# Report for exercise 5 from group H

Tasks addressed: 5

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Source code: https://gitlab.lrz.de/ga53rog/praktikum-ml-crowd

The work on tasks was divided in the following way:

| Ahmad Bin Qasim (03693345) | Task 1 | 33% |
|----------------------------|--------|-----|
|                            | Task 2 | 33% |
|                            | Task 3 | 33% |
|                            | Task 4 | 33% |
|                            | Task 5 | 33% |
| Kaan Atukalp (03709123)    | Task 1 | 33% |
|                            | Task 2 | 33% |
|                            | Task 3 | 33% |
|                            | Task 4 | 33% |
|                            | Task 5 | 33% |
| Martin Meinel (03710370)   | Task 1 | 33% |
|                            | Task 2 | 33% |
|                            | Task 3 | 33% |
|                            | Task 4 | 33% |
|                            | Task 5 | 33% |

## Report on task 1, Approximating functions

Part 1:

For part 1 we loaded the linear data from the "linear\_function.txt" file and tried to approximate the function linearly. We used a linear regression model to minimize the least square error. For this problem there exists a closed form solution to compute the matrix A which contains the parameters to map the input to the output with a minimal least square error to the original function, we want to approximate. The least squares error problem is defined by following equation:

$$\min_{\hat{f}} e(\hat{f}) = \min_{\hat{f}} ||F - \hat{f}(X)||^2 = \min_{A} ||F - XA^T||^2$$

Figure 1 shows the original linear data in blue and its linear approximation in orange. It can be easily seen that all data points are laying on the linear straight which was computed with the closed form solution. The data is linear so the function can be approximated perfectly.

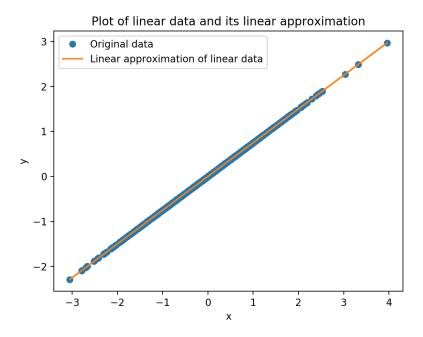


Figure 1: Plot of the linear data and its linear approximation

# Part 2: In the second part we use a nonlinear dataset from the "nonlinear function.txt" file and tried to approximate the function in a linear way again. Figure 2 shows then original data in blue again. The linear approximation of the function is shown in orange. It can be easily seen that the linear approximation fits very bad. The reason for that is that the function is nonlinear and we try to approximate it linearly.

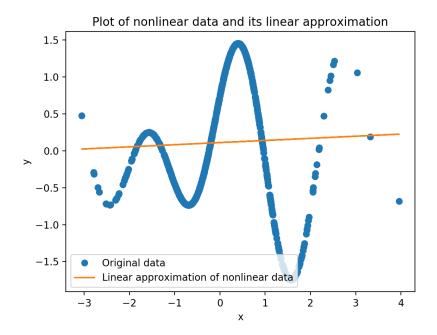


Figure 2: Nonlinear data and its linear approximation

# Part 3: After we tried to approximate the nonlinear dataset with a linear function in part 2, we now try to approximate

the unknown nonlinear function with a combination of radial basis function:

$$\phi_l(x) = \exp(-||x_l - x||^2/\epsilon^2)$$

 $x_l$  is the center of the basis function and usually just a randon point of the data set. There is one  $x_l$  for each radial basis function. We have to choose how many basis functions L we use to approximate the nonlinear function. Besides, we have to choose  $\epsilon$  appropriately. Figure 3 shows the original data in blue and the approximated function which makes use of radial basis functions in orange. It can be easily seen that the approximation is by far better than the linear approximation of part 2.

In general the approximation fits the original function quite well. We chose  $\epsilon$  according to the  $\epsilon$  in the diffusion maps task of the previous exercise sheet. This means we computed the distance matrix among all the x values and took the maximum value for  $\epsilon$ . This meaximum value is multiplied by 0.05. Besides, we use L=15 radial basis functions for the nonlinear approximation.

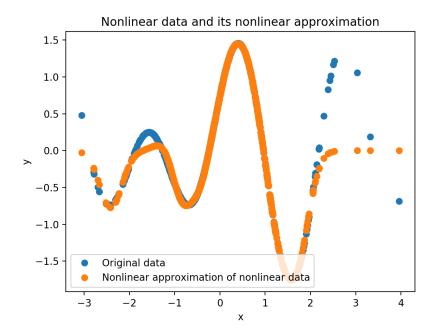


Figure 3: Nonlinear data and its nonlinear approximation with radial basis functions

It is not a good idea to use radial basis functions to approximate a linear function such as the linear data set of A. You can use the radial basis functions to approximate a linear data set, but you should use a linear approximator, because the computational cost of the radial basis function is higher due to the fact that the distance matrix for all x has to be computed to determinate  $\epsilon$ . Besides the parameters of L and  $\epsilon$  have to be chosen appropriately to obtain a good approximation.

#### Report on task 2, First step of a single pedestrian

They stepped successfully (see figure).

# Report on task 3, Approximating nonlinear vector fields

#### Part 1:

At first we compute a vector  $\hat{v}^{(k)}$  for every intial point  $x_0^{(k)}$  with the equation:

$$\hat{v}^{(k)} = \frac{x_1^{(k)} - x_0^{(k)}}{\Delta t}$$

We use the linear approximator to approximate the vector field and obtain A. After getting A we approximate  $x_1^{(k)}$  and compute the mean squarred error between the approximated and the known end points for a chosen  $\Delta t = 0.5$ . The mean squared error is 75.54.

#### Part 2:

Part 2 is similar to part 1, but this time we approximate the vector field with radial basis functions. We choose L = 10 and take for  $\epsilon$  the biggest value of a distance matrix between all initial points  $x_0$ . The mean squared error is 0.24.

The mean squarred error is extremely low, so the performance of the nonlinear approximator is very good. Consequently you can see that the vector field is nonlinear. Otherwise the mean squared error of the linear approximation would be lower. You can see that the difference between both mean squared errors is high, because the mean squared error of the nonlinear approximated vector field is very low.

#### Part 3:

We use for this part the nonlinear approximator, because in our opinion the vector field is nonlinear. The

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nonlinear approximator shows better performance in comparison to the lineaer approximator. We use the approximated vector field to solve the system for a larger time with all intitial points  $x_0$ .

Figure 4 shows the end state of the system. You can see several steady states. The steady states are at the following coordinates:

| x-coordinate of steady state  | -2.92 | 3.22 | 3.65  | -4.26 |
|-------------------------------|-------|------|-------|-------|
| y- coordinate of steady state | 3.13  | 1.85 | -1.27 | -3.65 |

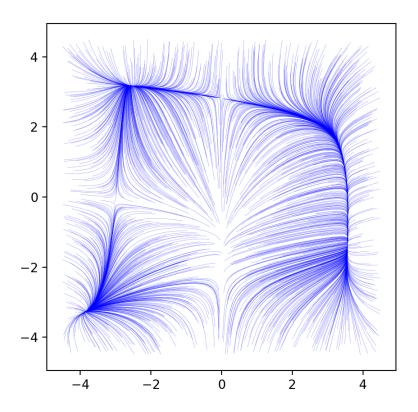


Figure 4: Predictions of  $x_1$  for a larger time given initial points  $x_0$ 

## Report on task 4, Obstacle avoidance

Pedestrians can avoid obstacles, using Dijkstras algorithm. See figure.

#### Report on task 5, Tests

TEST1: RiMEA scenario 1 (straight line, ignore premovement time)

- not done, but citing RiMEA guidelines -

TEST2: RiMEA scenario 4 (fundamental diagram, be careful with periodic boundary conditions).

- test successful -

TEST3: RiMEA scenario 6 (movement around a corner).

- test successful -

TEST4: RiMEA scenario

- test successful -

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