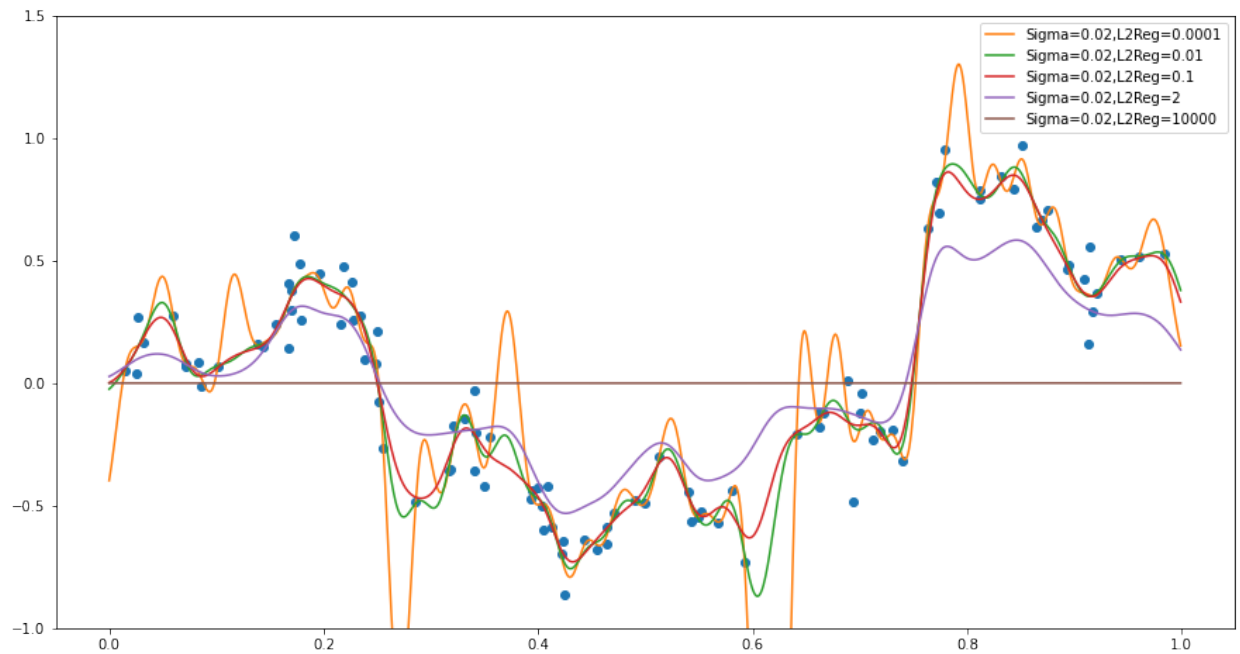
In [11]:
```
plt.figure(figsize=(15,8))
plot_step = .001
xpts = np.arange(0 , 1, plot_step).reshape(-1,1)
plt.plot(x_train,y_train,'o')
l2reg = 0.0001
for sigma in [.01,.1,1]:
    k = functools.partial(RBF_kernel, sigma=sigma)
    f = train_kernel_ridge_regression(x_train, y_train, k, l2reg=l2reg
    label = "Sigma="+str(sigma)+",L2Reg="+str(l2reg)
    plt.plot(xpts, f.predict(xpts), label=label)
plt.legend(loc = 'best')
plt.ylim(-1,1.5)
plt.show()
```



The smaller values of sigma, $\sigma \in 0.01$ for instance, the curve overfits the training data, and does not generalize well (least bias). With a lower sigma, say $\sigma \in 1$ the curve is much smoother with lower amplitude, and still does not fit the training data well (high bias). With $\sigma = .1$ we have the best fit of the curve.

Problem 28

In [12]:
```
plt.figure(figsize=(15,8))
plot_step = .001
xpts = np.arange(0 , 1, plot_step).reshape(-1,1)
plt.plot(x_train,y_train,'o')
sigma= .02
for l2reg in [.0001,.01,.1,2,10000]:
    k = functools.partial(RBF_kernel, sigma=sigma)
    f = train_kernel_ridge_regression(x_train, y_train, k, l2reg=l2reg
    label = "Sigma="+str(sigma)+",L2Reg="+str(l2reg)
    plt.plot(xpts, f.predict(xpts), label=label)

plt.legend(loc = 'best')
plt.ylim(-1,1.5)
plt.show()
```



As $\lambda \to \infty$ the curve loses its amplitude, becomes less volatile, and becomes a line. Specifically, its the line that fits all points with least euclidean distance loss, which in this case approaches 0.

In [13]:
```
from sklearn.base import BaseEstimator, RegressorMixin, ClassifierMixi

class KernelRidgeRegression(BaseEstimator, RegressorMixin):
    """sklearn wrapper for our kernel ridge regression"""

    def __init__(self, kernel="RBF", sigma=1, degree=2, offset=1, l2re
        self.kernel = kernel
        self.sigma = sigma
        self.degree = degree
        self.offset = offset
        self.l2reg = l2reg

    def fit(self, X, y=None):
        """
        This should fit classifier. All the "work" should be done here
        """
        if (self.kernel == "linear"):
            self.k = linear_kernel
        elif (self.kernel == "RBF"):
            self.k = functools.partial(RBF_kernel, sigma=self.sigma)
        elif (self.kernel == "polynomial"):
            self.k = functools.partial(polynomial_kernel,
                                       offset=self.offset, degree=self
        else:
            raise ValueError('Unrecognized kernel type requested.')

        self.kernel_machine_ = train_kernel_ridge_regression(X, y, sel

        return self

    def predict(self, X, y=None):
        try:
            getattr(self, "kernel_machine_")
        except AttributeError:
            raise RuntimeError("You must train classifer before predic

        return(self.kernel_machine_.predict(X))

    def score(self, X, y=None):
        # get the average square error
        return(((self.predict(X)-y)**2).mean())
```

Question 29

In [14]:
```
from sklearn.model_selection import GridSearchCV,PredefinedSplit
from sklearn.model_selection import ParameterGrid
from sklearn.metrics import mean_squared_error,make_scorer
import pandas as pd

test_fold = [-1]*len(x_train) + [0]*len(x_test)   #0 corresponds to te
predefined_split = PredefinedSplit(test_fold=test_fold)
```

In [15]:
```
param_grid = [{'kernel': ['RBF'],'sigma':[0.05, 0.055, 0.06],
               'l2reg': [0.271, 0.27, 0.269]},
              {'kernel':['polynomial'],'offset':[1.75, 1.8, 1.85],
               'degree':[5,6,7],'l2reg':[0.033, 0.034, 0.035]},
              {'kernel':['linear'],'l2reg': [3.2, 4, 4.5]}]
kernel_ridge_regression_estimator = KernelRidgeRegression()
grid = GridSearchCV(kernel_ridge_regression_estimator,
                    param_grid,
                    cv = predefined_split,
                    scoring = make_scorer(mean_squared_error,greater_i
                    return_train_score=True
                   )
grid.fit(np.vstack((x_train,x_test)),np.vstack((y_train,y_test)))
```

Out[15]:
```
GridSearchCV(cv=PredefinedSplit(test_fold=array([-1, -1, ...,  0,  0]
)),
             estimator=KernelRidgeRegression(),
             param_grid=[{'kernel': ['RBF'], 'l2reg': [0.271, 0.27, 0
.269],
                          'sigma': [0.05, 0.055, 0.06]},
                         {'degree': [5, 6, 7], 'kernel': ['polynomial
'],
                          'l2reg': [0.033, 0.034, 0.035],
                          'offset': [1.75, 1.8, 1.85]},
                         {'kernel': ['linear'], 'l2reg': [3.2, 4, 4.5
]}],
             return_train_score=True,
             scoring=make_scorer(mean_squared_error, greater_is_bette
r=False))
```

In [16]:

```
pd.set_option('display.max_rows', 20)
df = pd.DataFrame(grid.cv_results_)
# Flip sign of score back, because GridSearchCV likes to maximize,
# so it flips the sign of the score if "greater_is_better=FALSE"
df['mean_test_score'] = -df['mean_test_score']
df['mean_train_score'] = -df['mean_train_score']
cols_to_keep = ["param_degree", "param_kernel",
                "param_l2reg" ,"param_offset","param_sigma",
        "mean_test_score","mean_train_score"]
df_toshow = df[cols_to_keep].fillna('-')
df_toshow.sort_values(by=["mean_test_score"])
```

Out[16]:

	param_degree	param_kernel	param_l2reg	param_offset	param_sigma	mean_test_score	ı
1	-	RBF	0.271	-	0.055	0.013821	
4	-	RBF	0.270	-	0.055	0.013821	
7	-	RBF	0.269	-	0.055	0.013821	
8	-	RBF	0.269	-	0.06	0.013979	
5	-	RBF	0.270	-	0.06	0.013982	
...	...	...	...	...	...	...	
12	5	polynomial	0.034	1.75	-	0.046631	
15	5	polynomial	0.035	1.75	-	0.046974	
37	-	linear	4.000	-	-	0.164510	
38	-	linear	4.500	-	-	0.164511	
36	-	linear	3.200	-	-	0.164511	

39 rows × 7 columns

In [17]:

```
rbf = df_toshow[df_toshow['param_kernel']=='RBF']
rbf_min = rbf['mean_test_score'].min()
rbf_min_row = rbf[rbf['mean_test_score']==rbf_min]
print('Best parameters for RBF kernel:')
rbf_min_row
```

```
Best parameters for RBF kernel:
```

Out[17]:

	param_degree	param_kernel	param_l2reg	param_offset	param_sigma	mean_test_score	m
1	-	RBF	0.271	-	0.055	0.013821	

In [18]:
```
polynomial = df_toshow[df_toshow['param_kernel']=='polynomial']
poly_min = polynomial['mean_test_score'].min()
poly_min_row = polynomial[polynomial['mean_test_score']==poly_min]
print('Best parameters for polynomial kernel:')
poly_min_row
```

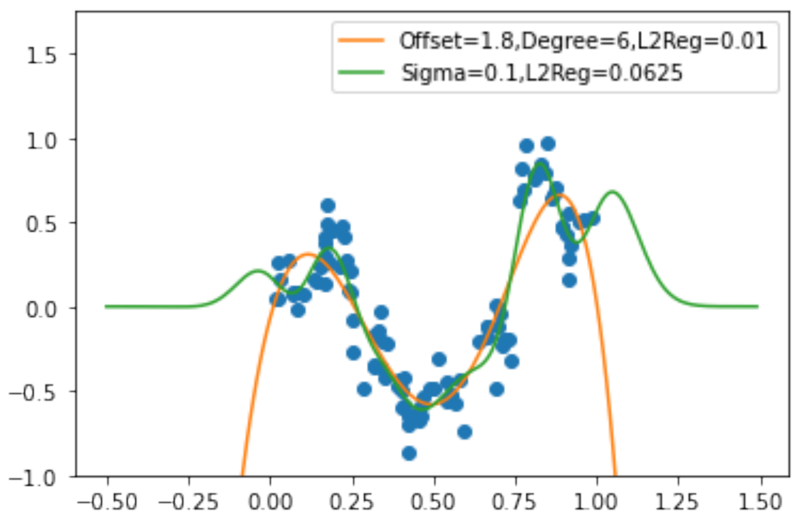
```
Best parameters for polynomial kernel:
```

Out[18]:

	param_degree	param_kernel	param_l2reg	param_offset	param_sigma	mean_test_score
22	6	polynomial	0.034	1.8	-	0.032405

Question 30

In [19]:
```
## Plot the best polynomial and RBF fits you found
plot_step = .01
xpts = np.arange(-.5 , 1.5, plot_step).reshape(-1,1)
plt.plot(x_train,y_train,'o')
#Plot best polynomial fit
offset= 1.8
degree = 6
l2reg = .01
k = functools.partial(polynomial_kernel, offset=offset, degree=degree)
f = train_kernel_ridge_regression(x_train, y_train, k, l2reg=l2reg)
label = "Offset="+str(offset)+",Degree="+str(degree)+",L2Reg="+str(l2r
plt.plot(xpts, f.predict(xpts), label=label)
#Plot best RBF fit
sigma = .1
l2reg= .0625
k = functools.partial(RBF_kernel, sigma=sigma)
f = train_kernel_ridge_regression(x_train, y_train, k, l2reg=l2reg)
label = "Sigma="+str(sigma)+",L2Reg="+str(l2reg)
plt.plot(xpts, f.predict(xpts), label=label)
plt.legend(loc = 'best')
plt.ylim(-1,1.75)
plt.show()
```



The best hyperparameters for the polynomial kernel were $Offset = 1.8,\ Degree = 6,\ l2reg = .034$ and for the RBF kernel the best parameters were $\sigma = 0.055,\ l2reg = 0.271$. Both curves seem to fit the graph reasonably well, though the RBF performed better with a lower min mean_test_score ($RBF = 0.013821, Polynomial = 0.032405$). This could be because the best fitting polynomial curve could not capture the intricacies of the data without increasing its degree substantially, at the risk of over fitting on the train set, while the RBF kernel with its smoother curves could actually capture structure within the data that would generalize well.

Question 31

Bayes function is defined in the following way:

$$E(y|x) = E(f(x) + \epsilon|x) \rightarrow E(f(x)|x) + E(\epsilon|x) = E(f(x))$$

We can now calculate the risk of the bayes decision function:

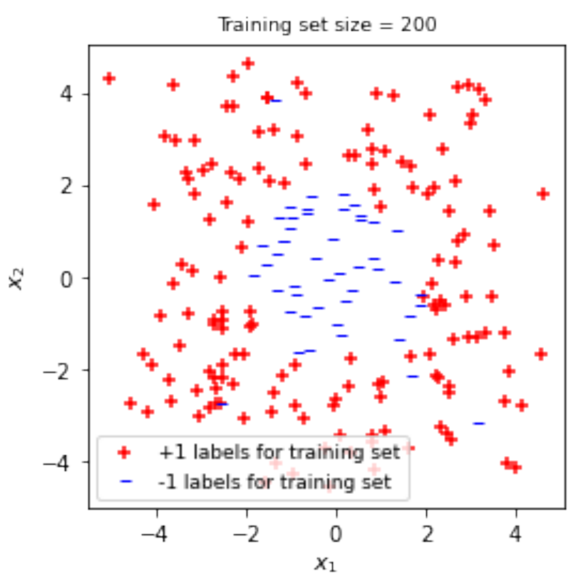
$$E((f(x) - y)^2) = E((f(x) - f(x) + epsilon)^2) = E(\epsilon^2) = .1^2$$

As

$$Var(\epsilon) = E(\epsilon^2) - E^2(\epsilon) = E(\epsilon^2) - 0 = E(\epsilon^2)$$

Question 32

In [20]:
```
# Load and plot the SVM data
#load the training and test sets
data_train,data_test = np.loadtxt("svm-train.txt"),np.loadtxt("svm-tes
x_train, y_train = data_train[:,0:2], data_train[:,2].reshape(-1,1)
x_test, y_test = data_test[:,0:2], data_test[:,2].reshape(-1,1)

#determine predictions for the training set
yplus = np.ma.masked_where(y_train[:,0]<=0, y_train[:,0])
xplus = x_train[~np.array(yplus.mask)]
yminus = np.ma.masked_where(y_train[:,0]>0, y_train[:,0])
xminus = x_train[~np.array(yminus.mask)]

#plot the predictions for the training set
figsize = plt.figaspect(1)
f, (ax) = plt.subplots(1, 1, figsize=figsize)

pluses = ax.scatter (xplus[:,0], xplus[:,1], marker='+', c='r',
                     label = '+1 labels for training set')
minuses = ax.scatter (xminus[:,0], xminus[:,1], marker=r'$-$',
                      c='b', label = '-1 labels for training set')

ax.set_ylabel(r"$x_2$", fontsize=11)
ax.set_xlabel(r"$x_1$", fontsize=11)
ax.set_title('Training set size = %s'% len(data_train), fontsize=9)
ax.axis('tight')
ax.legend(handles=[pluses, minuses], fontsize=9)
plt.show()
```



The data appears that it could be seperated by a quadratic boundary, (imagine a circle in the middle classifying the points). Additionally, a RBF boundary could work as well, as there is a circular distribution and you could imagine a guassian kernel coming out (as in the height extends to the z dimension) of the origin of the graph and decreasing otherwise.

Question 33

In [21]:
```
class train_soft_svm():
    def __init__(self, x_train, y_train, y_test, k, lambda_reg, epochs
        self.x_train = x_train
        self.y_train = y_train
        self.y_test = y_test
        self.k = k
        self.lambda_reg = lambda_reg
        self.epochs = epochs
        self.alpha = None

    def predict(self, values):
        return self.k(values,self.x_train) @ self.alpha

    def fit(self):
        #Initialize helper variables
        alpha = np.zeros(self.x_train.shape[0])
        epoch, t = 0, 2

        #Iterate over the epochs
        while epoch < self.epochs:
            for i in range(len(self.x_train)):

                alpha = alpha * (1-(1/t))
                y_hat = self.k(self.x_train[i].reshape(1,2),self.x_tra
                value = self.y_train[i] * y_hat

                #If we have a missclassification, subtract the second
                if value < 1:
                    step = y_train[i]/(t*self.lambda_reg)
                    alpha[i]+=1*step
                t += 1
            #Increment epoch counter variable
            epoch += 1
        self.alpha = alpha
        return True

    def classification_error(self,y_hats):
        error = 0
        for i in range(len(y_hats)):
            if y_hats[i] >= 0 and self.y_test[i] != 1:
                error += 1
            elif y_hats[i] < 0 and self.y_test[i] != -1:
                error += 1
        return error / len(y_hats)
```

Question 34

Took a comprehensive iterative approach, started ide then honed in by restriciting the range I was searching over to get the best hyper parameters

In [22]:
```
sigmas = np.arange(-3,0,.1)
lambda_regs = np.logspace(-5,-2, num=40)
rbf_test_accuracy = []
rbf_lambda_reg = []
rbf_sigma_list = []
for sigma in sigmas:
    for lambda_reg in lambda_regs:
        k = functools.partial(RBF_kernel, sigma=sigma)
        f = train_soft_svm(x_train, y_train, y_test, k, lambda_reg,20)
        f.fit()
        y_bar = f.predict(x_test)
        rbf_test_accuracy.append(f.classification_error(y_bar))
        rbf_lambda_reg.append(lambda_reg)
        rbf_sigma_list.append(sigma)

index = rbf_test_accuracy.index(min(rbf_test_accuracy))
print("Best min mean test error at",rbf_test_accuracy[index]*100,
      "% with sigma = ",rbf_sigma_list[index],
      "lambda =", rbf_lambda_reg[index])
```

```
Best min mean test error at 3.375 % with sigma =  -0.9999999999999982
lambda = 0.00041246263829013523
```

In [23]:
```
degrees = np.arange(1,5,1)
offsets = np.arange(1,10,20)
lambda_regs = np.logspace(-5,-3, num=40)
poly_offset_list = []
poly_lambda_list = []
poly_degree_list = []
polynomial_test_accuracy = []
for degree in degrees:
    for offset in offsets:
        for lambda_reg in lambda_regs:
            k = functools.partial(polynomial_kernel, offset=offset, de
            f = train_soft_svm(x_train, y_train, y_test, k, lambda_reg
            f.fit()
            y_bar = f.predict(x_test)
            polynomial_test_accuracy.append(f.classification_error(y_b
            poly_lambda_list.append(lambda_reg)
            poly_offset_list.append(offset)
            poly_degree_list.append(degree)

index = polynomial_test_accuracy.index(min(polynomial_test_accuracy))
print("Best min mean test error at",polynomial_test_accuracy[index]*10
      "% with offset = ",poly_offset_list[index],
      "degree = ", poly_degree_list[index],
      "lambda =", poly_lambda_list[index])
```

```
Best min mean test error at 5.625 % with offset =  1 degree =  2 lamb
da = 0.00043754793750741 84
```

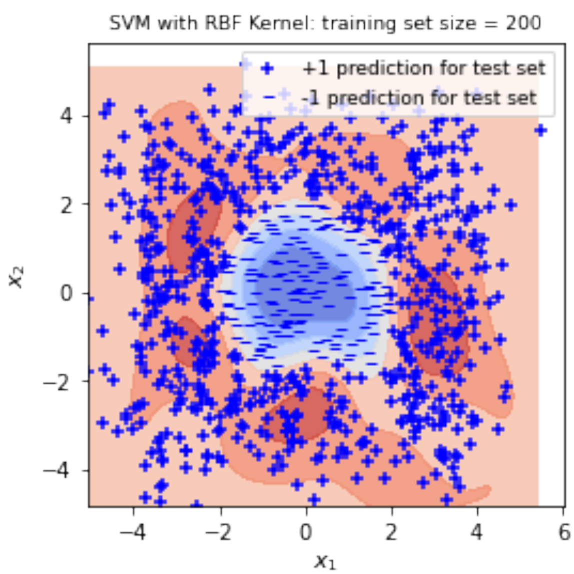
Question 35

RBF Kernel, Optimal Fit, $\sigma = -.99999$, $\lambda = .00412$

In [24]:
```
# Code to help plot the decision regions
# (Note: This ode isn't necessarily entirely appropriate for the quest
So think about what you are doing.)

sigma=1
k = functools.partial(RBF_kernel, sigma=-0.9999999999999982)
f = train_soft_svm(x_train, y_train, y_test, k, 0.0004124626382901352,
f.fit()
#determine the decision regions for the predictions
x1_min = min(x_test[:,0])
x1_max= max(x_test[:,0])
x2_min = min(x_test[:,1])
x2_max= max(x_test[:,1])
h=0.1
```

```
xx, yy = np.meshgrid(np.arange(x1_min, x1_max, h),
                     np.arange(x2_min, x2_max, h))

Z = f.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

#determine the predictions for the test set
y_bar = f.predict(x_test)
yplus = np.ma.masked_where(y_bar<=0, y_bar)
xplus = x_test[~np.array(yplus.mask)]
yminus = np.ma.masked_where(y_bar>0, y_bar)
xminus = x_test[~np.array(yminus.mask)]

print('Classification Error:',f.classification_error(y_bar)*100, '%')
#plot the learned boundary and the predictions for the test set
figsize = plt.figaspect(1)
f, (ax) = plt.subplots(1, 1, figsize=figsize)
decision =ax.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)
pluses = ax.scatter (xplus[:,0], xplus[:,1], marker='+', c='b',
                     label = '+1 prediction for test set')
minuses = ax.scatter (xminus[:,0], xminus[:,1], marker=r'$-$',
                      c='b', label = '-1 prediction for test set')
ax.set_ylabel(r"$x_2$", fontsize=11)
ax.set_xlabel(r"$x_1$", fontsize=11)
ax.set_title('SVM with RBF Kernel: training set size = %s'% len(data_t
ax.axis('tight')
ax.legend(handles=[pluses, minuses], fontsize=9)
plt.show()
```

```
Classification Error: 3.375 %
```

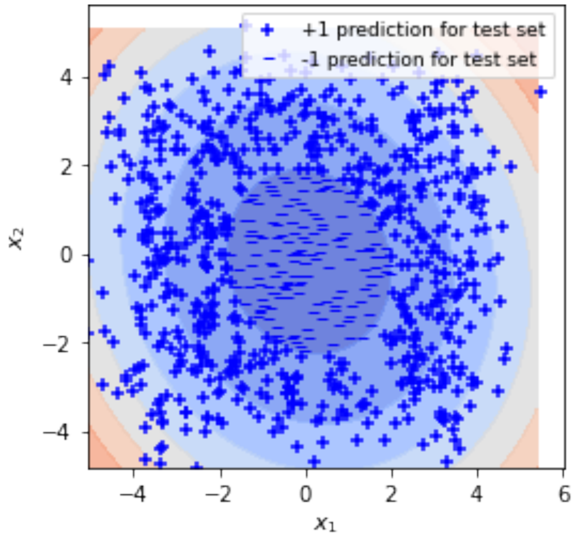


Polynomial Kernel, Optimal Fit, $Offset = 1$, $Degree = 2$, $\lambda = 0.0004375479375074184$

In [25]:
```
# Code to help plot the decision regions
# (Note: This ode isn't necessarily entirely appropriate for
the questions asked. So think about what you are doing.)

k = functools.partial(polynomial_kernel, offset=1,degree=2)
f = train_soft_svm(x_train, y_train, y_test, k, 0.0004375479375074184,
f.fit()
#determine the decision regions for the predictions
x1_min = min(x_test[:,0])
x1_max= max(x_test[:,0])
x2_min = min(x_test[:,1])
x2_max= max(x_test[:,1])
h=0.1
xx, yy = np.meshgrid(np.arange(x1_min, x1_max, h),
                     np.arange(x2_min, x2_max, h))

Z = f.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

#determine the predictions for the test set
y_bar = f.predict(x_test)
yplus = np.ma.masked_where(y_bar<=0, y_bar)
xplus = x_test[~np.array(yplus.mask)]
yminus = np.ma.masked_where(y_bar>0, y_bar)
xminus = x_test[~np.array(yminus.mask)]

print('Classification Error:',f.classification_error(y_bar)*100, '%')
#plot the learned boundary and the predictions for the test set
figsize = plt.figaspect(1)
f, (ax) = plt.subplots(1, 1, figsize=figsize)
decision =ax.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)
pluses = ax.scatter (xplus[:,0], xplus[:,1], marker='+', c='b',
                     label = '+1 prediction for test set')
minuses = ax.scatter (xminus[:,0], xminus[:,1], marker=r'$-$',
                      c='b', label = '-1 prediction for test set')
ax.set_ylabel(r"$x_2$", fontsize=11)
ax.set_xlabel(r"$x_1$", fontsize=11)
ax.set_title('SVM with RBF Kernel: training set size = %s'% len(data_t
ax.axis('tight')
ax.legend(handles=[pluses, minuses], fontsize=9)
plt.show()
```

```
Classification Error: 5.625 %
```

SVM with RBF Kernel: training set size = 200

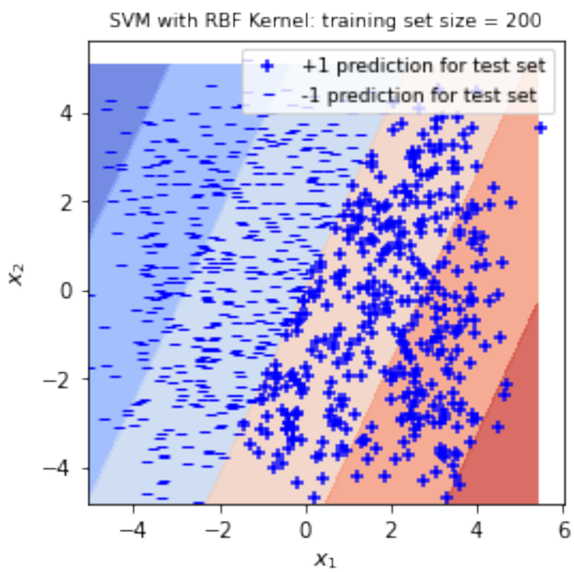


Linear Kernel, Optimal Fit

In [26]:
```
# Code to help plot the decision regions
# (Note: This ode isn't necessarily entirely appropriate for the quest

sigma=1
k = functools.partial(linear_kernel)
f = train_soft_svm(x_train, y_train, y_test, k, 1e-05,50)
f.fit()
#determine the decision regions for the predictions
x1_min = min(x_test[:,0])
x1_max= max(x_test[:,0])
x2_min = min(x_test[:,1])
x2_max= max(x_test[:,1])
h=0.1
xx, yy = np.meshgrid(np.arange(x1_min, x1_max, h),
                     np.arange(x2_min, x2_max, h))

Z = f.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

#determine the predictions for the test set
y_bar = f.predict(x_test)
yplus = np.ma.masked_where(y_bar<=0, y_bar)
xplus = x_test[~np.array(yplus.mask)]
yminus = np.ma.masked_where(y_bar>0, y_bar)
xminus = x_test[~np.array(yminus.mask)]

print('Classification Error:',f.classification_error(y_bar)*100, '%')
#plot the learned boundary and the predictions for the test set
figsize = plt.figaspect(1)
f, (ax) = plt.subplots(1, 1, figsize=figsize)
```

```
decision =ax.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)
pluses = ax.scatter (xplus[:,0], xplus[:,1], marker='+', c='b',
                     label = '+1 prediction for test set')
minuses = ax.scatter (xminus[:,0], xminus[:,1], marker=r'$-$',
                      c='b', label = '-1 prediction for test set')
ax.set_ylabel(r"$x_2$", fontsize=11)
ax.set_xlabel(r"$x_1$", fontsize=11)
ax.set_title('SVM with RBF Kernel: training set size = %s'% len(data_t
ax.axis('tight')
ax.legend(handles=[pluses, minuses], fontsize=9)
plt.show()
```

```
Classification Error: 49.875 %
```



In [ ]: