Assignment 1
Machine Learning in Robotics

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1 Estimating velocity motion model of a mobile robot through linear regression

In this exercise linear regression is used to learn the input, output mapping of a mobile robot where the inputs are velocity v and angular velocity w and the output is the pose x, y and θ. Furthermore, k-fold cross validation with $k = 5$ is used to avoid over fitting of the data.

The polynomial of the mapping is varied from 1 to 6. p_1 is the polynomial order used to estimate the position (x, y) and p_2 is the polynomial order used to estimate the orientation θ.

a) The optimal polynomial orders for $k = 2$ and $k = 5$ were respectively found to be $\mathbf{p} = [5, 3]$ and $\mathbf{p} = [4, 1]$ where $\mathbf{p} = [p_1 p_2]$.

b) Learned parameter values for both $k = 2$ and $k = 5$ are shown in table 1 where a_1 and a_2 contain the parameters for the position estimation and a_3 contains the parameters for the orientation estimation.

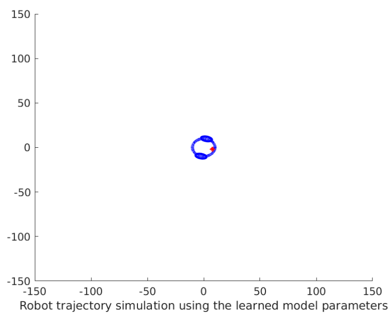
c) Figure 1 shows a visualization of the learned dynamics for four different combinations of velocity and angular velocity.

2 Handwritten digits classification using Bayesian classifier

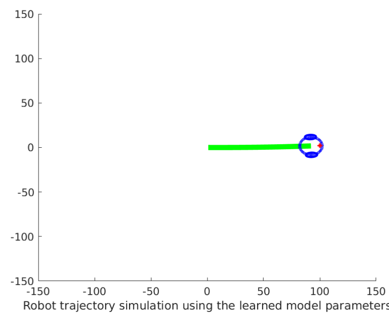
The goal of this exercise is to classify handwritten digits (0-9) using a Bayesian classifier. Since the dimension of an image is quite big, the data is projected onto a smaller dimension using PCA before it is classified.

Dimensions between 1 and 60 are tested, whereas $\mathbf{d} = \mathbf{48}$ results in the lowest classification error on the test set. The corresponding classification error is $\mathbf{3.62}$. The corresponding confusion matrix is shown in figure 2.

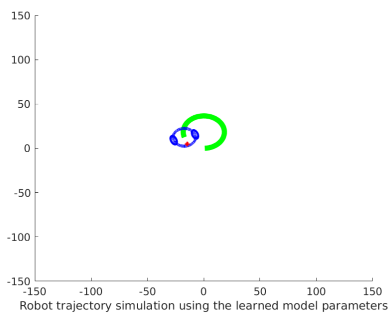
A plot of the classification errors when varying d from 1 to 60 is shown in figure 3. From this figure it can be seen that the error is converging already at $d \approx 30$.



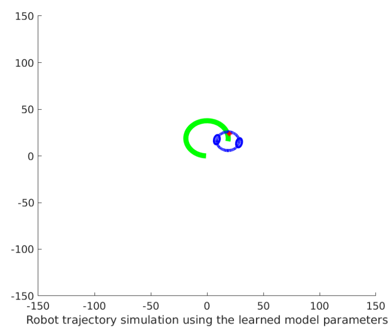
(a) $(v, w) = (0, 0.05)$



(b) $(v, w) = (1, 0)$



(c) $(v, w) = (1, 0.05)$



(d) $(v, w) = (-1, -0.05)$

Figure 1: Simulated robot trajectories based on learned dynamics

digit	0	1	2	3	4	5	6	7	8	9
0	0.99	0	0	0	0	0	0	0	0.01	0
1	0	0.97	0.01	0	0	0	0	0	0.02	0
2	0	0	0.97	0	0	0	0	0	0.02	0
3	0	0	0.01	0.96	0	0	0	0	0.02	0
4	0	0	0	0	0.98	0	0	0	0	0.01
5	0	0	0	0.02	0	0.96	0	0	0.01	0
6	0.01	0	0	0	0	0.01	0.96	0	0.01	0
7	0	0	0.03	0	0	0	0	0.93	0.01	0.02
8	0	0	0.01	0.01	0	0.01	0	0	0.97	0.01
9	0	0	0.01	0.01	0.01	0	0	0.01	0.01	0.94

Figure 2: Confusion matrix for optimal d

$k=2$			$k=5$		
a_1	a_2	a_3	a_1	a_2	a_3
0.00221	-0.00269	-0.00060	0.00250	-0.00432	0.00081
0.92173	-0.00136	-0.00017	0.91976	-0.00100	-0.00032
0.00657	-0.01154	0.99971	-0.00286	0.00145	0.99870
-0.00163	0.47304	0.00084	-0.00074	0.46798	0.00032
-0.00099	2.445e-4	0.00013	-0.00103	0.00057	
0.00248	-0.00827	0.00178	0.00137	-0.00253	
0.00231	7.470e-5	-0.00014	0.00249	-0.00103	
-1.166e-5	4.381e-5	-4.522e-6	0.00014	1.925e-5	
-0.01301	0.01644	-0.00062	-0.00027	-0.00167	
0.00012	-0.00098	-1.322e-5	6.693e-5	-0.00067	
1.284e-5	-5.289e-6		1.306e-5	-7.846e-6	
-0.00446	0.00430		-0.00428	0.00348	
-4.310e-05	-4.419e-6		-4.517e-5	8.716e-6	
-1.670e-6	-2.691e-7				
0.0026	-0.00381				
-4.024e-7	2.102e-6				

Table 1: Learned parameters for input, output mapping

3 Human motion clustering

In this exercise motion data from a human is clustered into 7 clusters/classes using two different unsupervised clustering algorithms.

a) The results of the classification of the three gestures using the k-means algorithm are shown in figures 4a-4c.

b) The results of the classification of the three gestures using the non-uniform binary split algorithm are shown in figures 5a-5c.

From these results it is clear that the k-means algorithm clusters the data more logically in this scenario as the clusters actually follow the given motions.

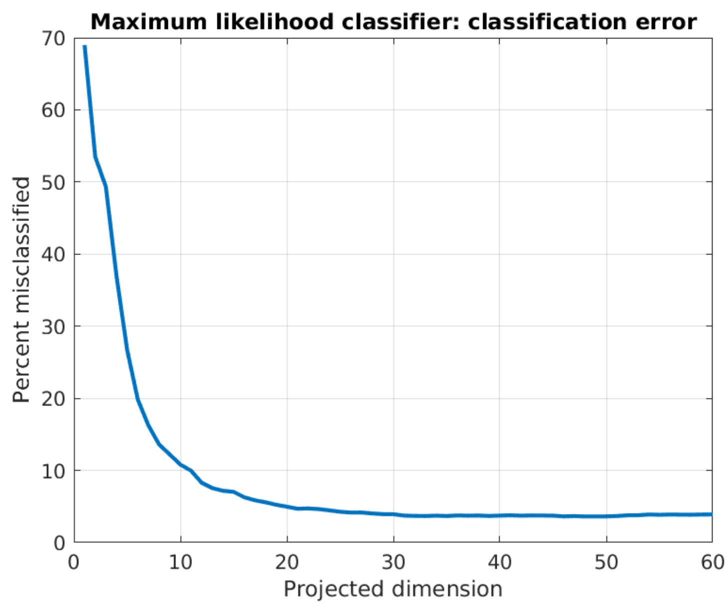
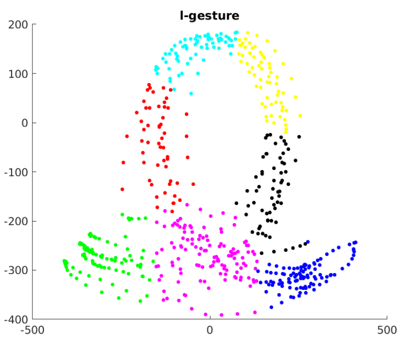
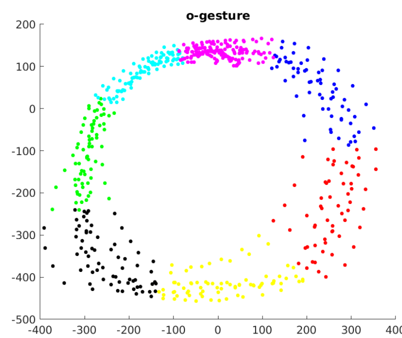


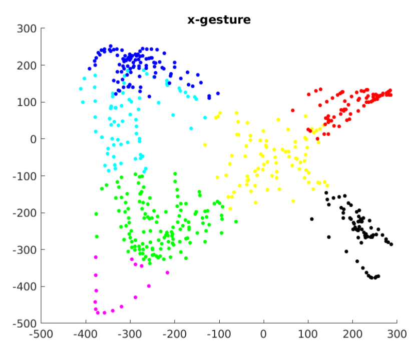
Figure 3: Plot of classification errors corresponding dimension d



(a)

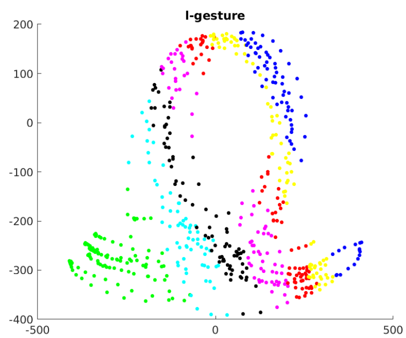


(b)

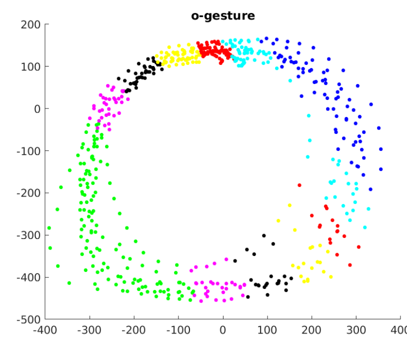


(c)

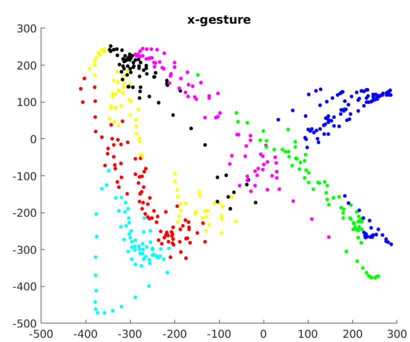
Figure 4: Results of k-means algorithm clustering



(a)



(b)



(c)

Figure 5: Results of non-uniform binary split algorithm clustering