Assignment 7

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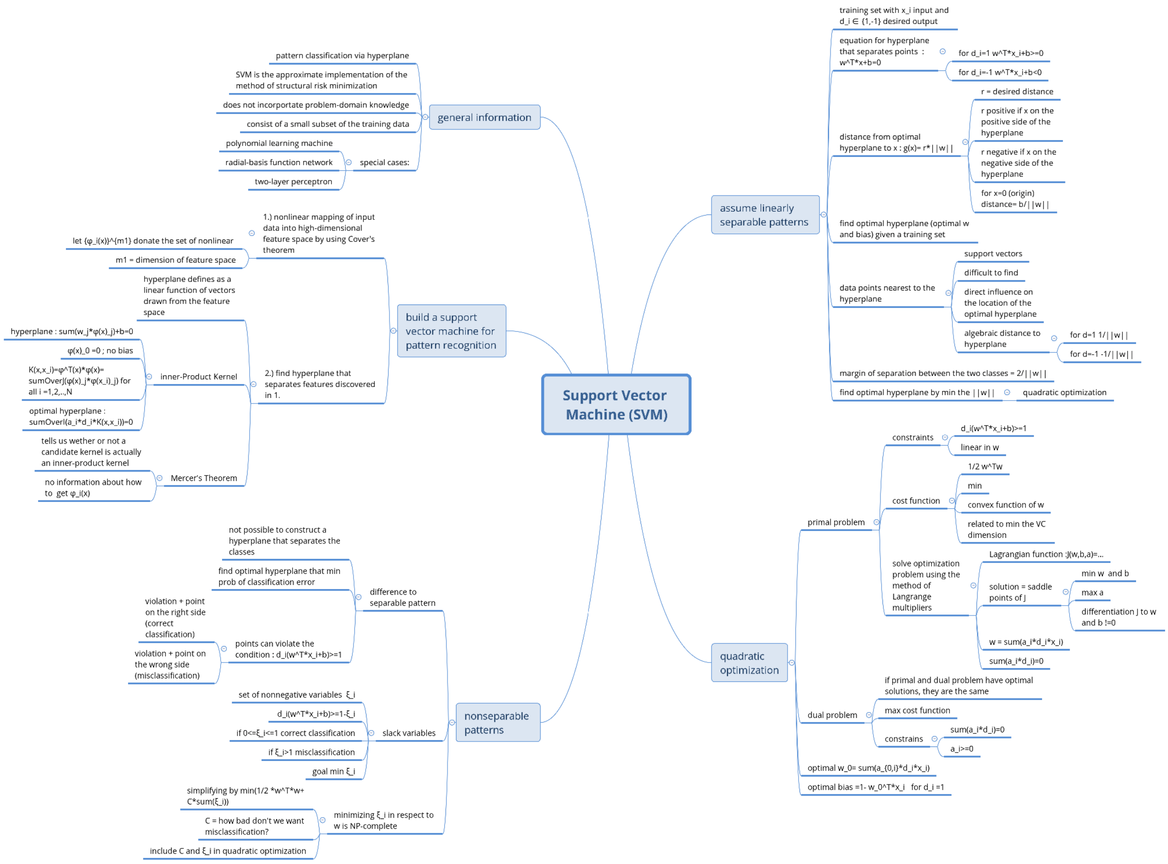
1

In [4]:

```
from IPython.display import Image
Image("SVM.png")
```

Out[4]:



2

What is the lowest order polynomial decison function ?

a) $f(x) = ax^2 + bx + c$
b) $f(x) = ax^3 + bx^2 + cx + d$
c) $f(x) = ax + b$

What are the numbers of hidden neurons for a SVM with Gaussian basis function

The number of hidden neurons is determined by the number of support vectors.

a) 3 hidden neurons
b) 4 hidden neurons
c) 2 hidden neurons

3

In [5]:

```
import numpy as np
import sklearn.svm as svm
import matplotlib.pyplot as plt
%matplotlib inline
```

In [11]:

```
class MoonPair:
    def __init__(self, r, w, d, noise_probability=0):
        self.r = r
        self.w = w
        self.d = d
        self.noise_probability = noise_probability

    def get_region_a_point(self, sure=False):
        if not sure and np.random.rand() < self.noise_probability:
            return self.get_region_b_point(True)
        while True:
            point = np.array([np.random.rand() * (self.r + self.w/2) * 2 - (self.r
                              np.random.rand() * (self.r + self.w/2)])
            norm = np.linalg.norm(point)
            if norm < self.r + self.w/2 and norm > self.r - self.w/2:
                return point

    def get_region_b_point(self, sure=False):
        if not sure and np.random.rand() < self.noise_probability:
            return self.get_region_a_point(True)
        while True:
            point = np.array([np.random.rand() * (self.r + self.w/2) * 2 - self.w/2
                              -np.random.rand() * (self.r + self.w/2) - self.d])
            norm = np.linalg.norm(point - np.array([self.r, -self.d]))
            if norm < self.r + self.w/2 and norm > self.r - self.w/2:
                return point

    def print_pair(self):
        points_a = []
        points_b = []
        for i in range(1000):
            points_a.append(self.get_region_a_point())
            points_b.append(self.get_region_b_point())

        points_a = np.array(points_a)
        points_b = np.array(points_b)
        plt.figure()
        plt.axis('equal')
        plt.title("r = " + str(self.r) + ", w = " + str(self.w) + \
                  ", d = " + str(self.d) + ", noise = " + str(self.noise_probabilit
        plt.scatter(points_a[:,0], points_a[:,1])
        plt.scatter(points_b[:,0], points_b[:,1])
        plt.legend(["A", "B"])
        plt.show()

    def generate_sample_set(self, size, sure=False):
        sample = []
        for i in range(round(size / 2)):
            sample.append(np.hstack((self.get_region_a_point(sure), 'A')))
            sample.append(np.hstack((self.get_region_b_point(sure), 'B')))
        return np.array(sample)

    def try_svm(self, machine, train_size, test_size, plot_errors=False):
        train_set = self.generate_sample_set(train_size)
        input = np.array(train_set[:,0:2], dtype=float)
        output = train_set[:,2]
        machine.fit(input, output)

        test_set = self.generate_sample_set(test_size, sure=True)
```

```
        test_input = np.array(test_set[:,0:2], dtype=float)

        prediction = machine.predict(test_input)
        x = 0
        error = 0
        error_colors = []
        for i in prediction:
            if i != test_set[x, 2]:
                error = error + 1
                error_colors.append("r")
            else:
                error_colors.append("g")
            x = x + 1
        error = error / test_size
        plt.axis('equal')
        plt.title("Result of SVM classification (error = " + \
                  str(np.round(error, 2)) + ")\n" + "Kernel: " + machine.kernel + "
                  str(self.r) + ", w = " + str(self.w) + ", d = " + str(self.d))
        if plot_errors:
            plt.scatter(test_input[np.where(prediction == test_set[:,2])][:,0], \
                        test_input[np.where(prediction == test_set[:,2])][:,1], c="
            plt.scatter(test_input[np.where(prediction != test_set[:,2])][:,0], \
                        test_input[np.where(prediction != test_set[:,2])][:,1], c="
            plt.legend(["classified correctly", "classified wrongly"])
        else:
            plt.scatter(test_input[np.where(prediction == 'A')][:,0], \
                        test_input[np.where(prediction == 'A')][:,1])
            plt.scatter(test_input[np.where(prediction == 'B')][:,0], \
                        test_input[np.where(prediction == 'B')][:,1])

        plt.legend(["classified as A", "classified as B"])
        plt.show()
        return error
```

In [7]:

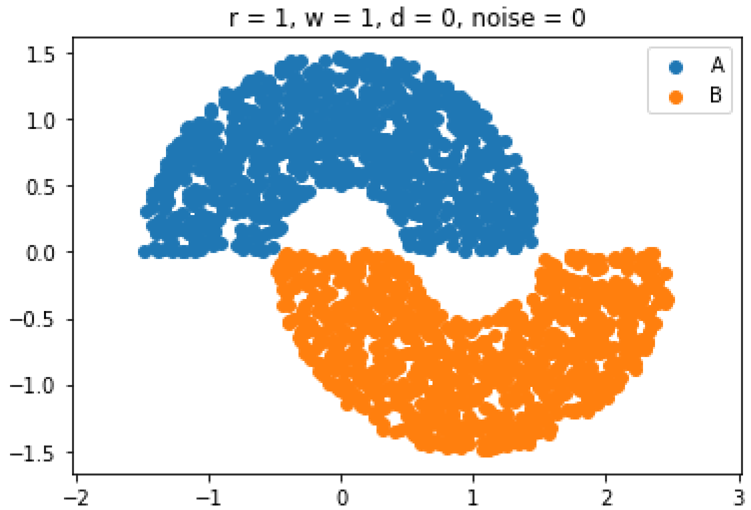
```
# Disable jupyter notebook scrolling
```

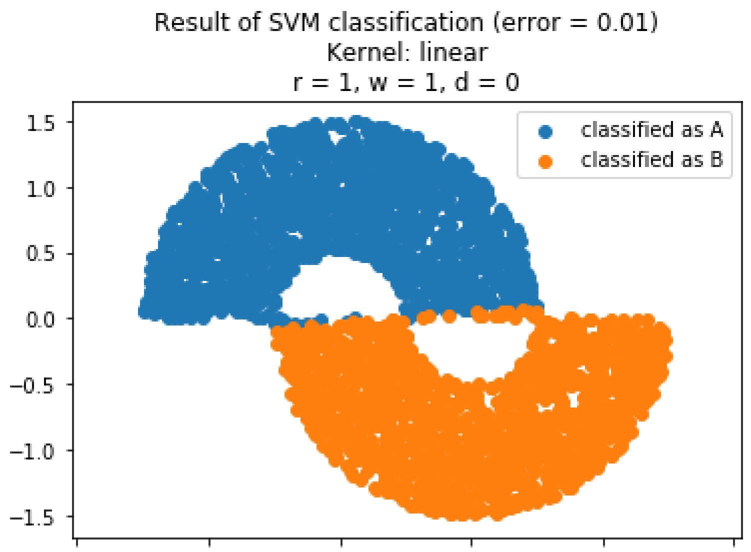
In [8]:

```
%%javascript
IPython.OutputArea.prototype._should_scroll = function(lines) {
    return false;
}
```

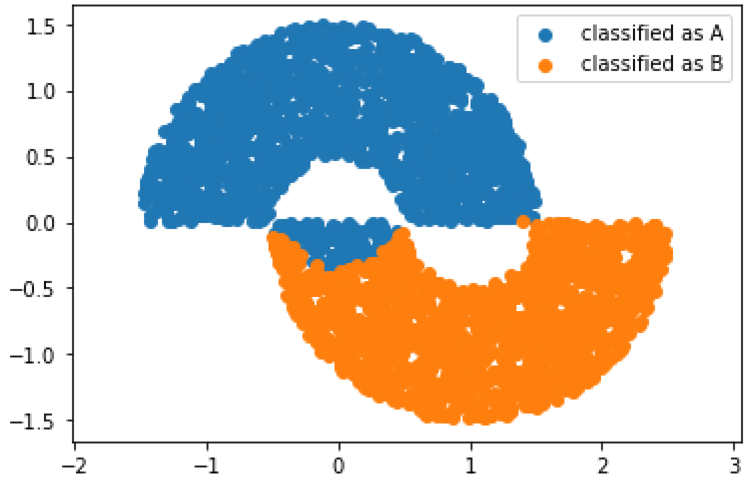
In [14]:

```
train_size = 1000
test_size = 3000

cases = []
cases.append(MoonPair(1, 1, 0))
cases.append(MoonPair(1, 1, -1/2))
cases.append(MoonPair(1, 1, -1))
cases.append(MoonPair(1, 1, -3/2))
cases.append(MoonPair(1, 1, 0, noise_probability=0.2))

kernels = ["linear", "poly", "rbf", "sigmoid"]

for case in cases:
    case.print_pair()
    errors = []
    for kernel_ in kernels:
        errors.append(case.try_svm(svm.SVC(kernel=kernel_), \
                train_size, test_size))

    plt.figure()
    plt.bar(range(len(errors)), errors)
    plt.xticks(range(len(errors)), kernels)
    plt.xlabel("Kernels")
    plt.ylabel("Error")
    plt.title("Comparison of kernels")
    plt.show()
```

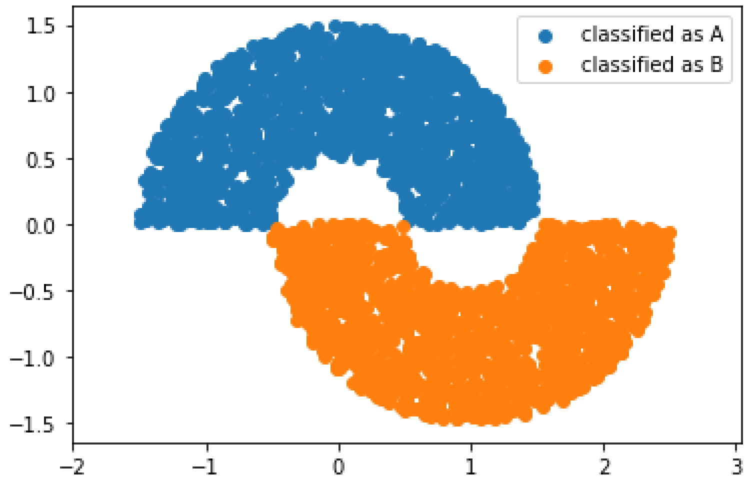




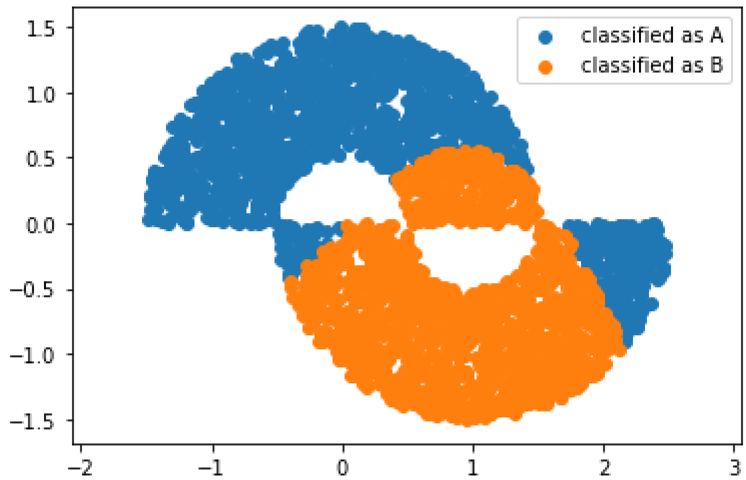
Result of SVM classification (error = 0.04)
Kernel: poly
r = 1, w = 1, d = 0

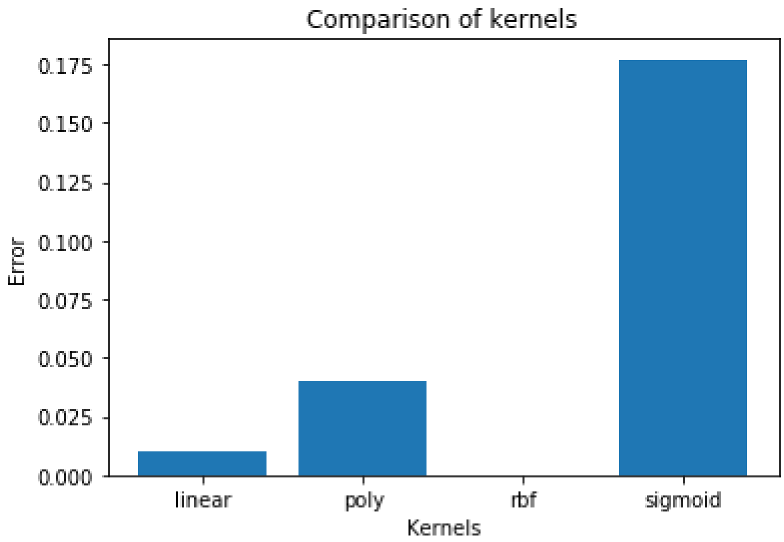


Result of SVM classification (error = 0.0)
Kernel: rbf
r = 1, w = 1, d = 0

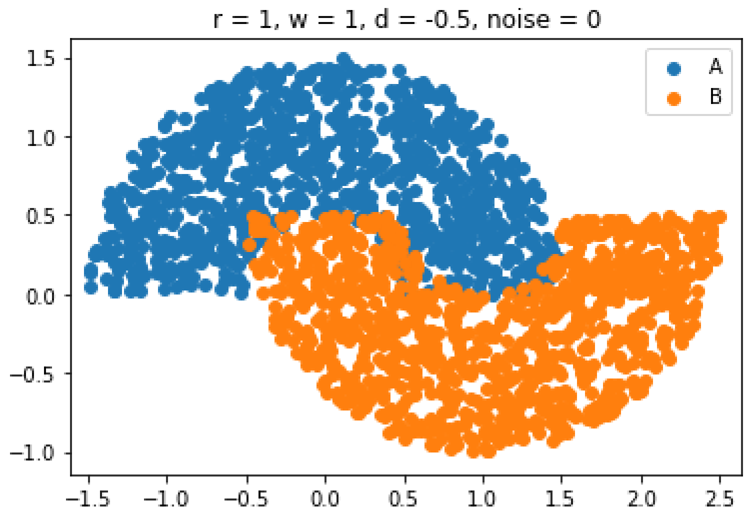


Result of SVM classification (error = 0.18)
Kernel: sigmoid
r = 1, w = 1, d = 0

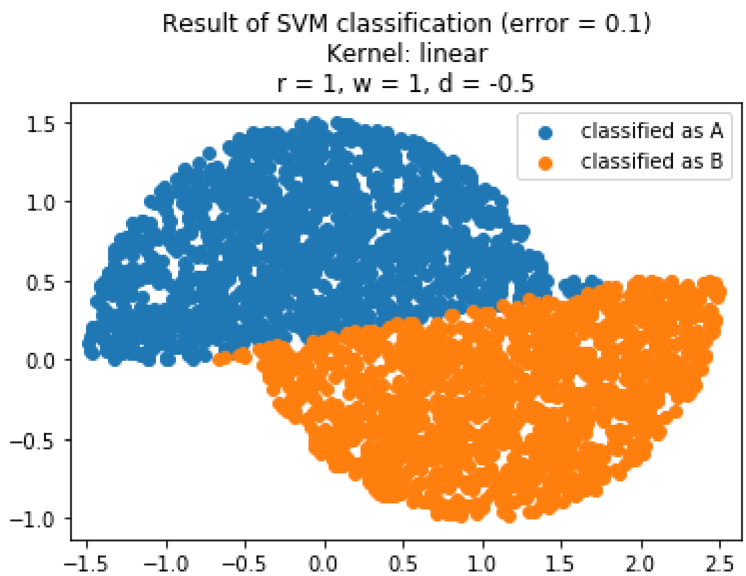




Comparison of kernels
Error
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
linear
poly
rbf
sigmoid
Kernels

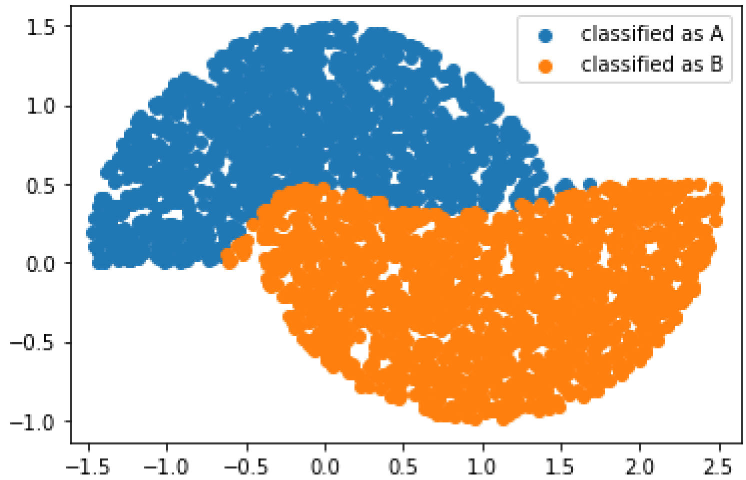


r = 1, w = 1, d = -0.5, noise = 0
A
B
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5

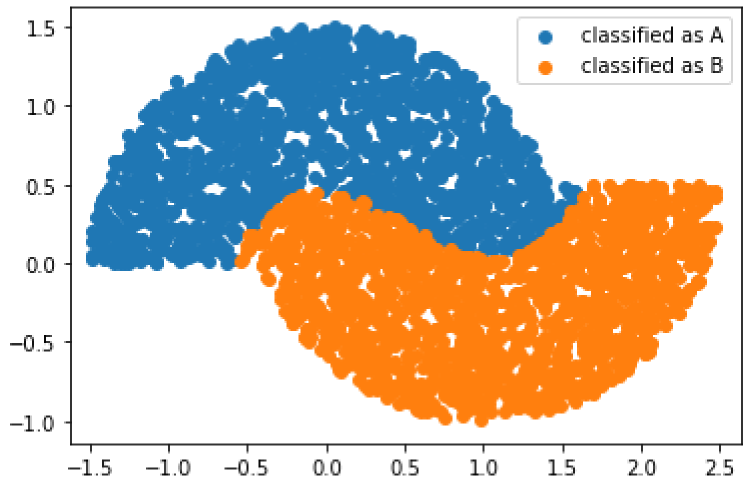


Result of SVM classification (error = 0.1)
Kernel: linear
r = 1, w = 1, d = -0.5
classified as A
classified as B
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5

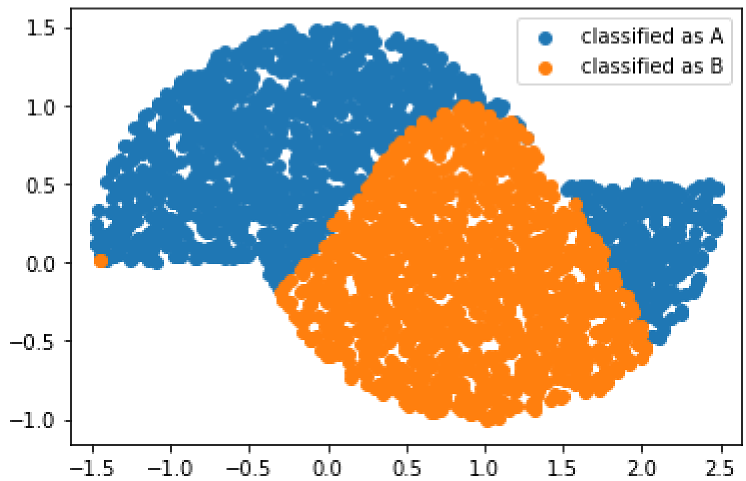
Result of SVM classification (error = 0.07)
Kernel: poly
r = 1, w = 1, d = -0.5

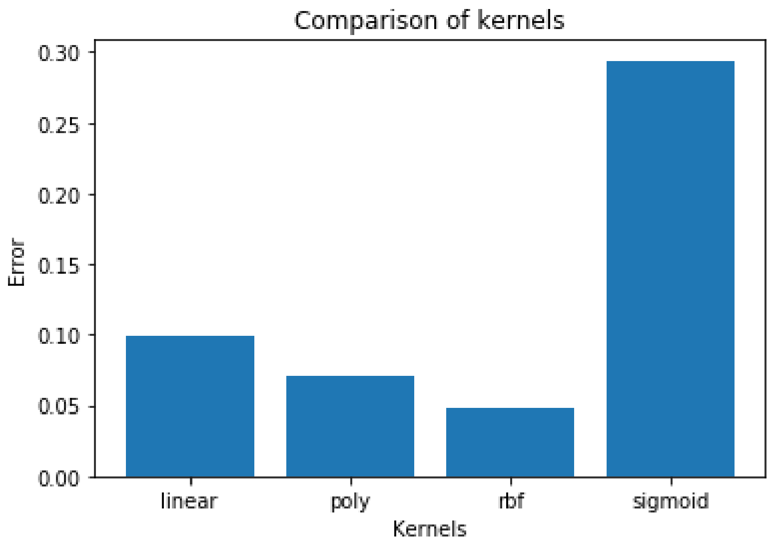


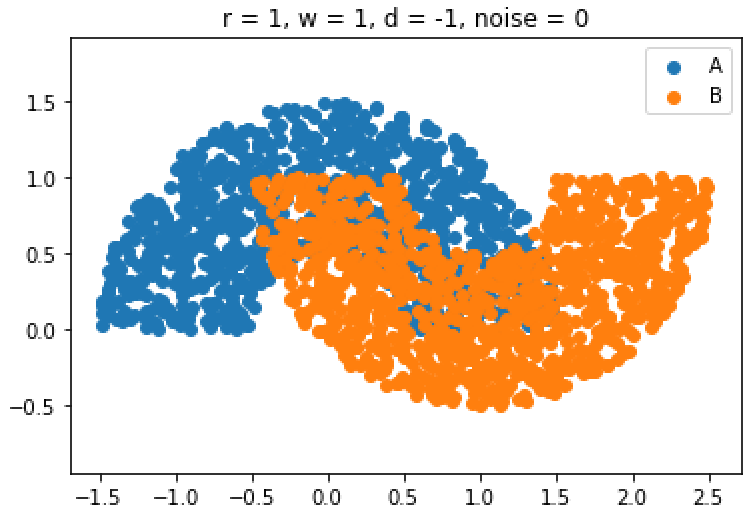
Result of SVM classification (error = 0.05)
Kernel: rbf
r = 1, w = 1, d = -0.5

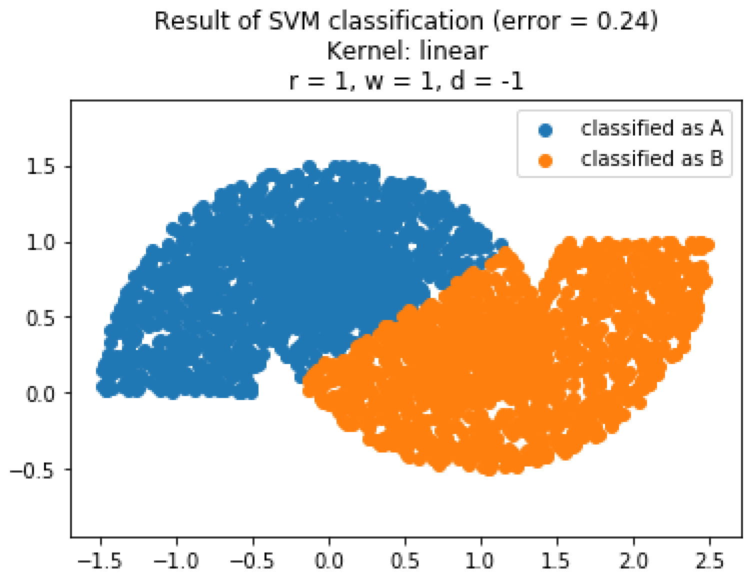


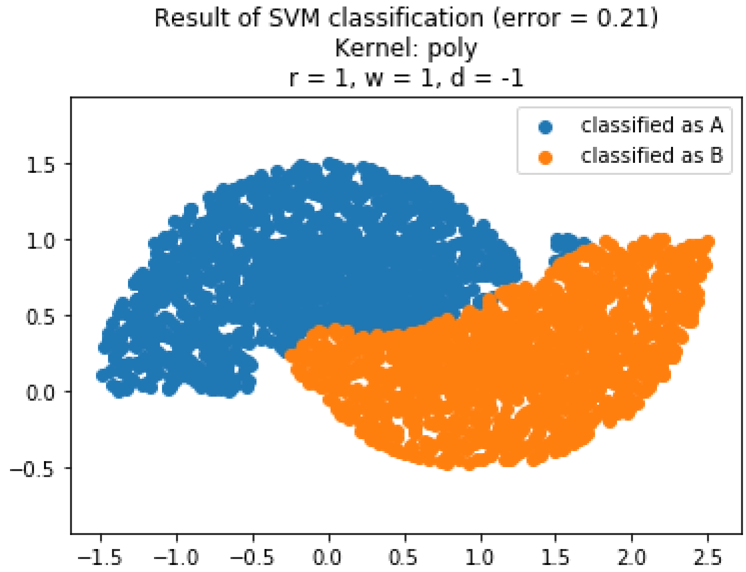
Result of SVM classification (error = 0.29)
Kernel: sigmoid
r = 1, w = 1, d = -0.5

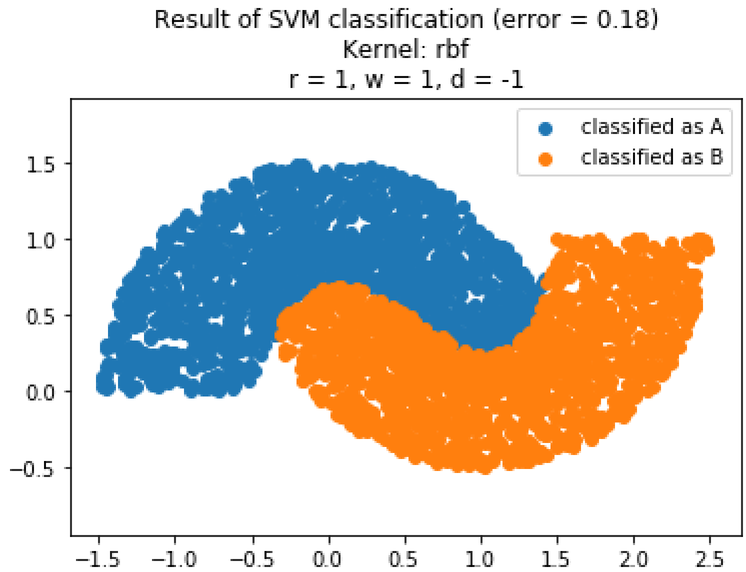


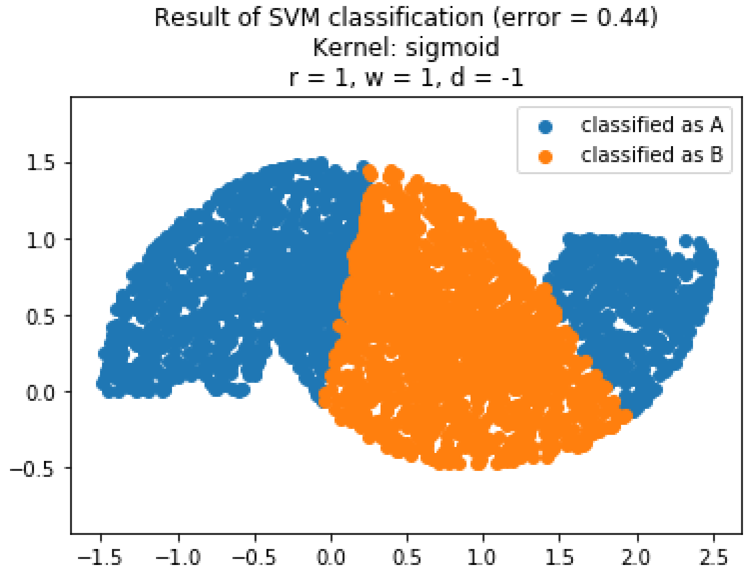

Comparison of kernels
Error
Kernels
linear
poly
rbf
sigmoid


r = 1, w = 1, d = -1, noise = 0
A
B

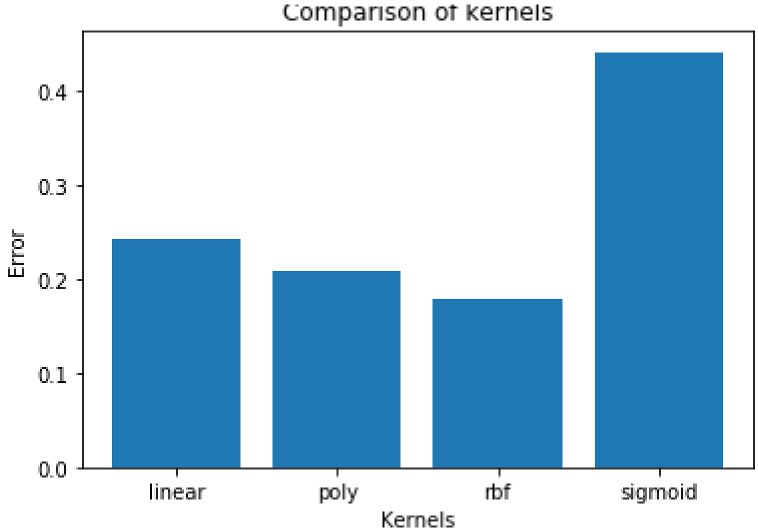

Result of SVM classification (error = 0.24)
Kernel: linear
r = 1, w = 1, d = -1
classified as A
classified as B


Result of SVM classification (error = 0.21)
Kernel: poly
r = 1, w = 1, d = -1
classified as A
classified as B

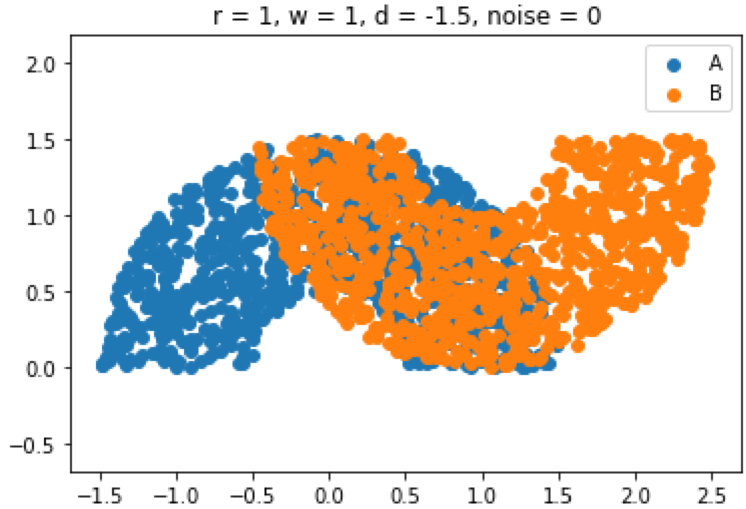

Result of SVM classification (error = 0.18)
Kernel: rbf
r = 1, w = 1, d = -1
classified as A
classified as B


Result of SVM classification (error = 0.44)
Kernel: sigmoid
r = 1, w = 1, d = -1
classified as A
classified as B

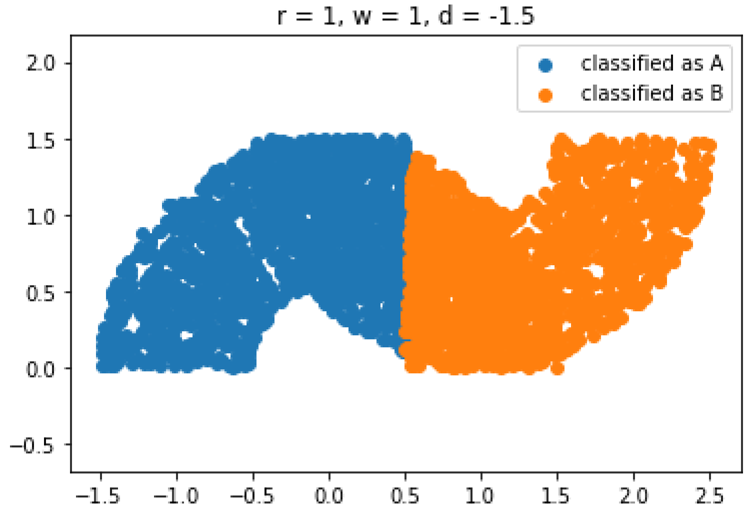
Comparison of kernels



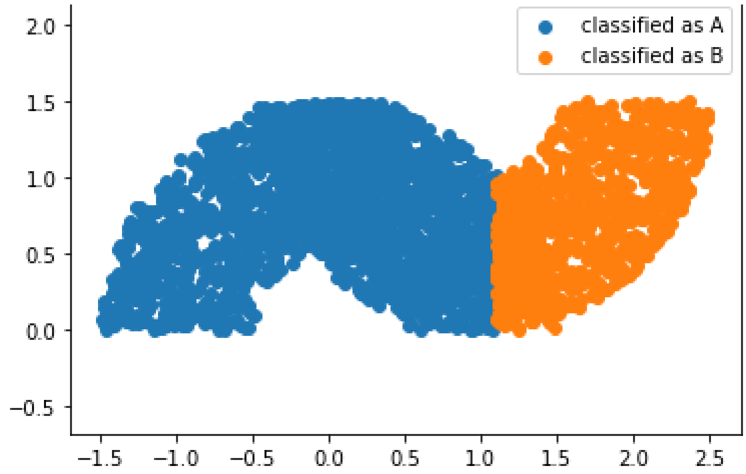
r = 1, w = 1, d = -1.5, noise = 0



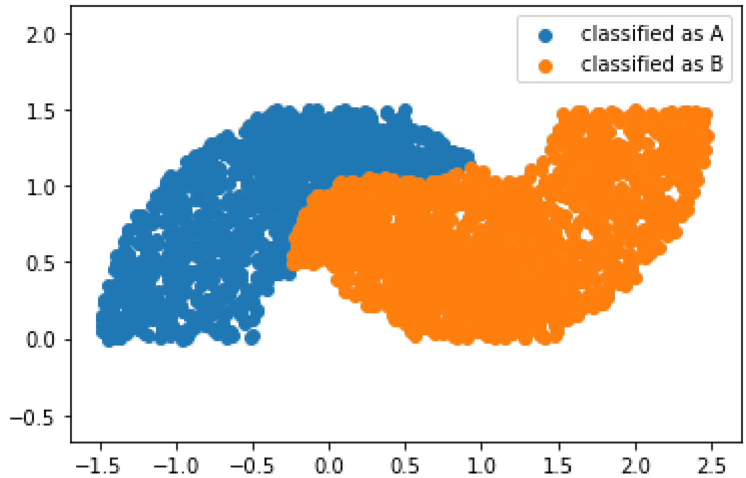
Result of SVM classification (error = 0.33)
Kernel: linear
r = 1, w = 1, d = -1.5



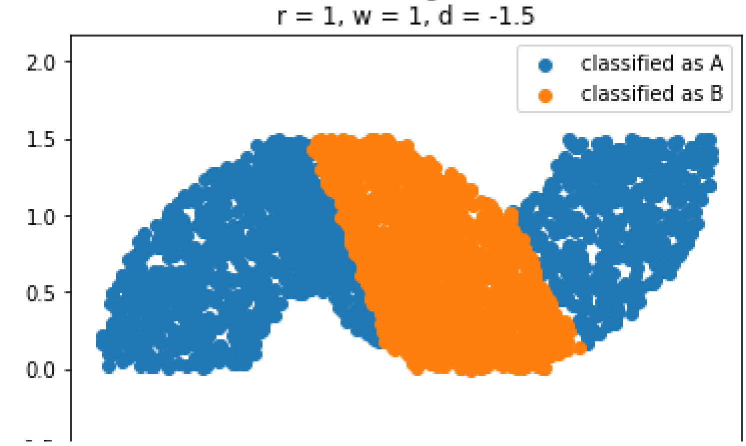
Result of SVM classification (error = 0.31)
Kernel: poly
r = 1, w = 1, d = -1.5

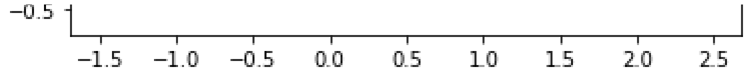


Result of SVM classification (error = 0.3)
Kernel: rbf
r = 1, w = 1, d = -1.5

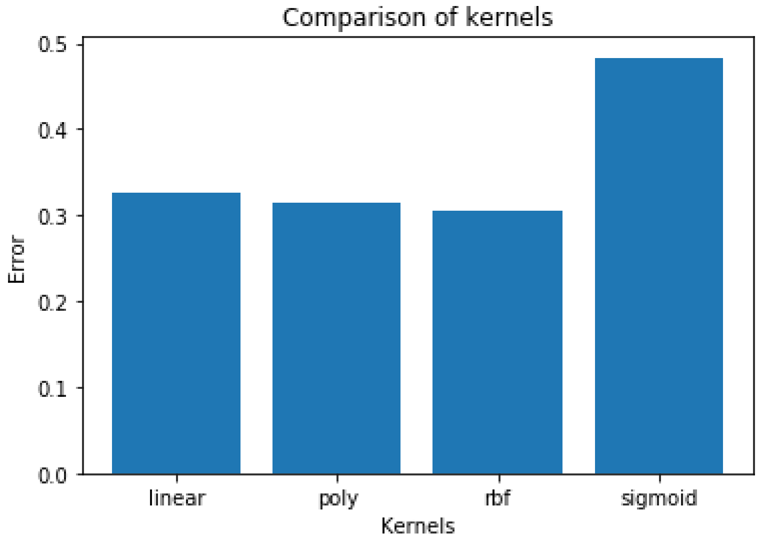


Result of SVM classification (error = 0.48)
Kernel: sigmoid
r = 1, w = 1, d = -1.5

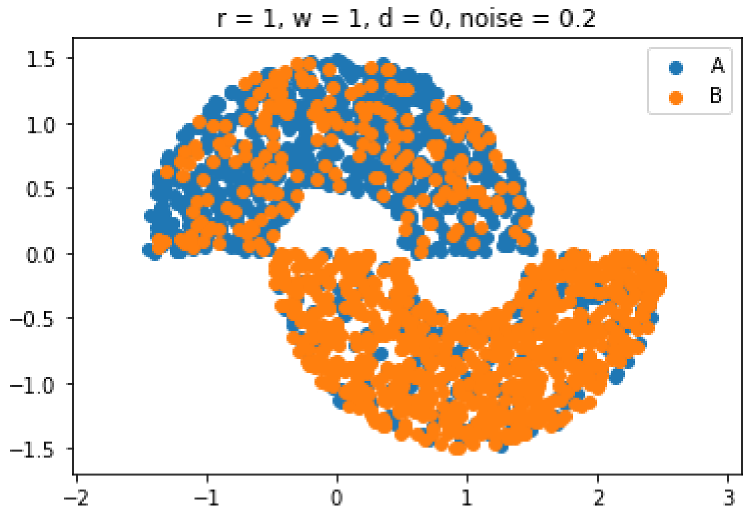




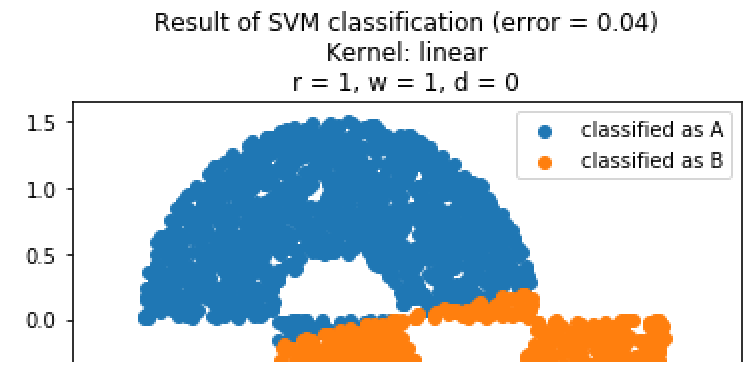
−0.5
−1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0 2.5



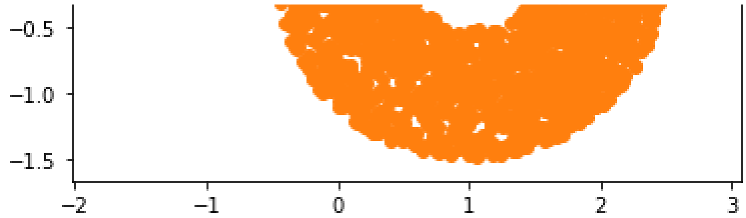
Comparison of kernels
Error
0.0 0.1 0.2 0.3 0.4 0.5
linear
poly
rbf
sigmoid
Kernels



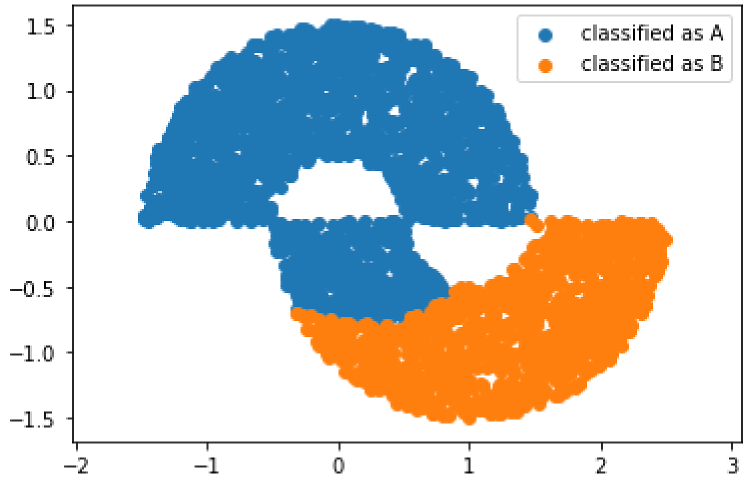
r = 1, w = 1, d = 0, noise = 0.2
A
B
1.5 1.0 0.5 0.0 −0.5 −1.0 −1.5
−2 −1 0 1 2 3



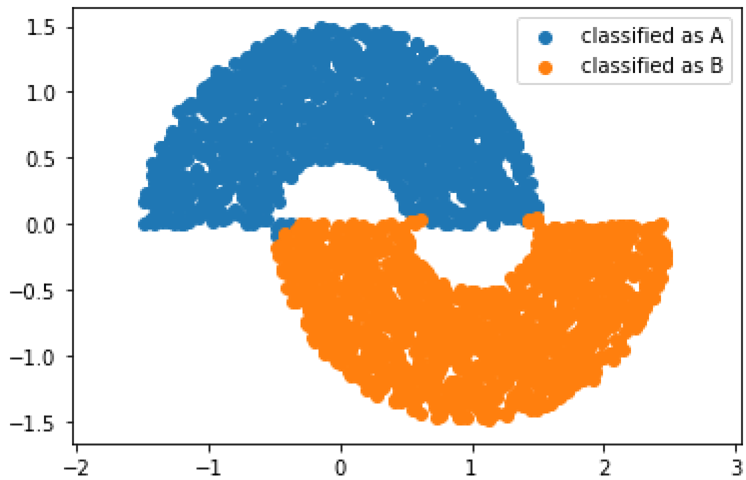
Result of SVM classification (error = 0.04)
Kernel: linear
r = 1, w = 1, d = 0
classified as A
classified as B
1.5 1.0 0.5 0.0



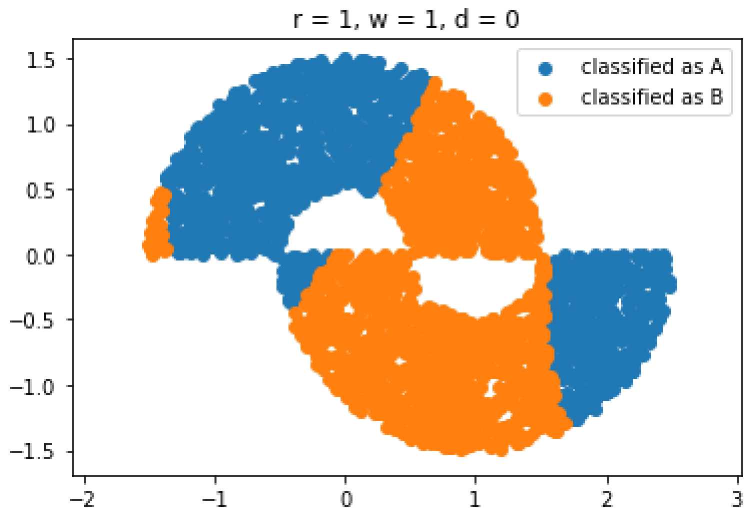
Result of SVM classification (error = 0.13)
Kernel: poly
r = 1, w = 1, d = 0

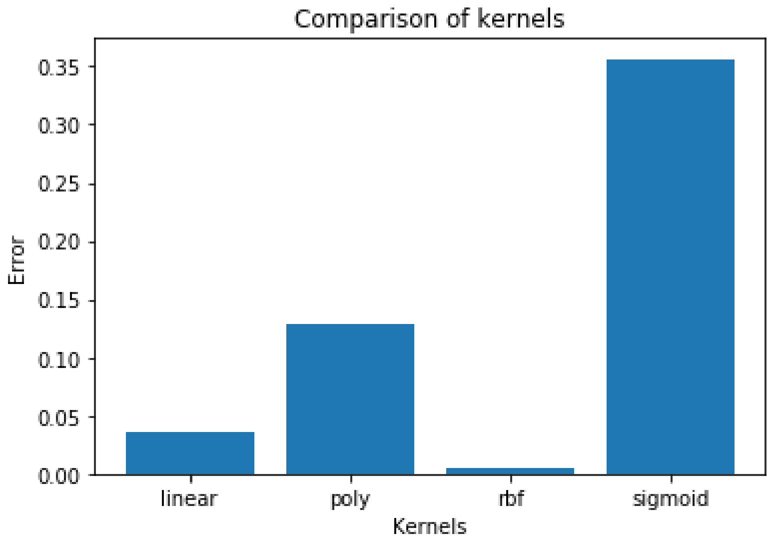


Result of SVM classification (error = 0.0)
Kernel: rbf
r = 1, w = 1, d = 0



Result of SVM classification (error = 0.36)
Kernel: sigmoid





In the provious plots we can see that the radial basis kernel works very well for all tasks. Even strong noise lets the SVM work pretty good. The sigmoid kernel performs worst in all cases.

In [ ]: