

Machine Intelligence II - Team MensaNord

Sheet 08

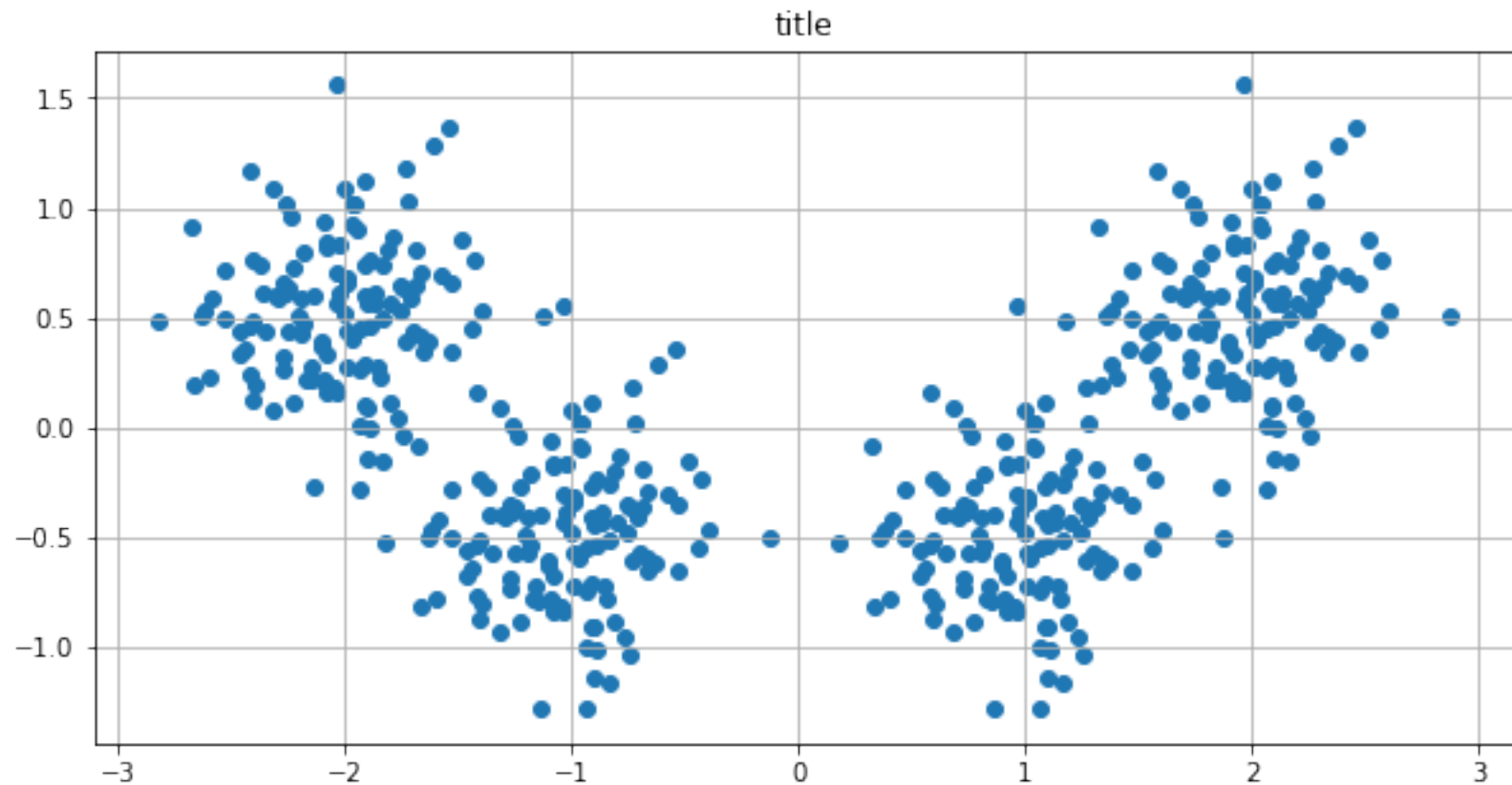
- Nikolai Zaki
- Alexander Moore
- Johannes Rieke
- Georg Hoelger
- Oliver Atanaszov

```
In [1]: from __future__ import division, print_function
import matplotlib.pyplot as plt
%matplotlib inline
import scipy.stats
import numpy as np
import math
```

```
In [2]: data = np.loadtxt("cluster.dat").T
print(data.shape)
mean = np.mean(data, 0)
print(mean)
```

```
plt.figure(figsize=(10, 5))
plt.scatter(data.T[0], data.T[1])
plt.title('title')
plt.grid()
plt.show()
```

```
(500, 2)
[-0.03206334  0.02905982]
```



```

In [3]: Ks = [2, 3, 4, 5, 6, 7, 8]
        tmax = 5
        Error = [0.0 for i in range(tmax)]
        colors = ['blue', 'green', 'red', 'brown', 'c', 'yellow', 'gray', 'm']

        for k in Ks:

            print("k = ", k)
            print("data at start")
            w = [[mean[0] + np.random.random() - 0.5,
                    mean[1] + np.random.random() - 0.5]
                  for i in range(k)]
            w = np.asarray(w)

            plt.figure(figsize=(10, 5))
            plt.scatter(data.T[0], data.T[1])
            plt.scatter(w.T[0], w.T[1])
            plt.title('data and prototypes')
            plt.grid()
            plt.show()

            m = [[0.0 for i in range(k)] for i in range(data.shape[0])]

            # 41.pdf page 8
            for loop in range(tmax):

                m = [[0.0 for i in range(k)] for i in range(data.shape[0])]
                m = np.asarray(m)

                # calculate vector m
                for alpha in range(data.shape[0]):
                    dist_diff = data[alpha] - w
                    dist_abs = [0.0 for i in range(k)]

```

```

        for i in range(k):
            dist_abs[i] = math.hypot(dist_diff[i, 0], dist_diff[i, 1])
        q = np.argmin(dist_abs)
        m[alpha][q] = 1

    # calculate error function
    for q in range(k):
        for alpha in range(data.shape[0]):
            dist = (data[alpha] - w[q])
            Error[loop] += m[alpha][q] * math.hypot(dist[0], dist[1])
            Error[loop] /= 2 * data.shape[0]

        # update vector w
        for q in range(k):
            number_of_elements = np.sum(m.T[q])
            if number_of_elements != 0:
                mass = np.dot(m.T[q].T, data)
                w[q] = mass / number_of_elements

    # IDENT THIS (one tab more) TO SEE EVERY STEP
    print("data at end")
    plt.figure(figsize=(10, 5))
    for alpha in range(data.shape[0]):
        plt.scatter(data[alpha][0], data[alpha][1], c=colors[np.argmax(m[alpha])])
    plt.scatter(w.T[0], w.T[1], c='yellow')
    plt.title('data and prototypes')
    plt.grid()
    plt.show()

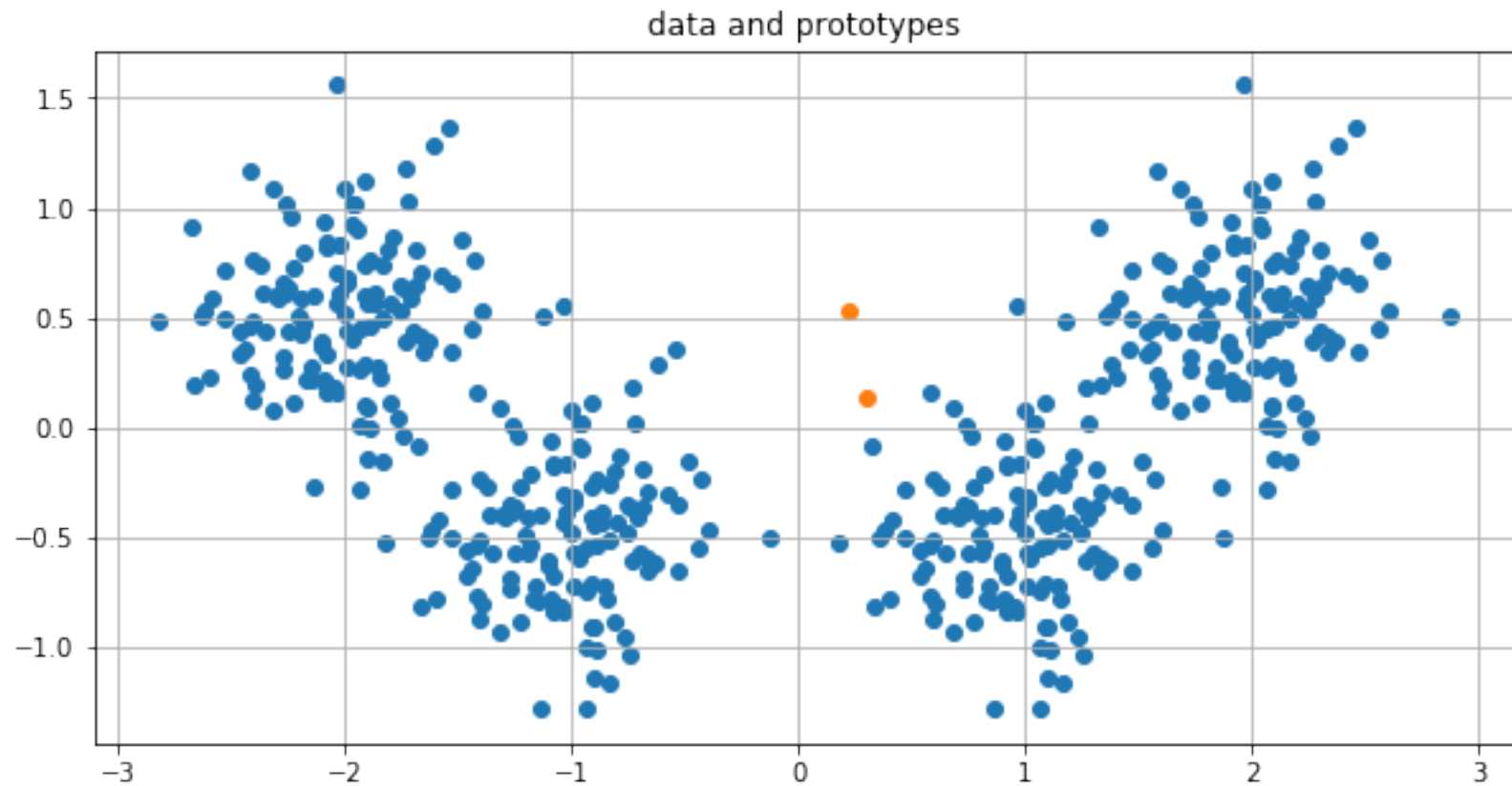
    print("error")
    plt.figure(figsize=(10, 5))
    plt.plot(Error)

```

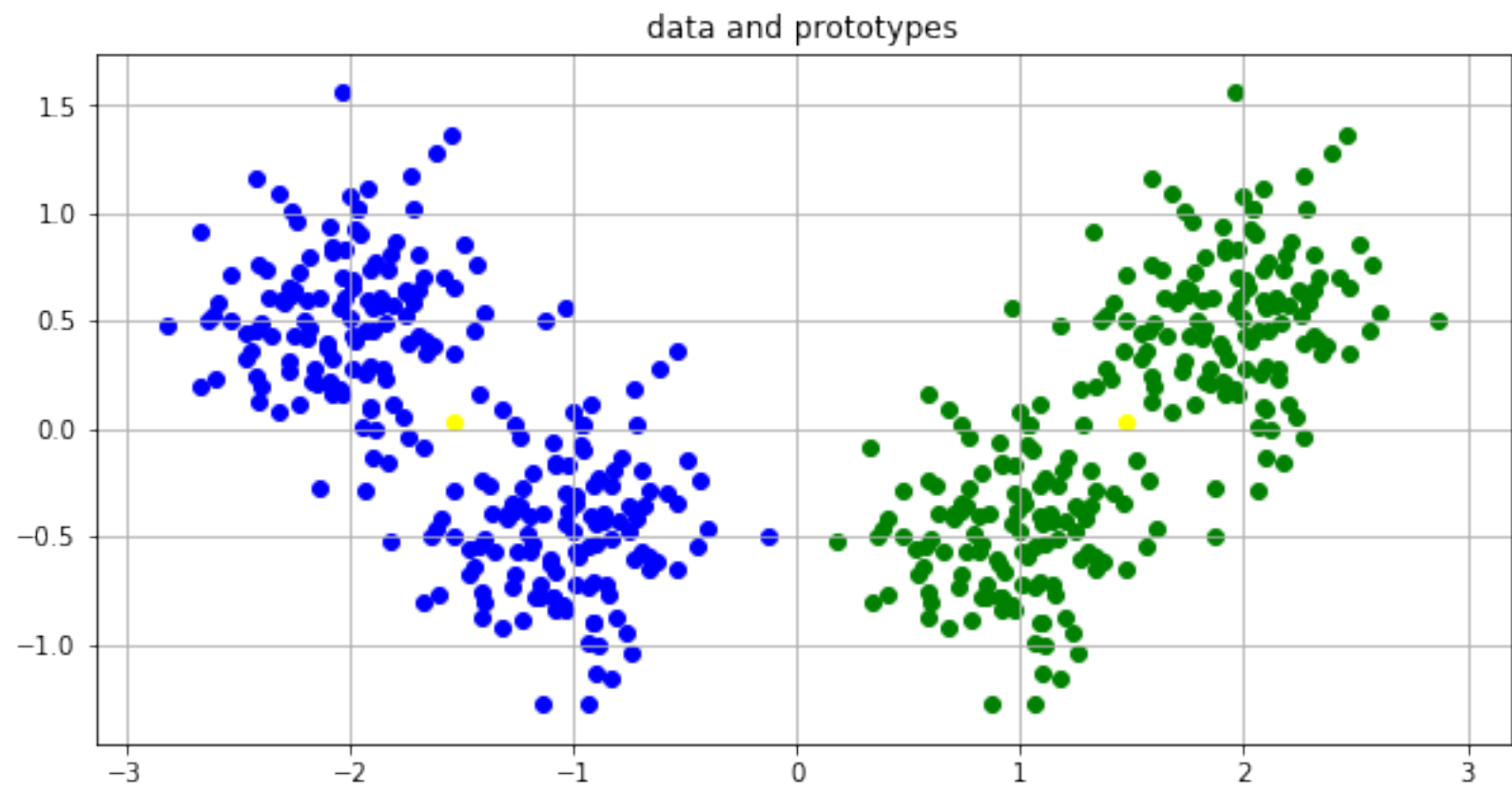
```
plt.title('Error before iteration X')  
plt.grid()  
plt.show()
```

k = 2

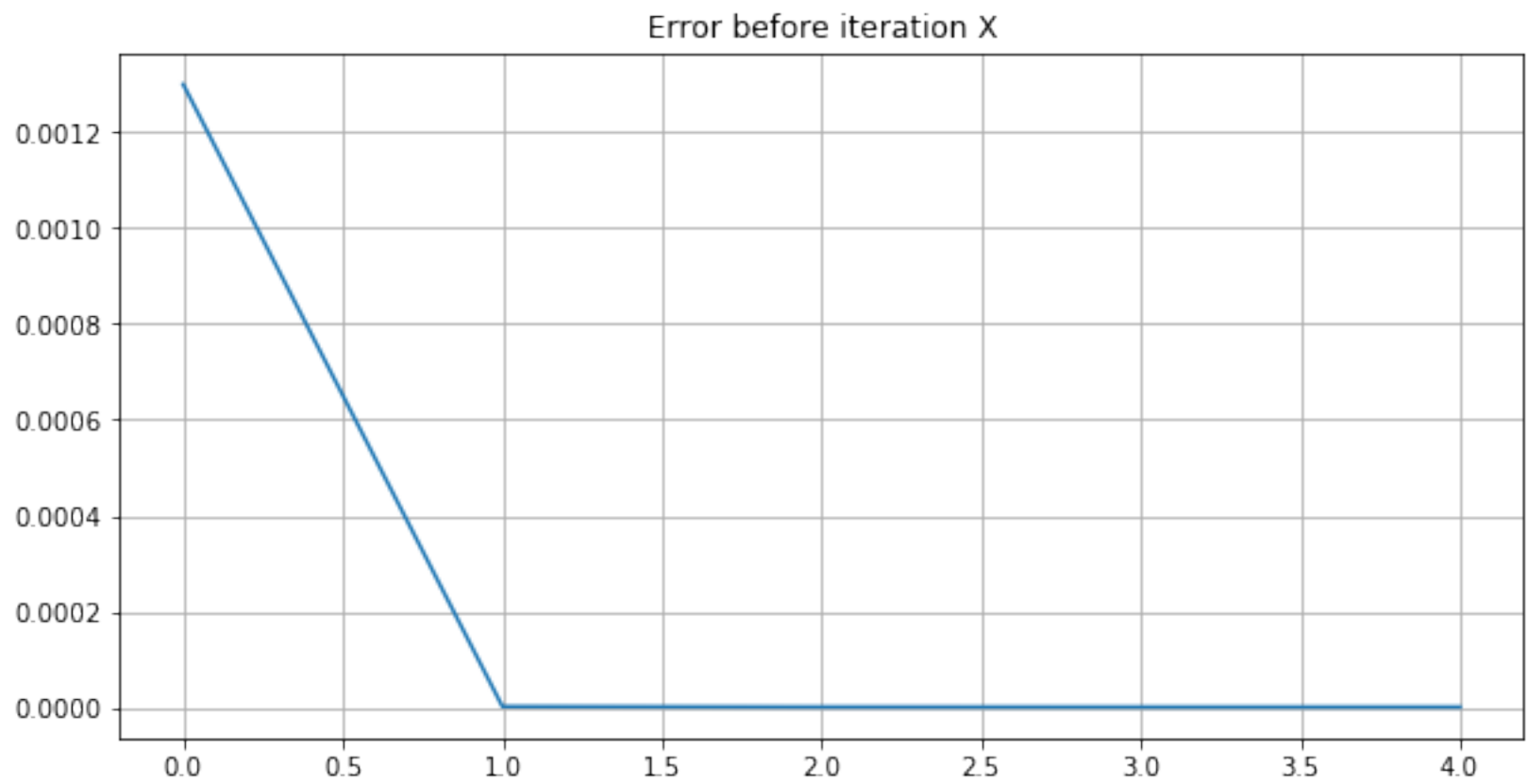
data at start



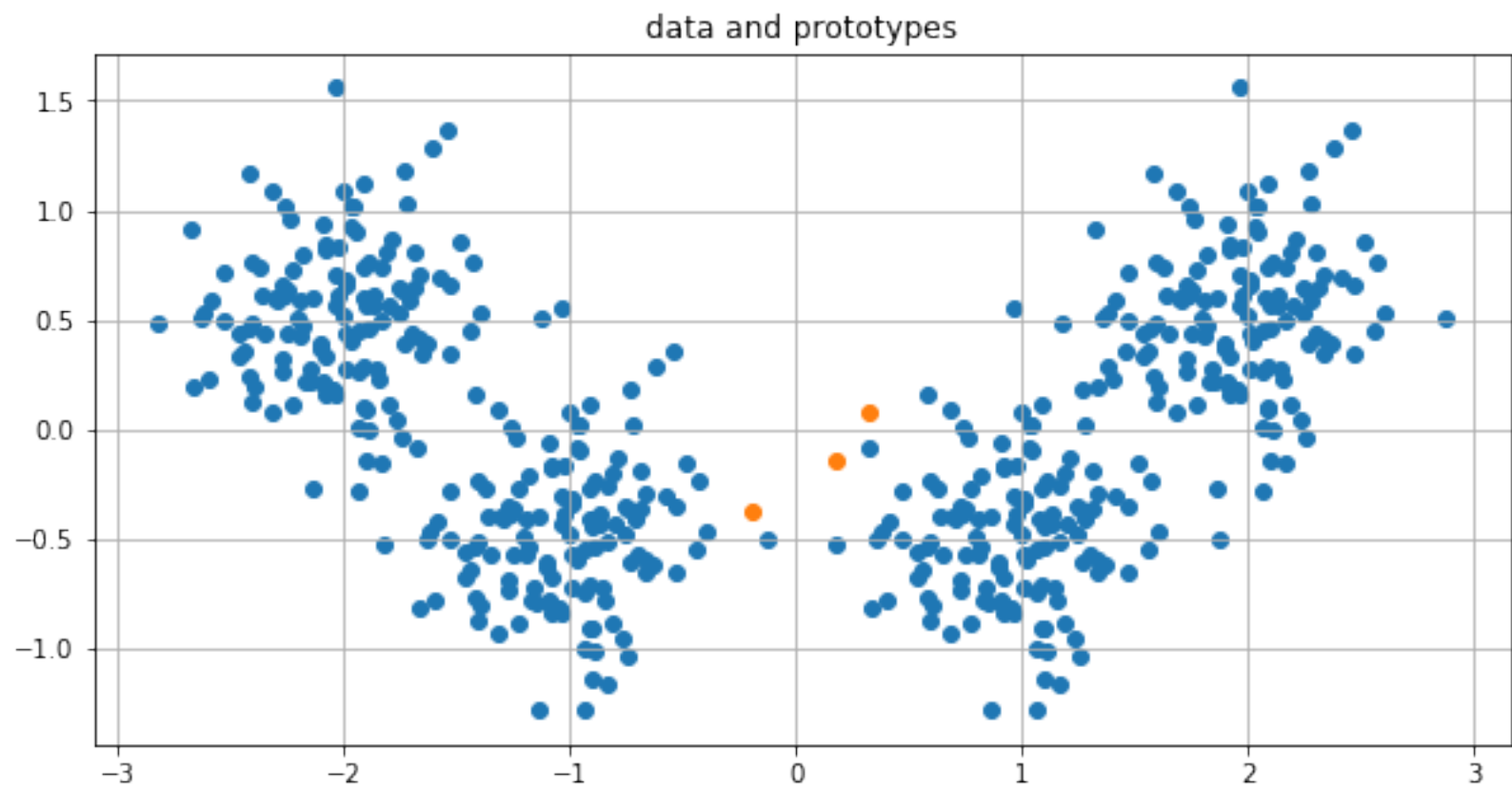
data at end



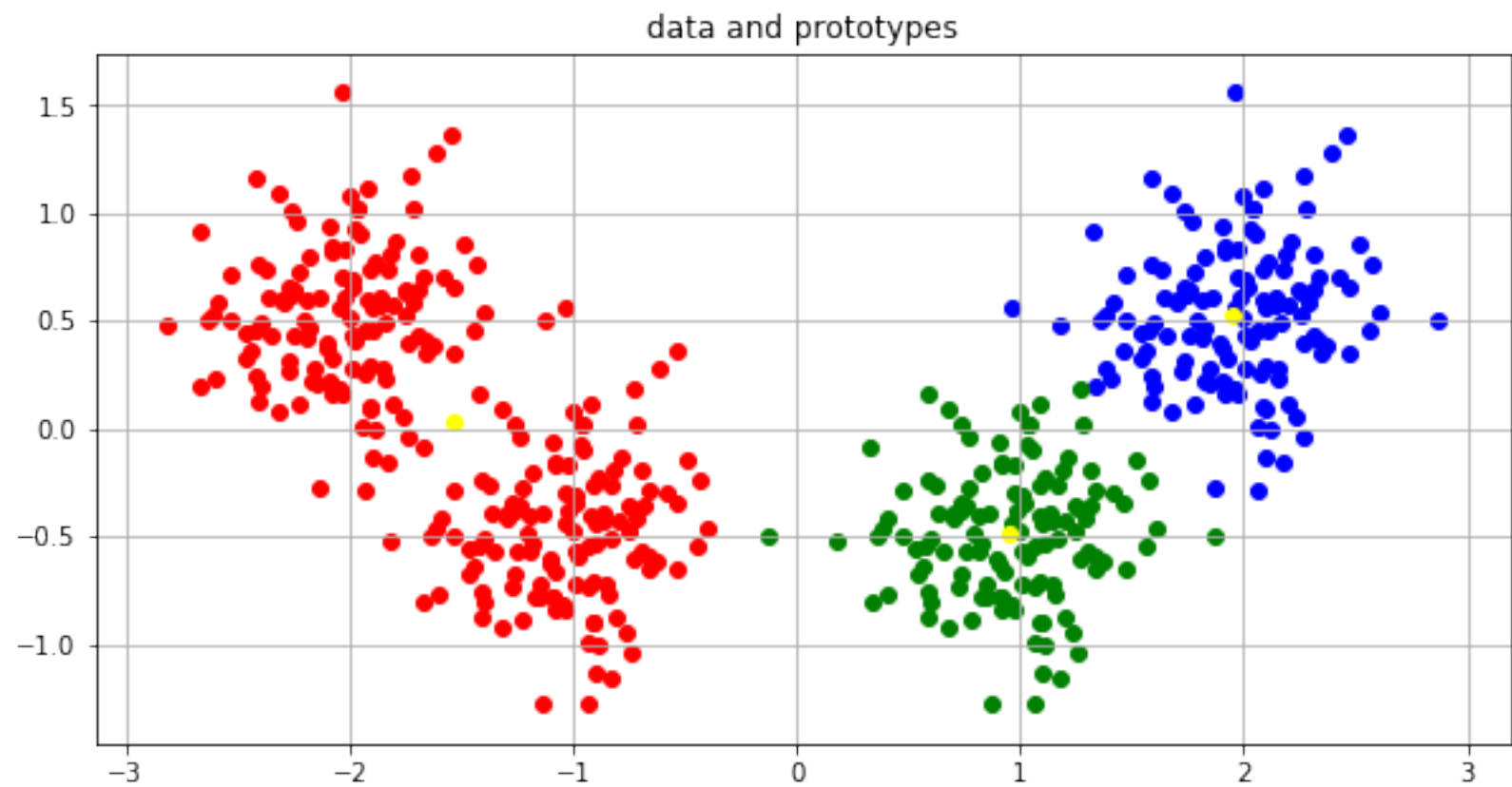
error



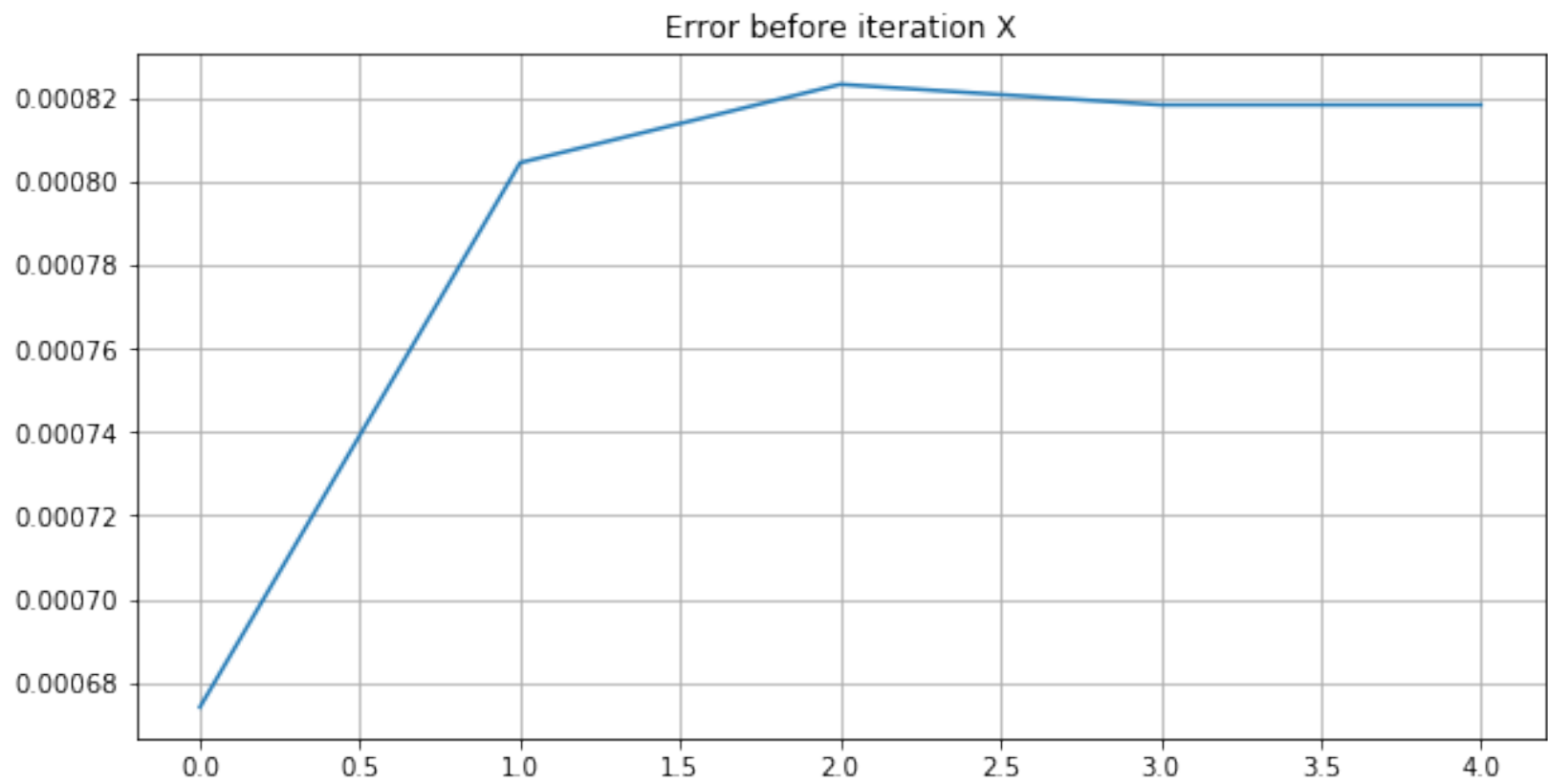
k = 3
data at start



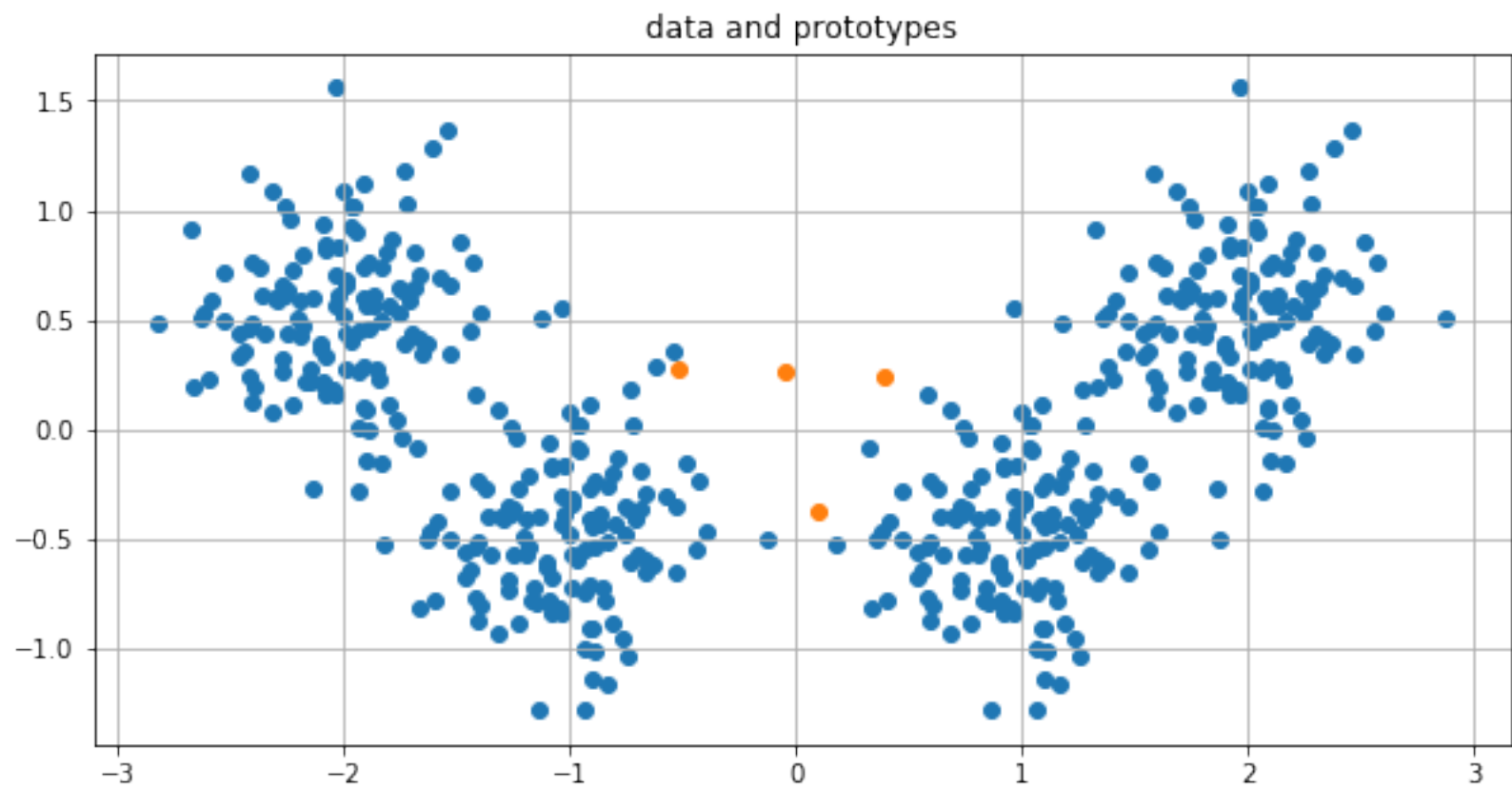
data at end



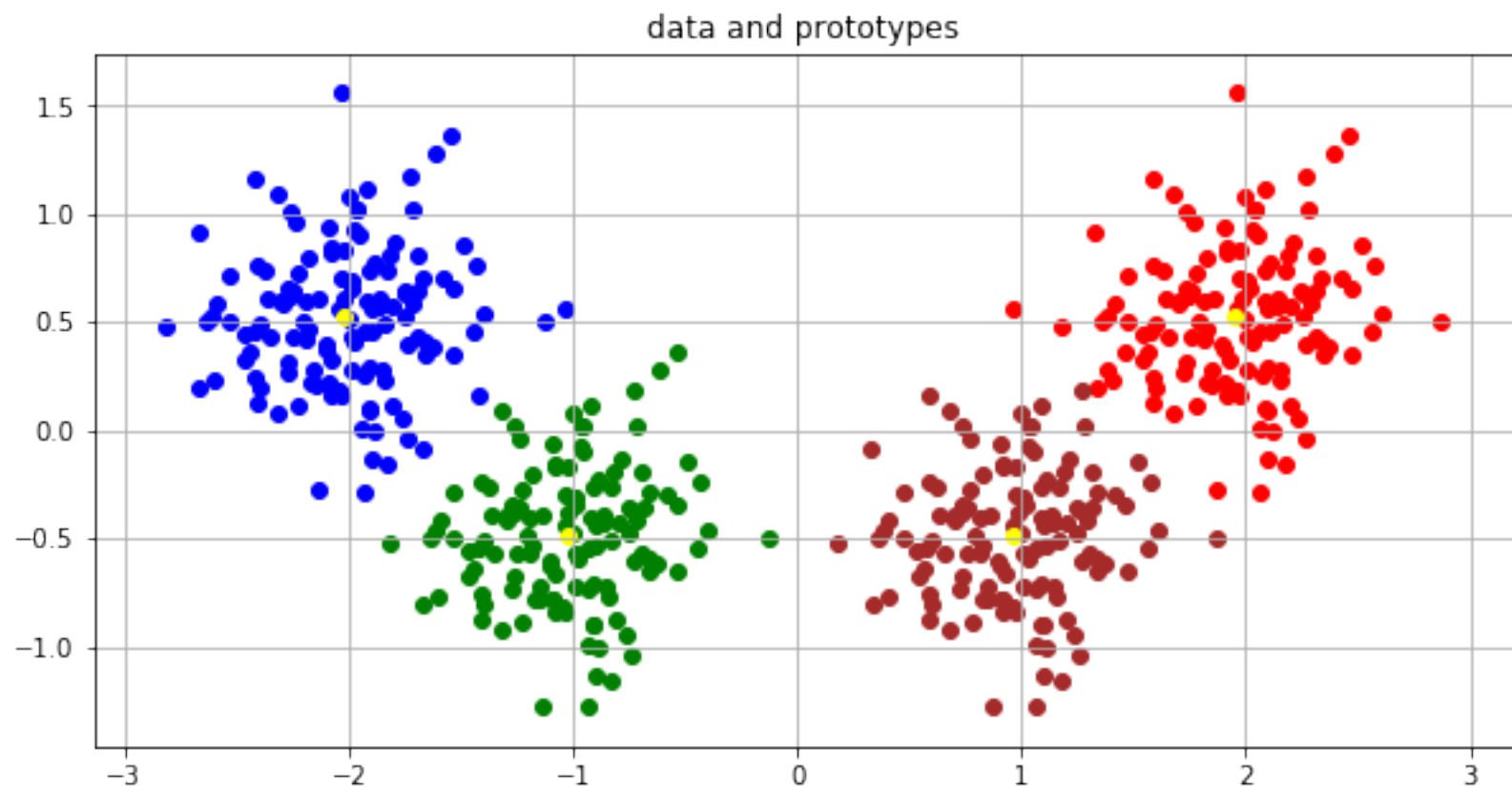
error



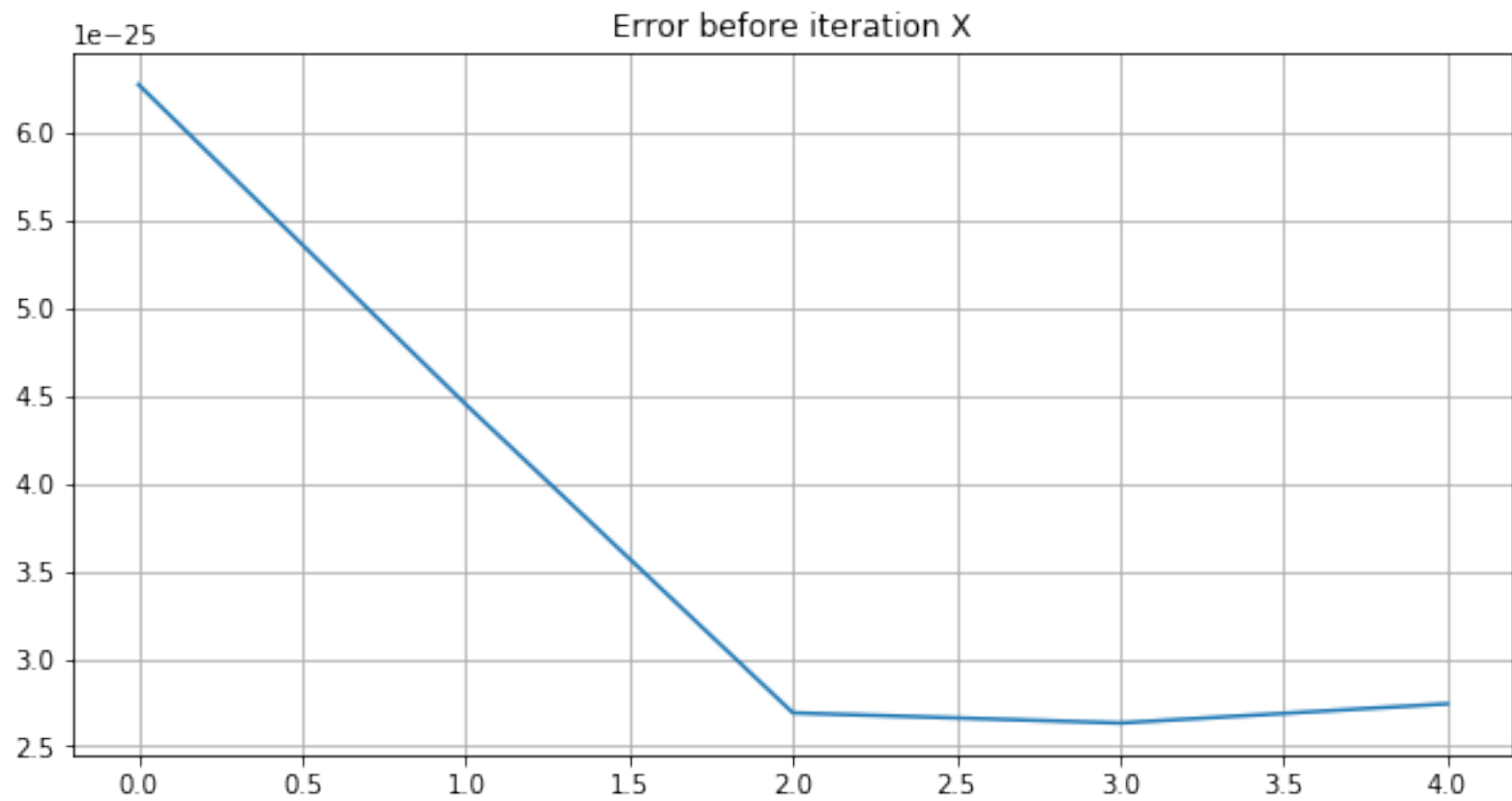
k = 4
data at start



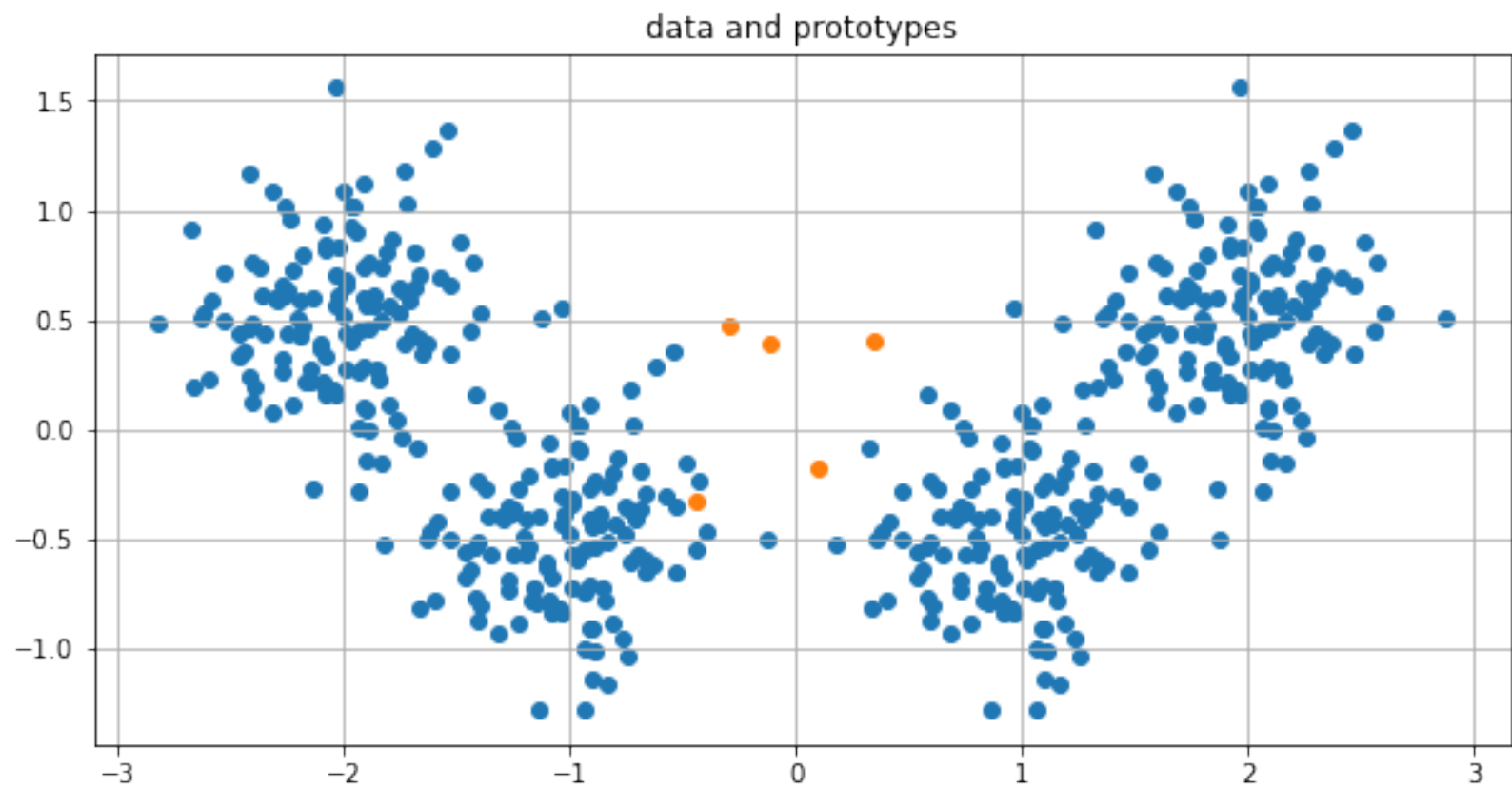
data at end



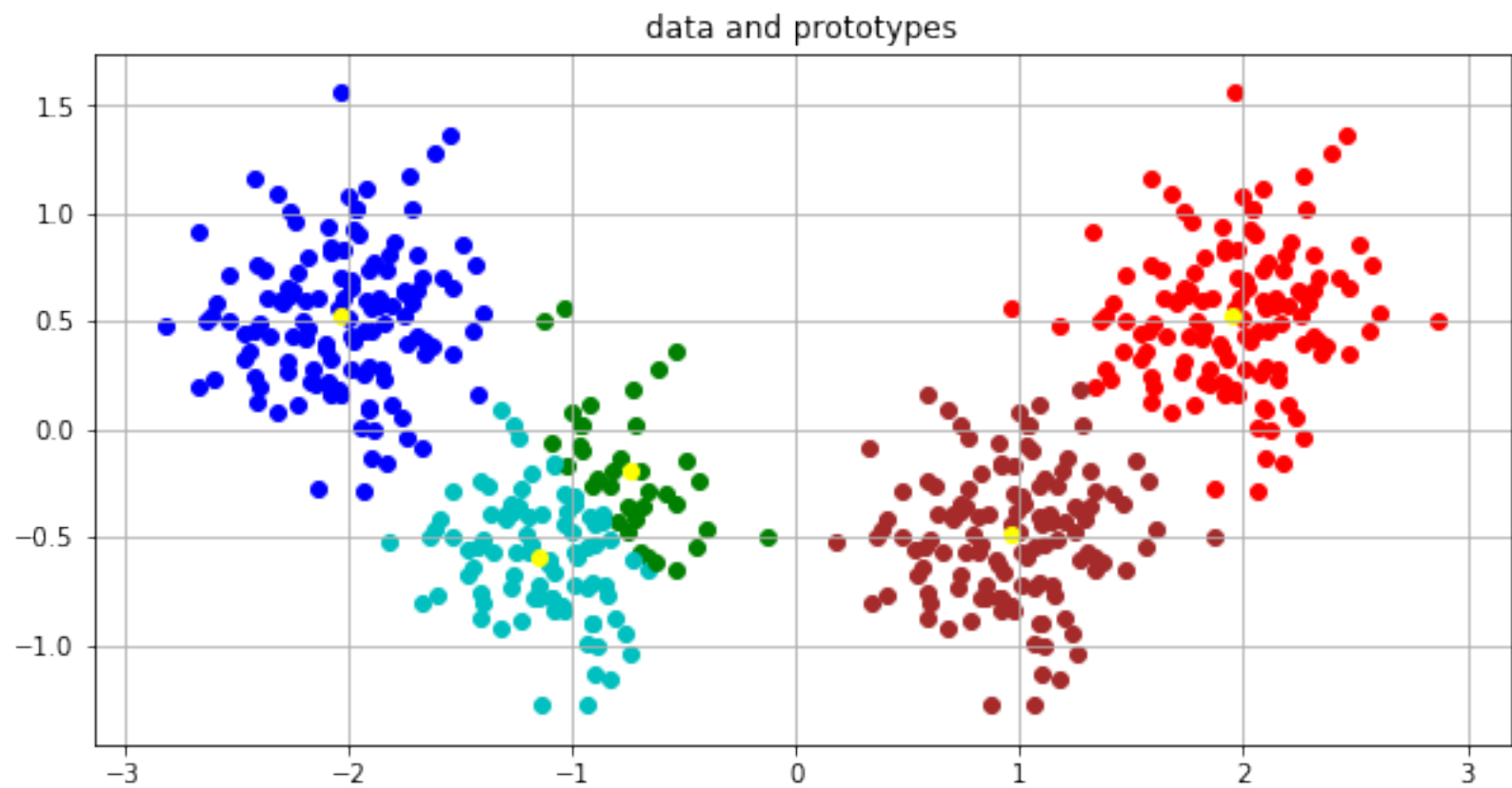
error



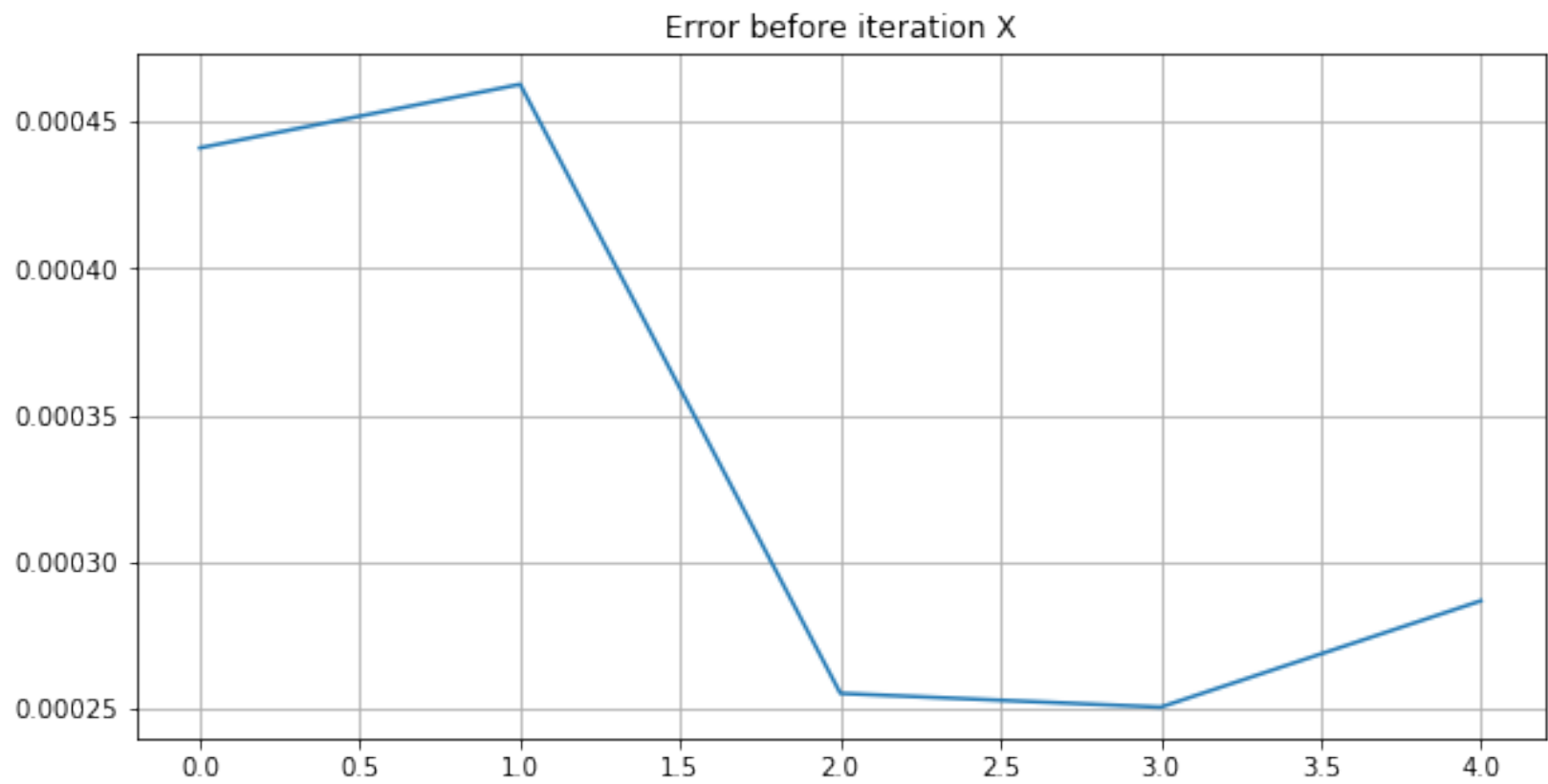
k = 5
data at start



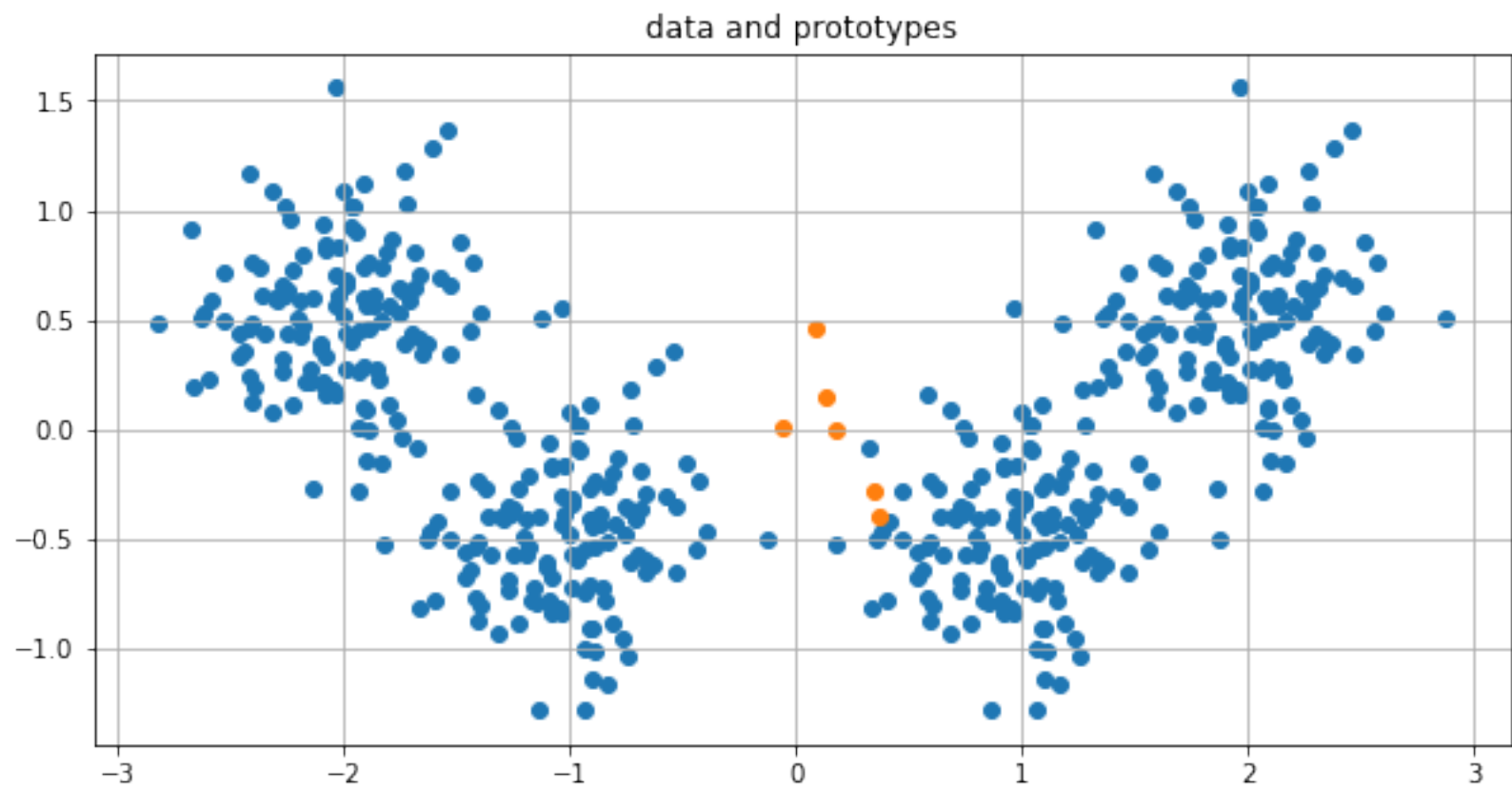
data at end



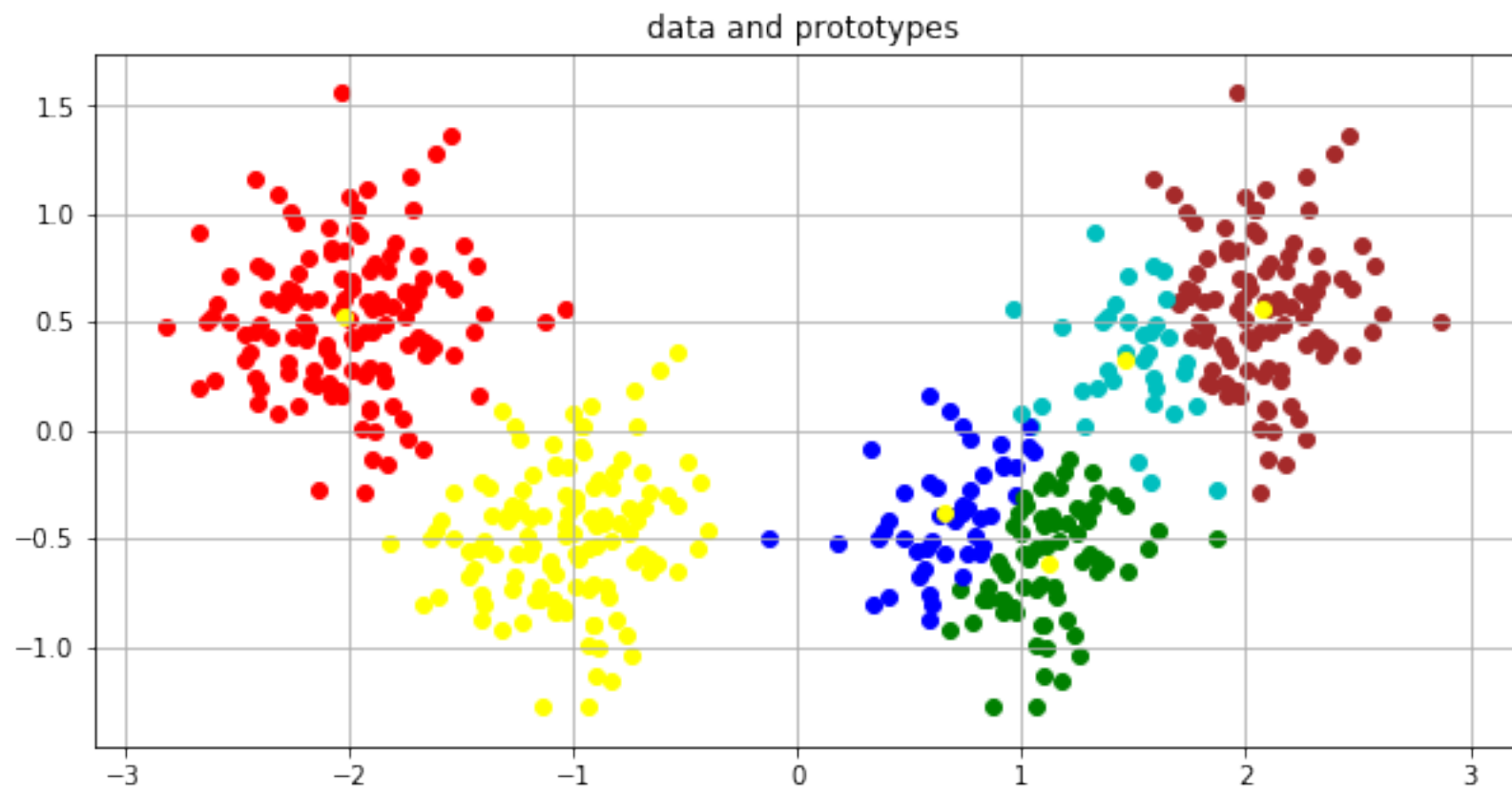
error



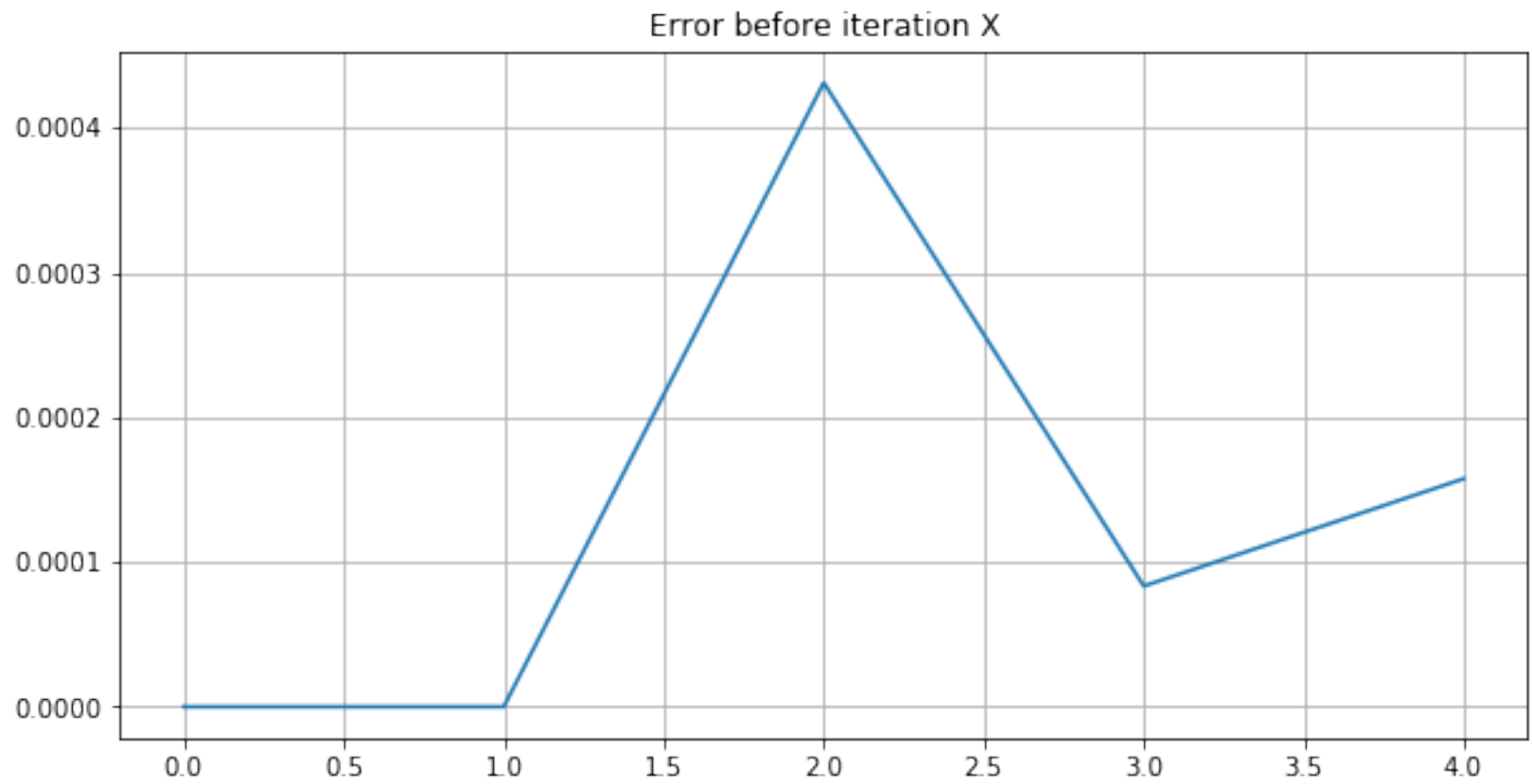
k = 6
data at start



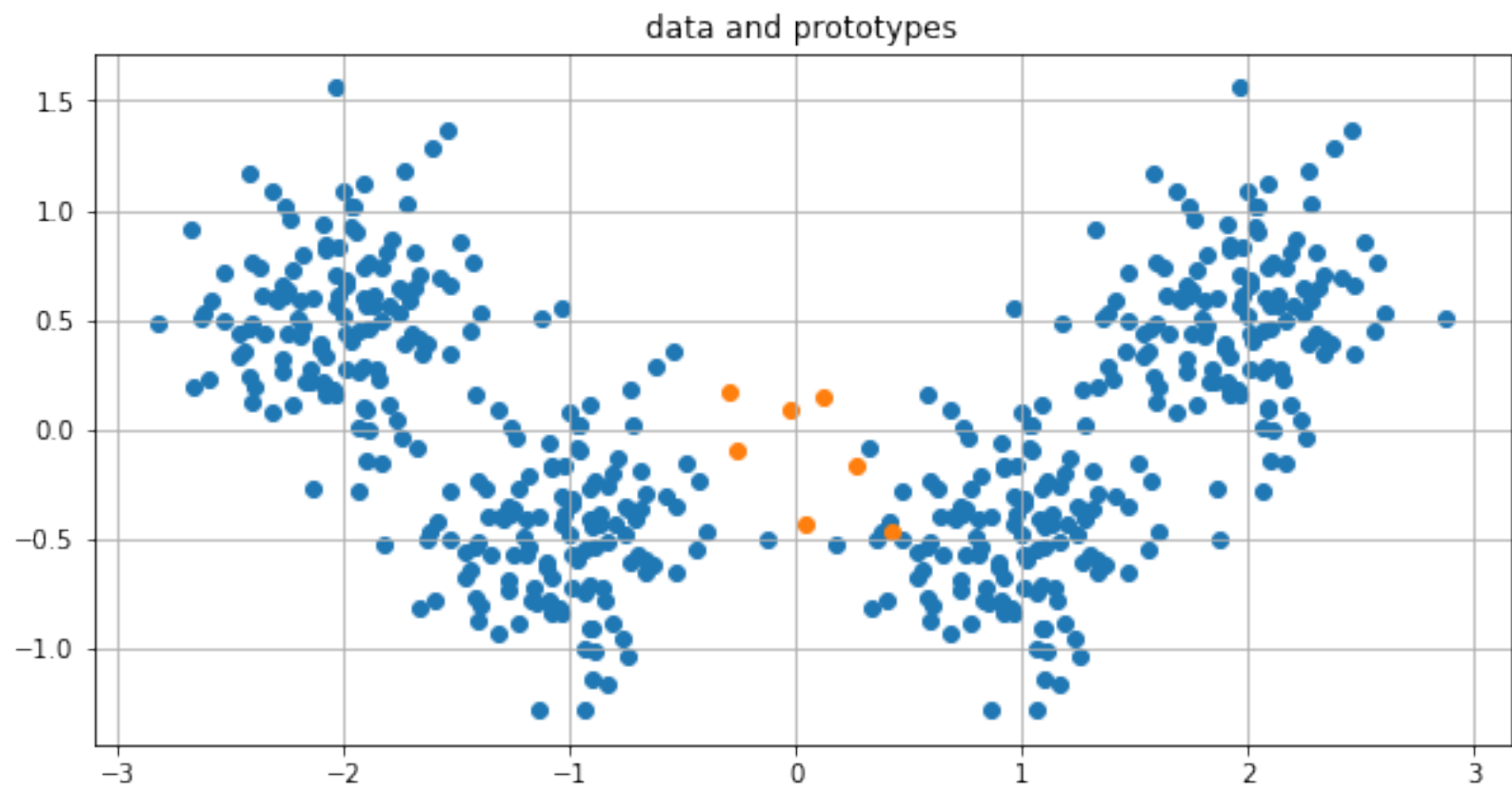
data at end



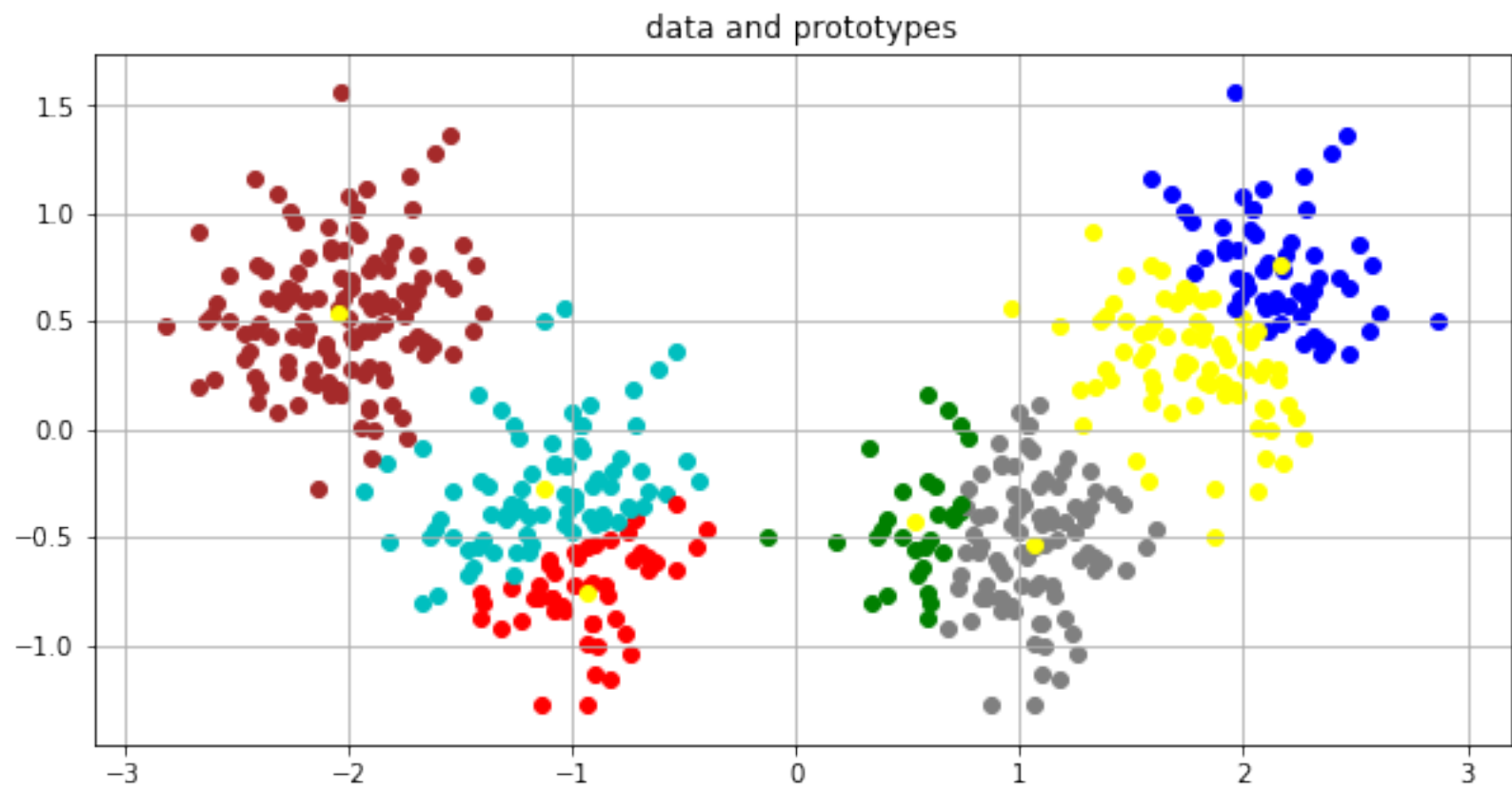
error



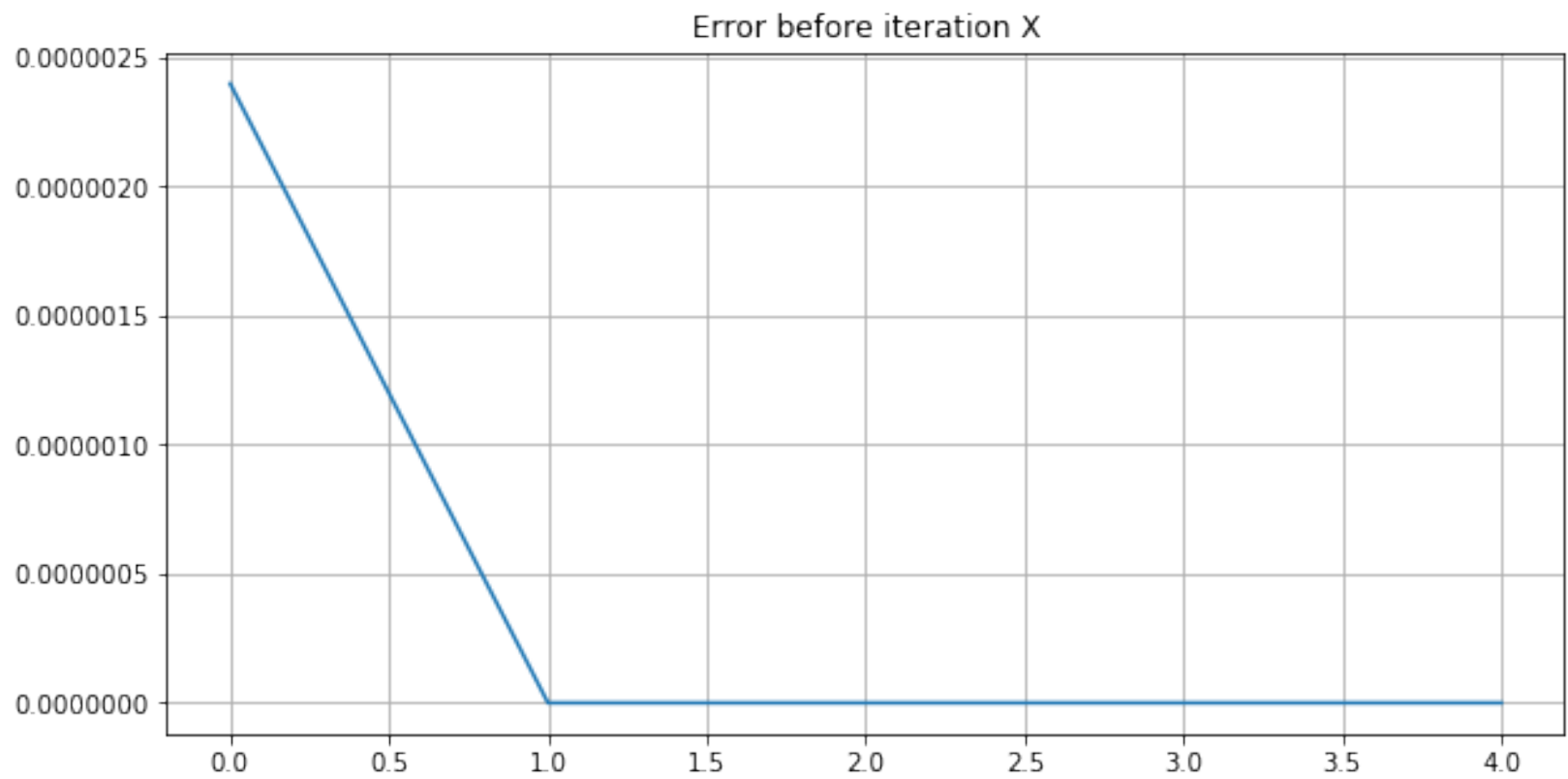
k = 7
data at start



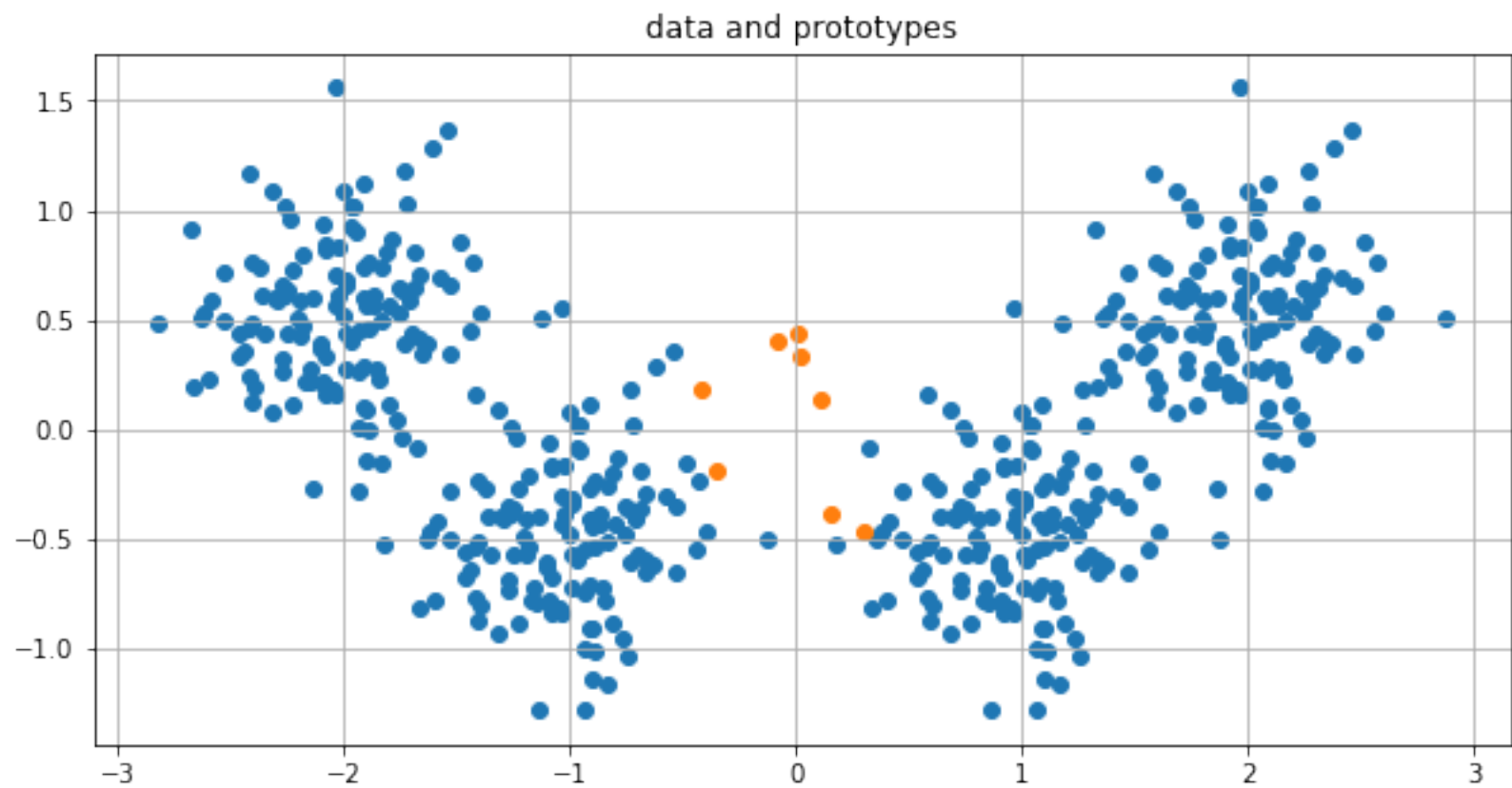
data at end



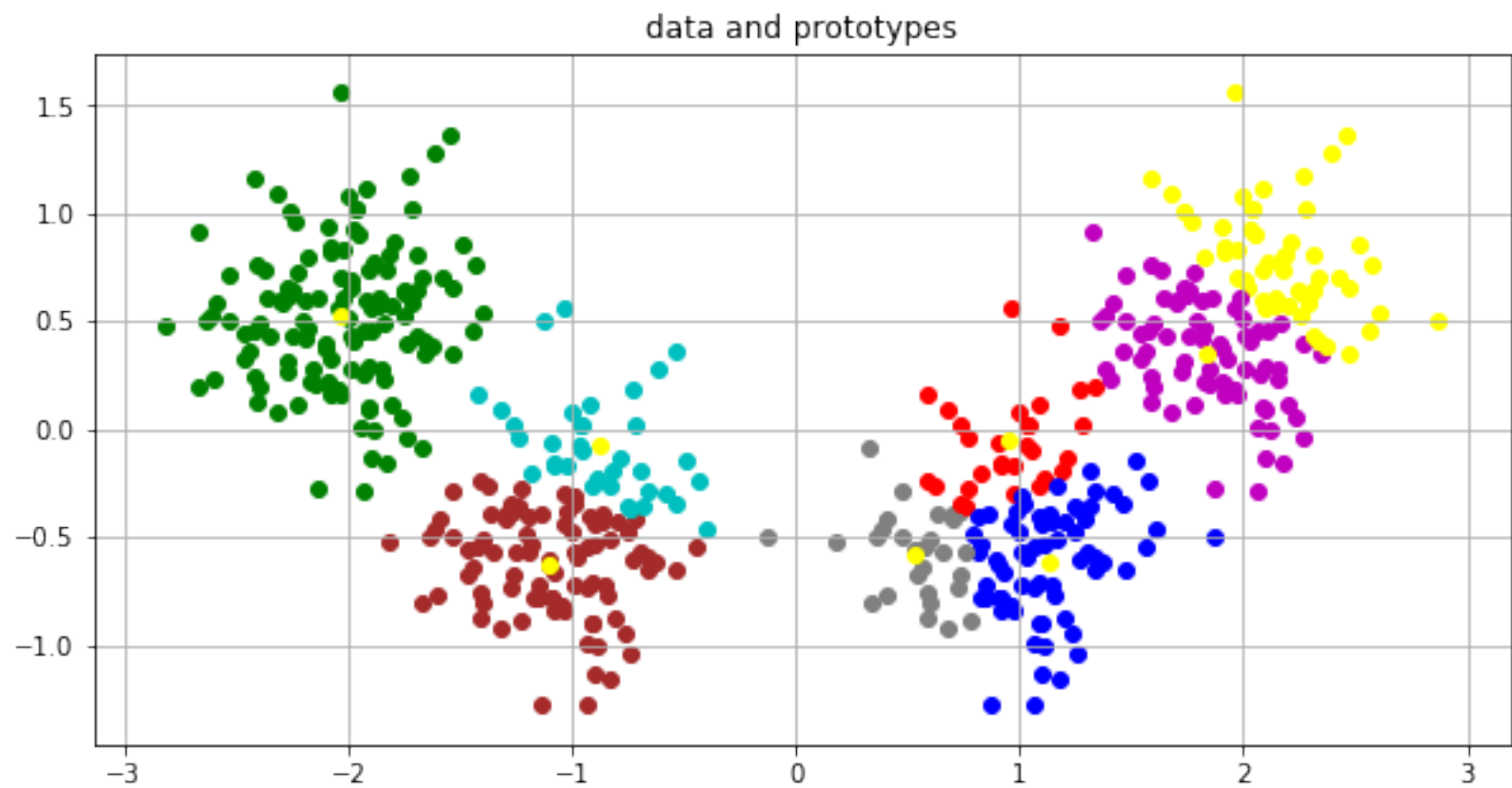
error



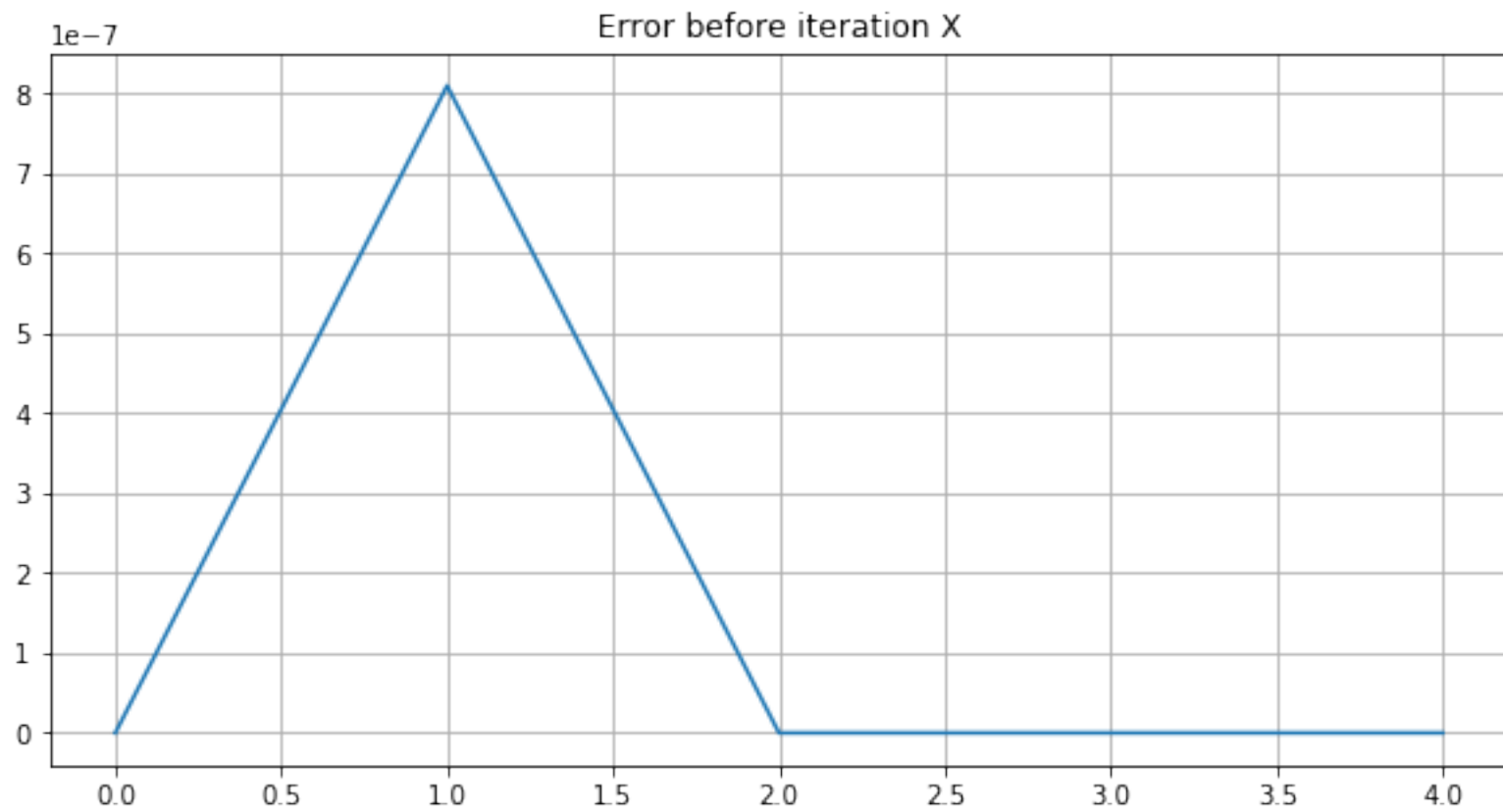
k = 8
data at start



data at end



error



Exercise 2

```

In [4]: observations = np.loadtxt('cluster.dat')

def online_Kmeans(observations, tau = .99, eps = .1, max_iter=0, K=4):
    """the online K-means algorithm (8) for the scripts
    return centroids positions over iteration in iterations x centroids x coo
rdinates
and error over iterations"""
    no_samples = np.shape(observations)[1]
    data_mean = np.mean(observations,axis=1)
    if max_iter == 0:
        max_iter = no_samples
    W = np.zeros((max_iter,K,2))
    W[0] = np.random.normal(loc=data_mean, scale=np.std(observations,axis=1),
size = (K,2)) #each row is a prototype
    err = np.zeros(max_iter)
    for t in range(0,max_iter-1):
        err[t] = error(W[t],observations)
        x = observations[:,t%no_samples]
        if t>=int(max_iter/4):
            eps = tau*eps
            dist = np.linalg.norm(W[t]-x,axis=1)
            q = np.argmin(dist)
            W[t+1]=np.copy(W[t])
            W[t+1,q] += eps*(x-W[t,q])
        err[-1] = error(W[-1],observations)
    return W, err

def error(W, observations):
    no_samples = np.shape(observations)[1]
    labels = Kmeans_classifier(W, observations)
    err = 0
    for i in range(len(W)):
        err += np.sum(np.linalg.norm(observations[:,labels==i]-W[i][:,np.newa

```

```

xis],axis=0))
    err/=(2*no_samples)
    return err

def Kmeans_classifier(W, observations):
    """Classify the samples according to their closest centroid
    returns an array of indices corresponding to the classes
    """

    distances = observations-W[:, :, np.newaxis] #shape is prototype x coordinate x sample
    distances = np.linalg.norm(distances,axis = 1) #ith row is euclidean distance to ith prototype for all samples
    labels = np.argmin(distances, axis = 0)
    return labels

def plot_sequence(W,observations,n_iter):
    """plot 6 scatters plots of the data together
    with the centroids at different times"""
    snapshots = np.linspace(0,n_iter-1,6)
    fig, ax = plt.subplots(2,3,figsize=(16,8))
    ax = ax.ravel()
    xcoords, ycoords = [], []
    for j, i in enumerate(snapshots):
        ax[j].scatter(observations[0],observations[1],c="b",alpha=.5,marker='.' )
        ax[j].scatter(W[int(i), :, 0],W[int(i), :, 1],c= 'r')
        ax[j].set_title('after {} iterations'.format(int(i)))
        xcoords.append(W[int(i), :, 0])
        ycoords.append(W[int(i), :, 1])
    ax[-1].scatter(W[0, :, 0],W[0, :, 1],c= 'r',marker='*')
    ax[-1].plot(xcoords,ycoords,c='r')
    plt.show()

```

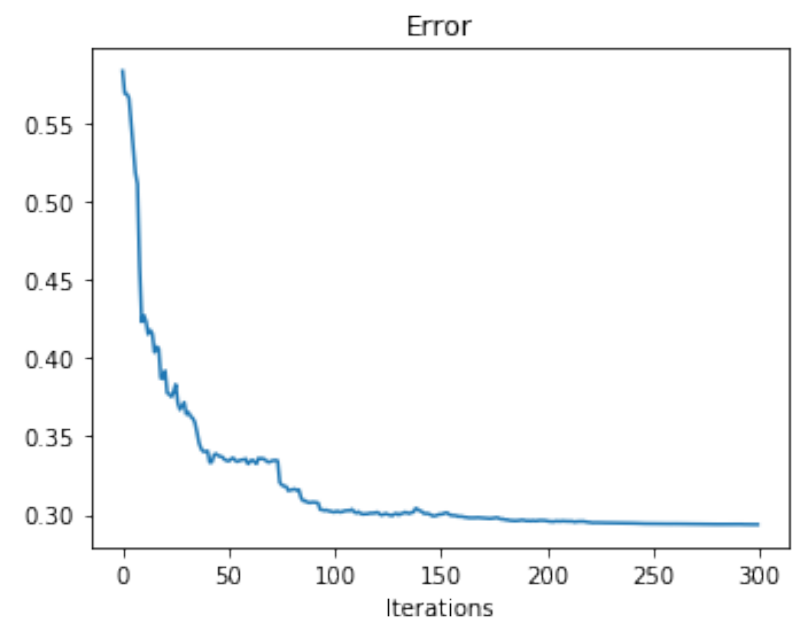
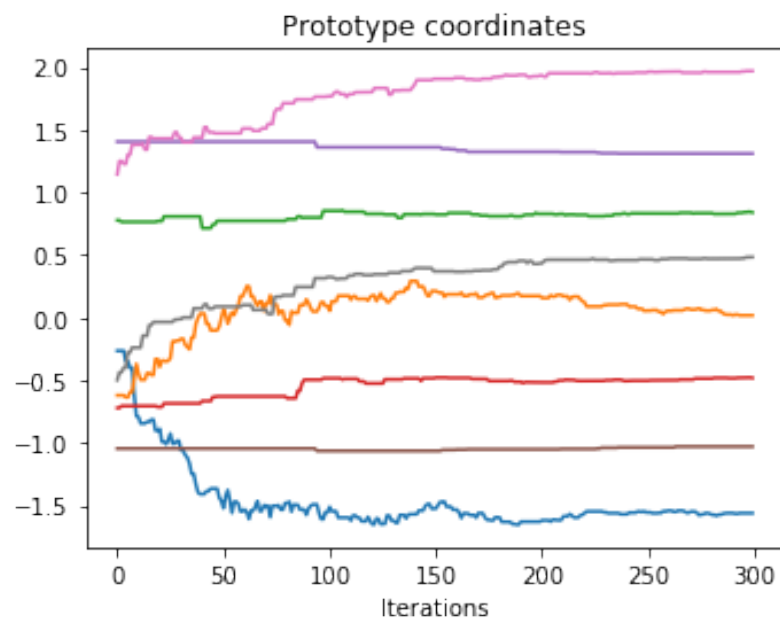
```

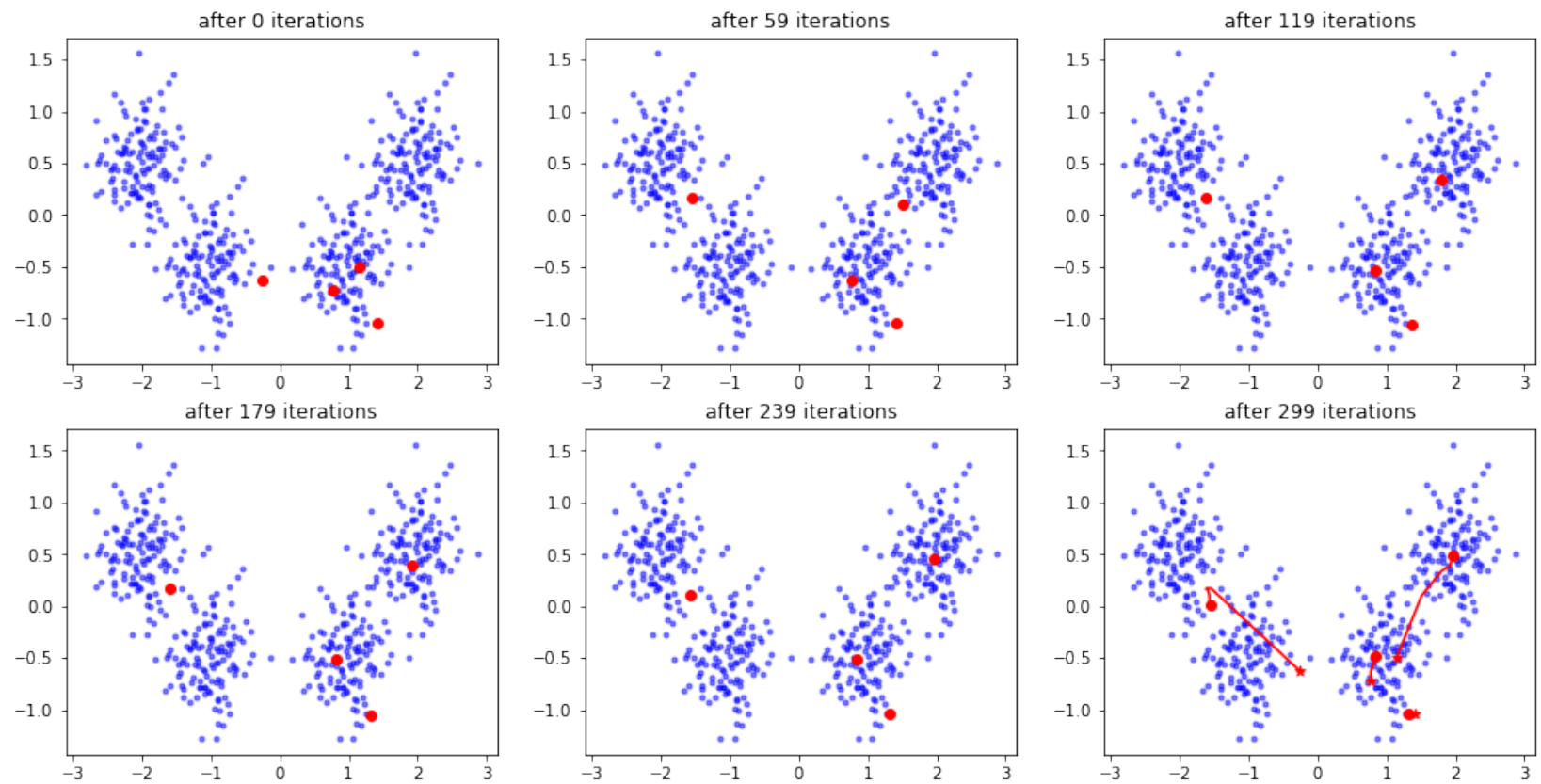
def plot_err(W,err):
    """plot the coordinates of the prototypes and
    the error against the iterations"""
    fig, ax = plt.subplots(1,2,figsize = (12,4))
    for i in range(len(W[0])):
        ax[0].plot(W[:,i,0])
        ax[0].plot(W[:,i,1])
    ax[0].set_title('Prototype coordinates')
    ax[1].plot(err)
    ax[1].set_title('Error')
    plt.setp(ax,xlabel='Iterations')
    plt.show()

def exercise2(observations,n_iter):
    """Train a K-means classifier with new initialization and do all the plotting"""
    W, err = online_Kmeans(observations, max_iter=n_iter);
    plot_err(W,err)
    plot_sequence(W,observations,n_iter)

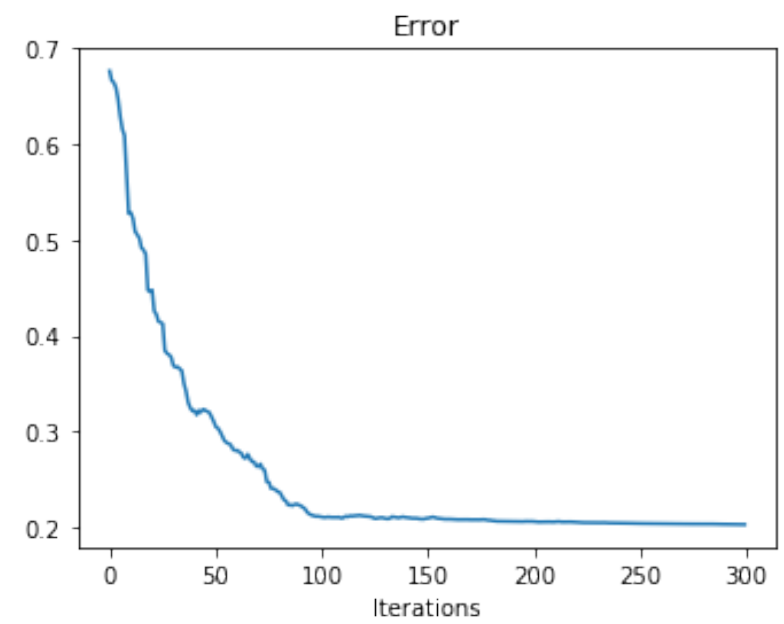
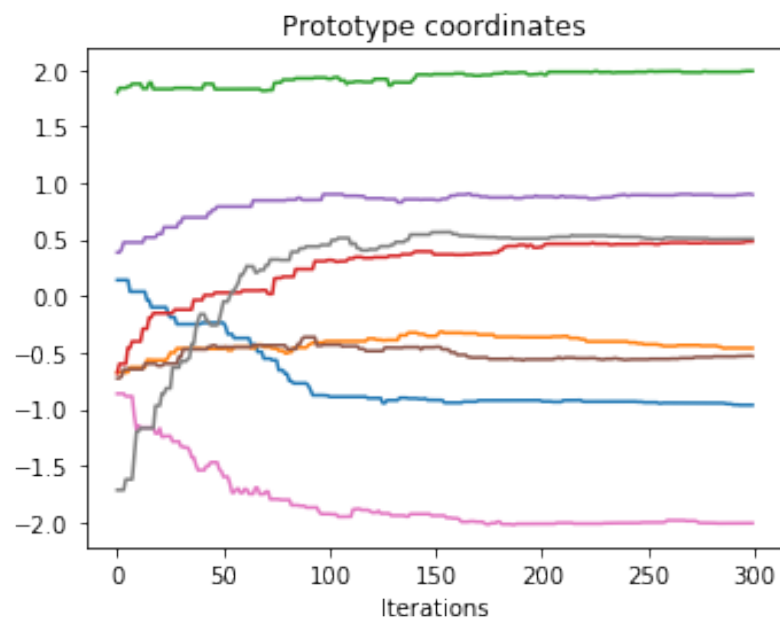
```

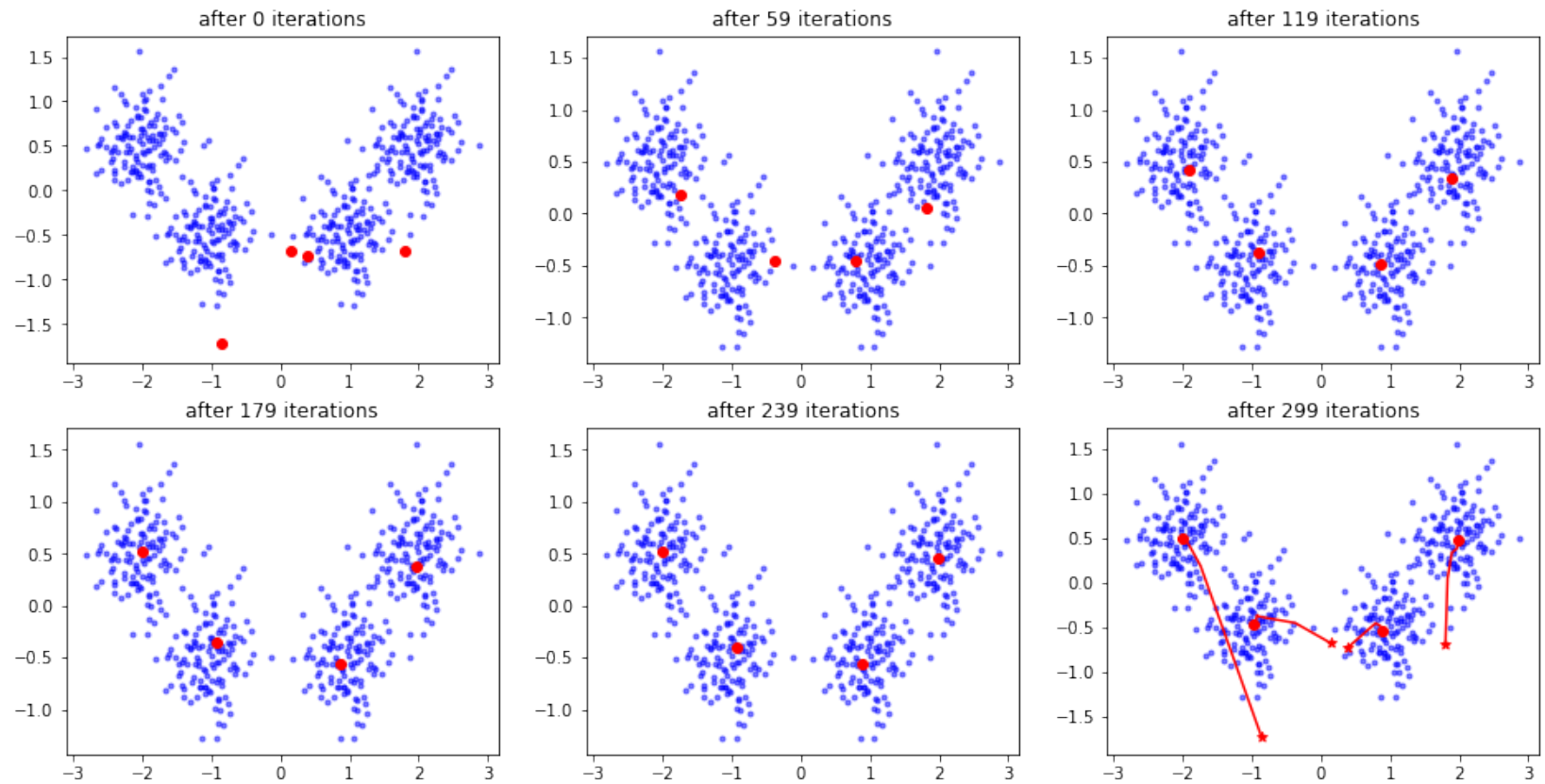
```
In [5]: exercise2(observations,300)
```





In [6]: `exercise2(observations,300)`





Exercise 3

a) + b)

```
In [7]: k = 8  
        gamma = 0.001
```



```

In [8]: betas = np.arange(0.2, 20.1, 1)

w_initial = np.array([mean + np.random.rand(2) - 0.5 for i in range(k)])

distances = np.zeros(k)
assignment_probabilities = np.zeros((k, len(data)))
w_final_per_beta = []

for beta in betas:
    print('Simulating for beta =', beta)

    w = w_initial.copy() # use same initial prototypes for each beta
    distances[:] = np.inf

    while any(distances > gamma):
        w_old = w.copy()
        assignment_probabilities[:, :] = 0

        for q in range(k):
            for alpha in range(len(data)):
                #print(q, alpha)
                assignment_probabilities[q, alpha] = np.exp(- beta / 2 * np.linalg.norm(data[alpha] - w[q])**2) / np.sum(np.exp(- beta / 2 * np.linalg.norm(data[alpha] - w[r])**2) for r in range(k))

                w[q] = np.sum(assignment_probabilities[q, alpha] * data[alpha] for alpha in range(len(data))) / np.sum(assignment_probabilities[q, alpha] for alpha in range(len(data)))

        distances = np.linalg.norm(w - w_old, axis=1)
        #print(distances)

```

```
w_final = w.copy()  
w_final_per_beta.append(w.copy())  
  
w_final_per_beta = np.array(w_final_per_beta)
```

```
Simulating for beta = 0.2  
Simulating for beta = 1.2  
Simulating for beta = 2.2  
Simulating for beta = 3.2  
Simulating for beta = 4.2  
Simulating for beta = 5.2  
Simulating for beta = 6.2  
Simulating for beta = 7.2  
Simulating for beta = 8.2  
Simulating for beta = 9.2  
Simulating for beta = 10.2  
Simulating for beta = 11.2  
Simulating for beta = 12.2  
Simulating for beta = 13.2  
Simulating for beta = 14.2  
Simulating for beta = 15.2  
Simulating for beta = 16.2  
Simulating for beta = 17.2  
Simulating for beta = 18.2  
Simulating for beta = 19.2
```

c)

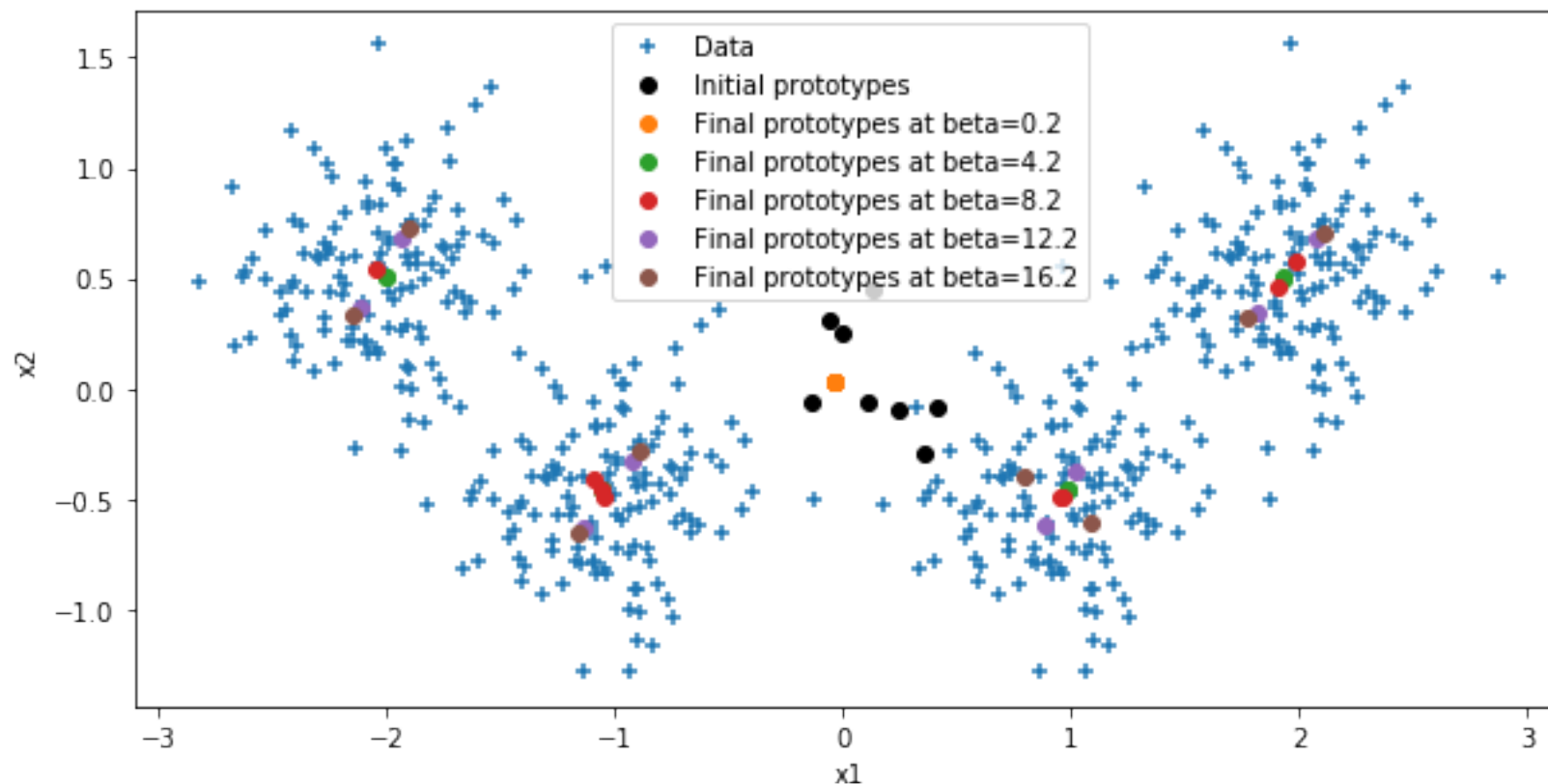
```
In [9]: # Plot data
plt.figure(figsize=(10, 5))
plt.scatter(data[:, 0], data[:, 1], label='Data', marker='+')

# Plot initial prototypes.
plt.scatter(w_initial[:, 0], w_initial[:, 1], c='k', label='Initial prototypes')

# Plot final prototypes. Only show a small part of the solutions, otherwise it gets too messy.
for w_final, beta in zip(w_final_per_beta[:, :4], betas[:, :4]):
    plt.scatter(w_final[:, 0], w_final[:, 1], label='Final prototypes at beta={}'.format(beta))

plt.xlabel('x1')
plt.ylabel('x2')
plt.legend()
```

Out[9]: <matplotlib.legend.Legend at 0x7fa3a2aa5390>

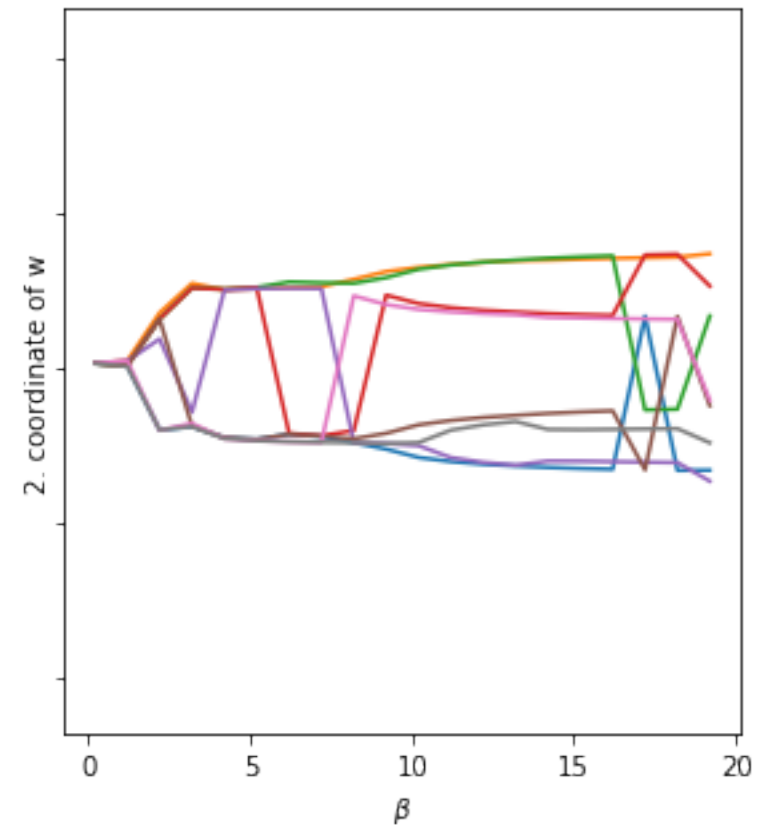
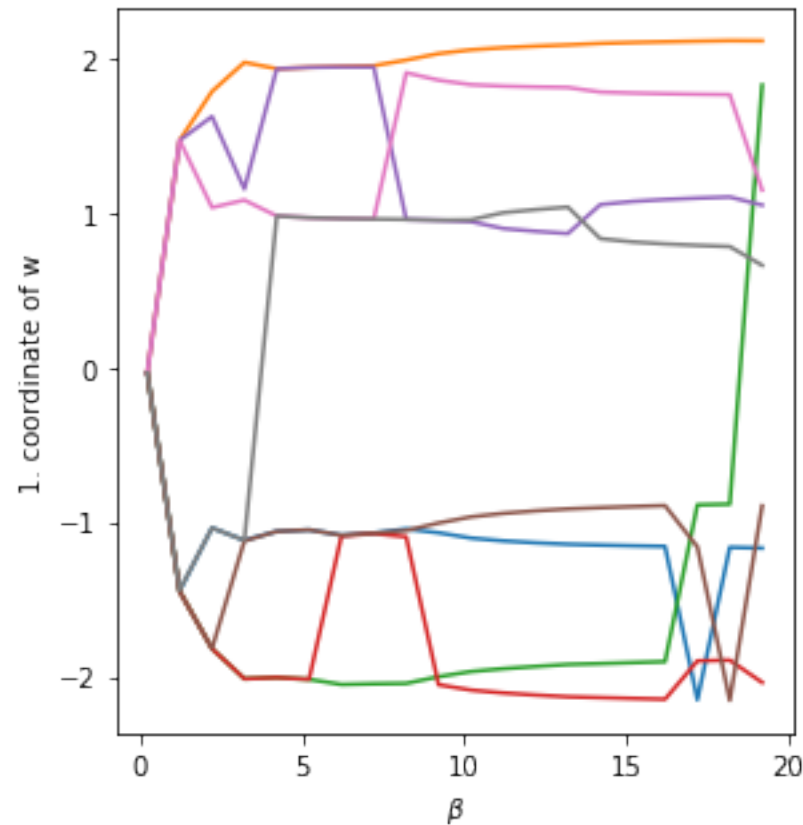


d)

```
In [10]: w_final_per_beta = np.array(w_final_per_beta)

fig, axes = plt.subplots(1, 2, sharex=True, sharey=True, figsize=(10, 5))
for i, ax in enumerate(axes.flatten()):
    plt.sca(ax)
    plt.plot(betas, w_final_per_beta[:, i])

    plt.xlabel(r'$\beta$')
    plt.ylabel('{}. coordinate of w'.format(i+1))
```



As can be seen in the plots, for small β , the prototypes converge to the origin (both coordinates become 0). For larger β , the prototypes move to larger values and do a better job at modeling the clusters (see also the scatter plot above)

e)

```

In [11]: ks = [2, 4, 6, 8]

beta_0 = 0.2
beta_f = 20
tau = 1.1

w_initial = np.array([mean + np.random.rand(2) - 0.5 for i in range(k)])

distances = np.zeros(k)
assignment_probabilities = np.zeros((k, len(data)))
w_final_per_k = []

for k in ks:

    print('Simulating for k =', k)

    beta = beta_0
    w = w_initial[:k].copy() # use same initial prototypes for each k

    while beta < beta_f:

        distances[:] = np.inf

        while any(distances > gamma):
            w_old = w.copy()
            assignment_probabilities[:, :] = 0

            for q in range(k):
                for alpha in range(len(data)):
                    #print(q, alpha)
                    assignment_probabilities[q, alpha] = np.exp(- beta / 2 *
np.linalg.norm(data[alpha] - w[q])**2) / np.sum(np.exp(- beta / 2 * np.linalg
.norm(data[alpha] - w[r])**2) for r in range(k))

```

```
        w[q] = np.sum(assignment_probabilities[q, alpha] * data[alpha]
] for alpha in range(len(data))) / np.sum(assignment_probabilities[q, alpha]
for alpha in range(len(data)))
```

```
distances = np.linalg.norm(w - w_old, axis=1)
#print(distances)
```

```
beta *= tau
```

```
w_final = w.copy()
w_final_per_k.append(w_final)
```

Simulating for k = 2

Simulating for k = 4

Simulating for k = 6

Simulating for k = 8

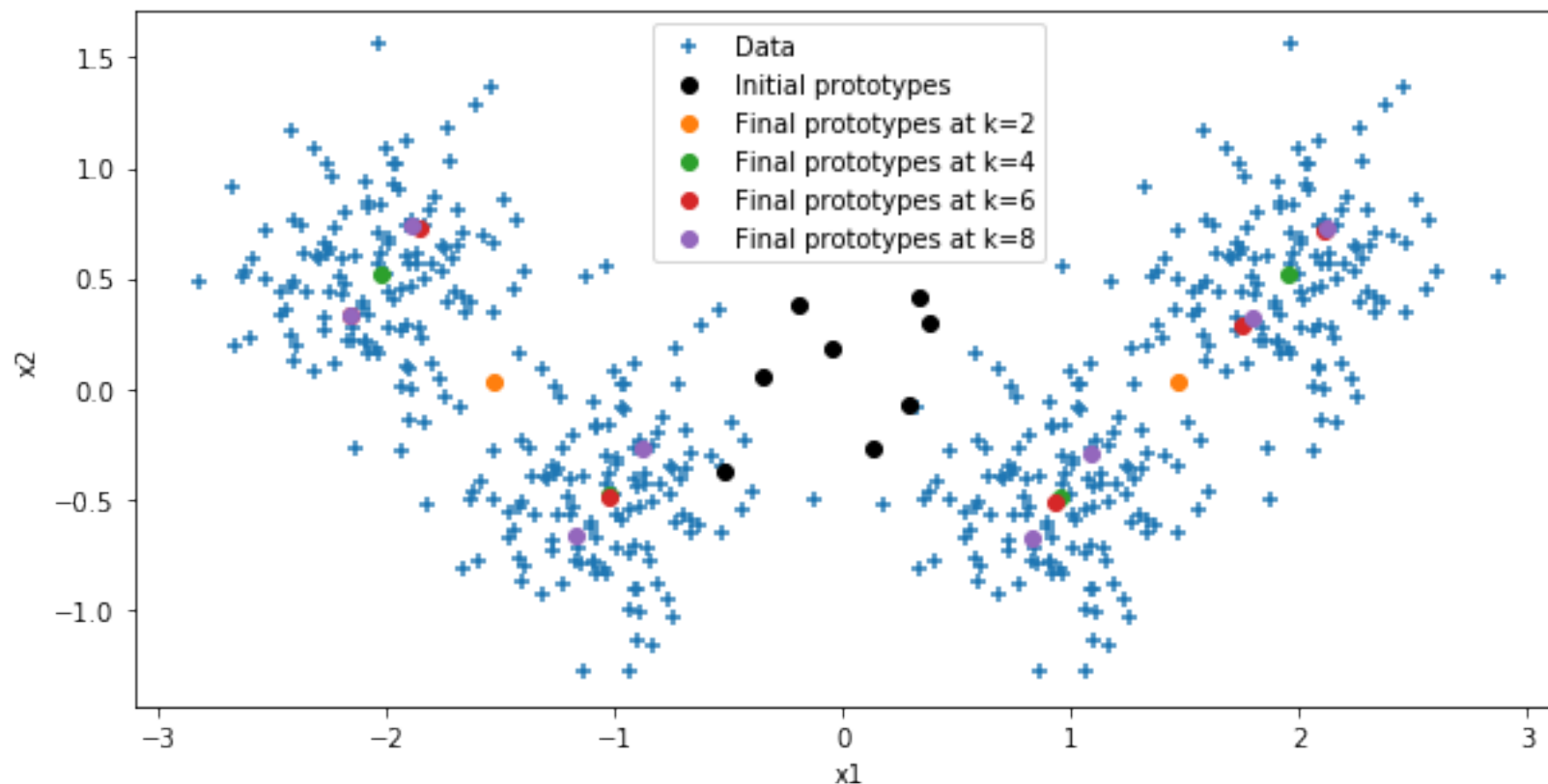
```
In [12]: # Plot data
plt.figure(figsize=(10, 5))
plt.scatter(data[:, 0], data[:, 1], label='Data', marker='+')

# Plot initial prototypes.
plt.scatter(w_initial[:, 0], w_initial[:, 1], c='k', label='Initial prototype
s')

# Plot final prototypes.
for w_final, k in zip(w_final_per_k, ks):
    plt.scatter(w_final[:, 0], w_final[:, 1], label='Final prototypes at k={}
'.format(k))

plt.xlabel('x1')
plt.ylabel('x2')
plt.legend()
```

Out[12]: <matplotlib.legend.Legend at 0x7fa3a2b36630>



Note that all initial prototypes (i.e. $k=8$) are shown here. For simulations with smaller values of k , only the first few prototypes are used in the simulation.

In []: