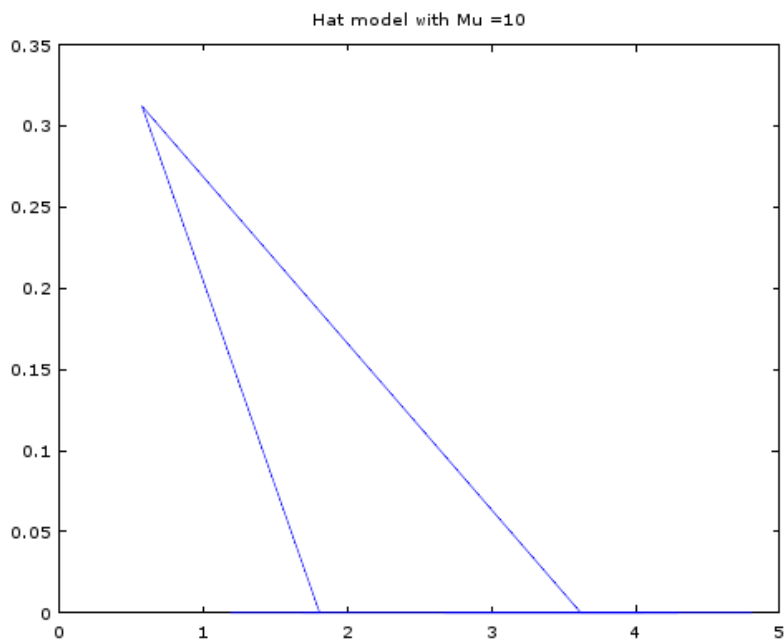
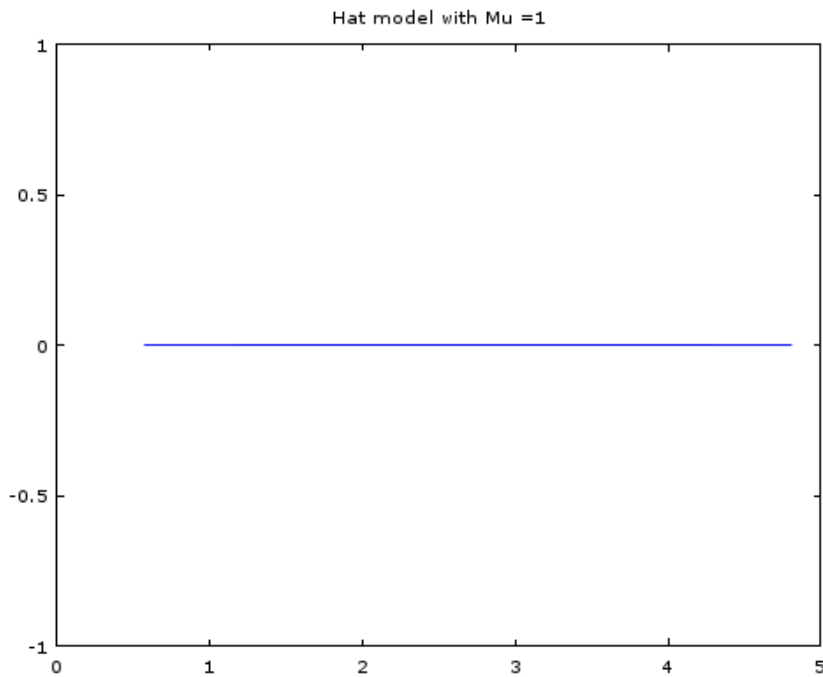


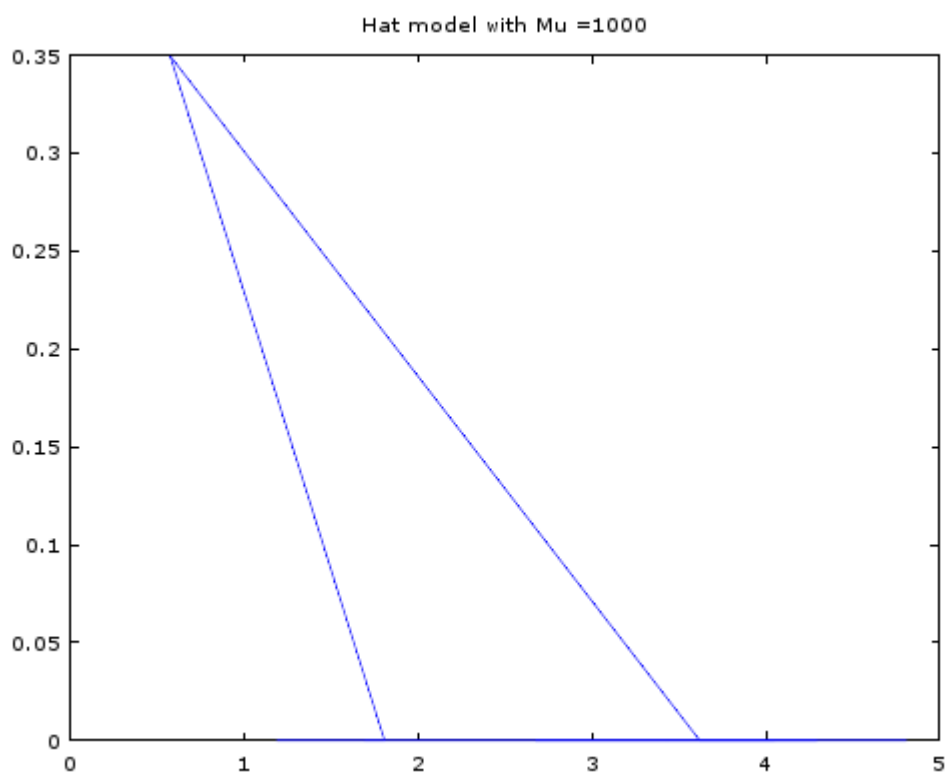
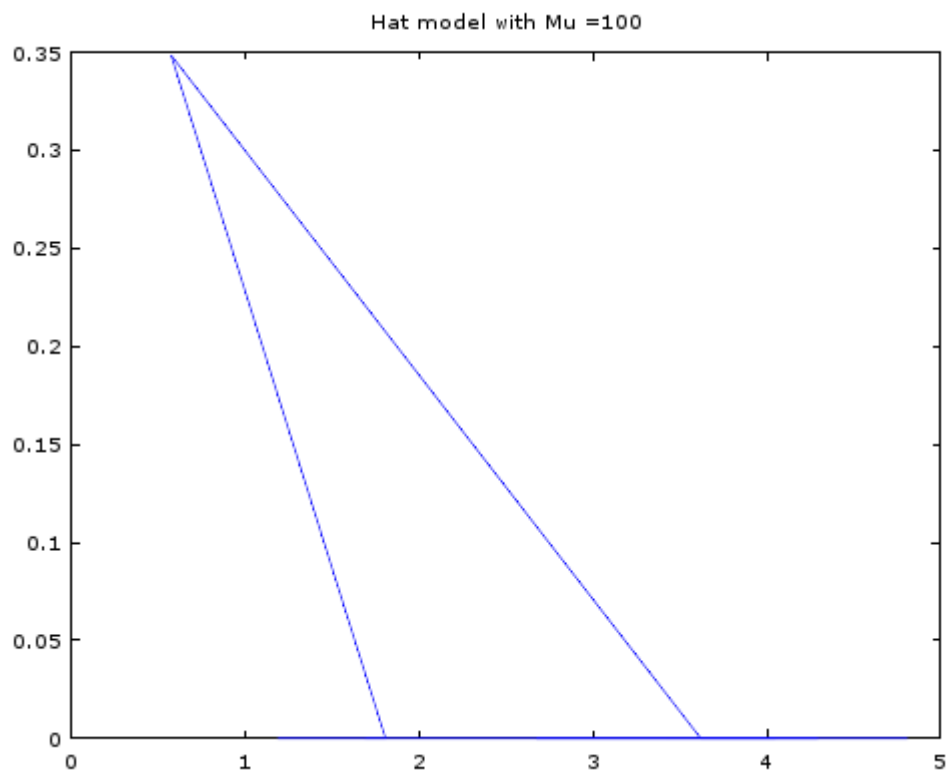
Lab 4: linear regression

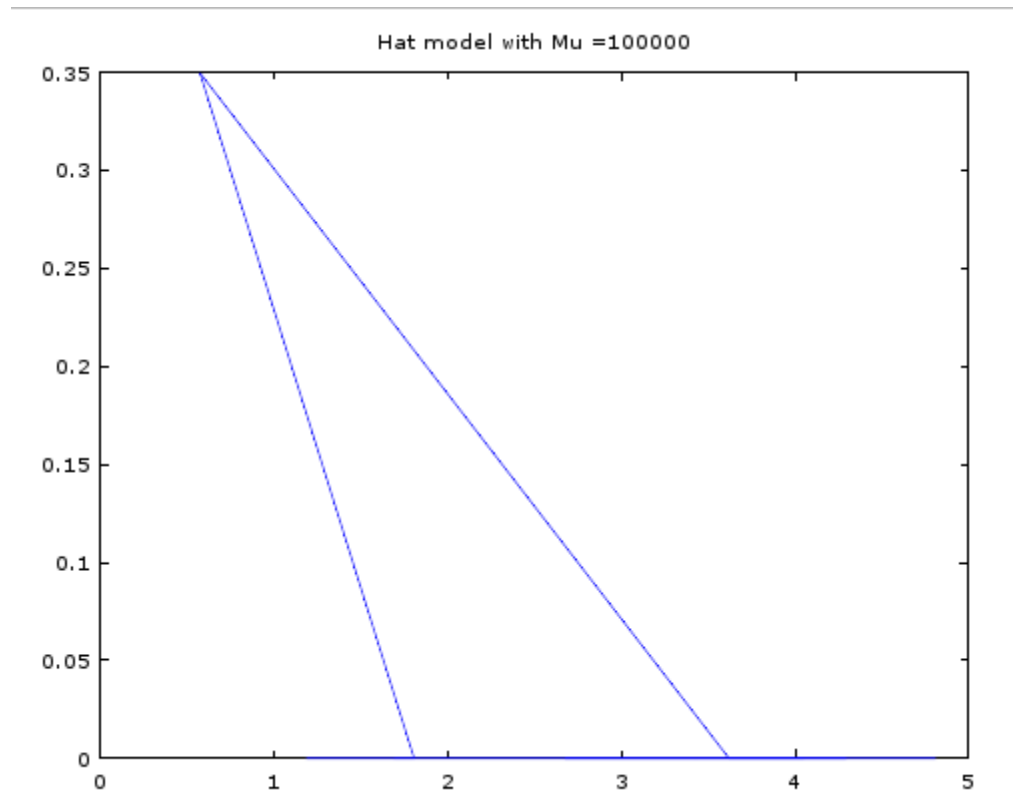
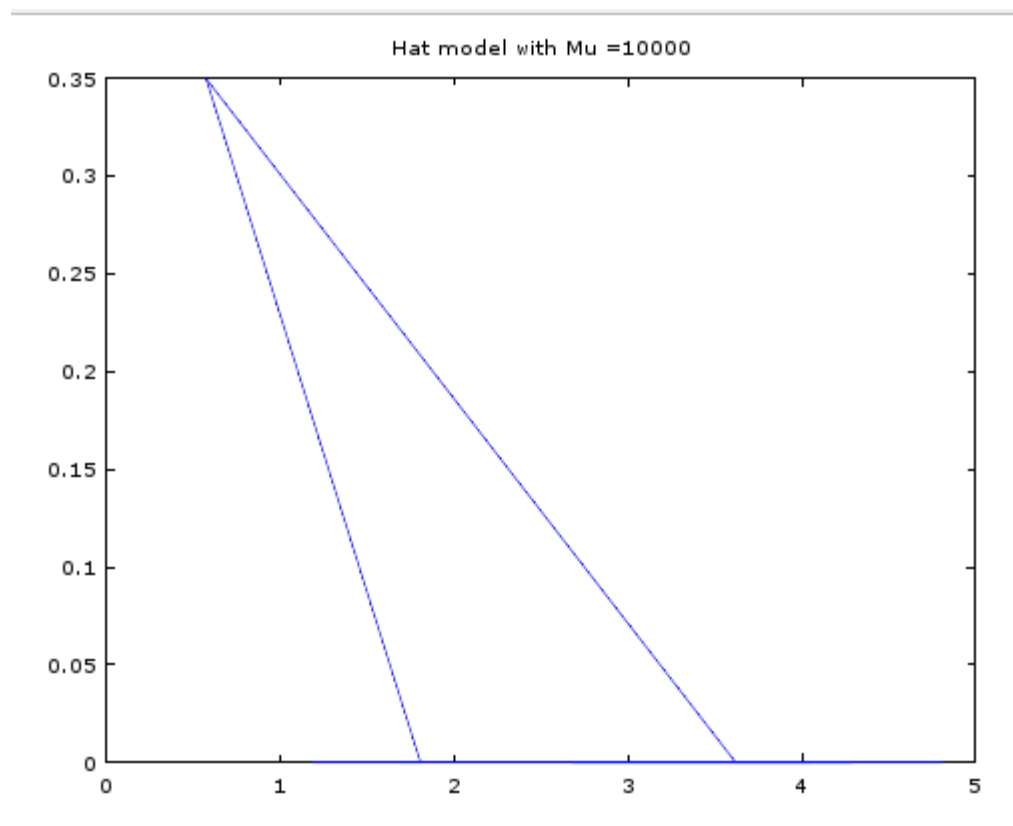
2. (4) Train the model on the data in simple.mat using $M = 10$ hat functions and $\mu = 10^{-5}$. Plot and turn in the learned model (the function fitted to the data) on the interval $[0; 2\pi]$.

-- shown below (3) with the rest of the graphs

3. Do the same for other values of the hyperparameter such as $\mu = 10$ and $\mu = 1$.







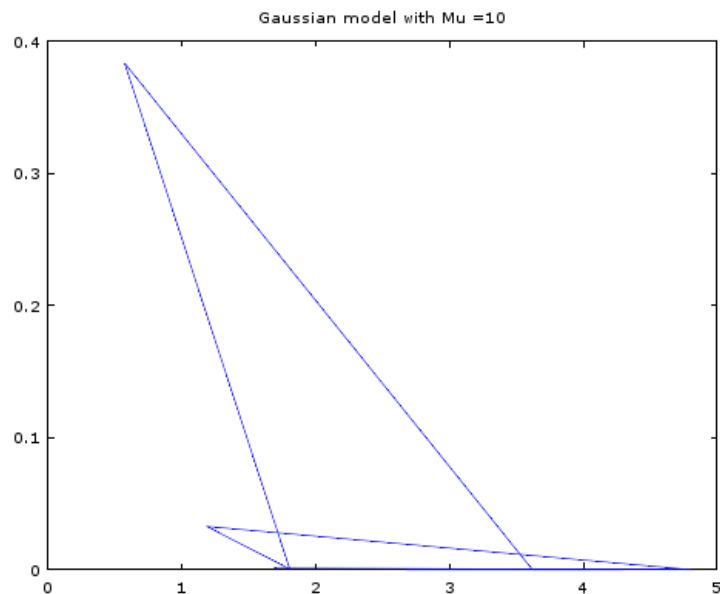
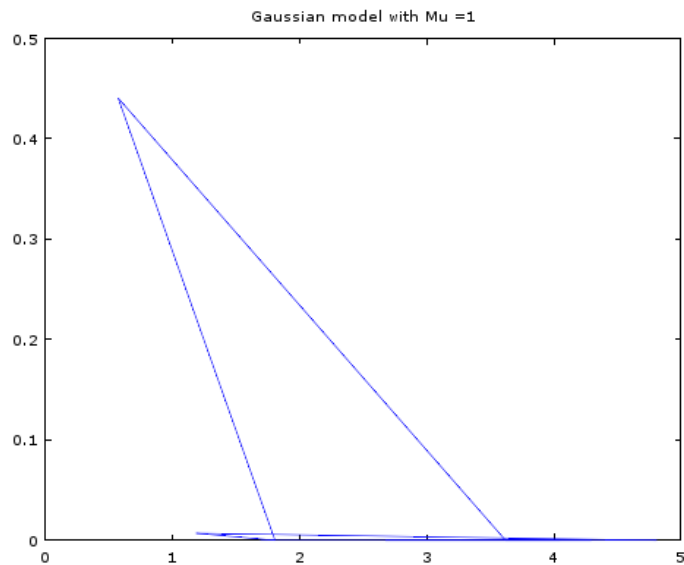
4. (2) What, if anything, is the hyperparameter controlling? How does it impact the solution to the problem?

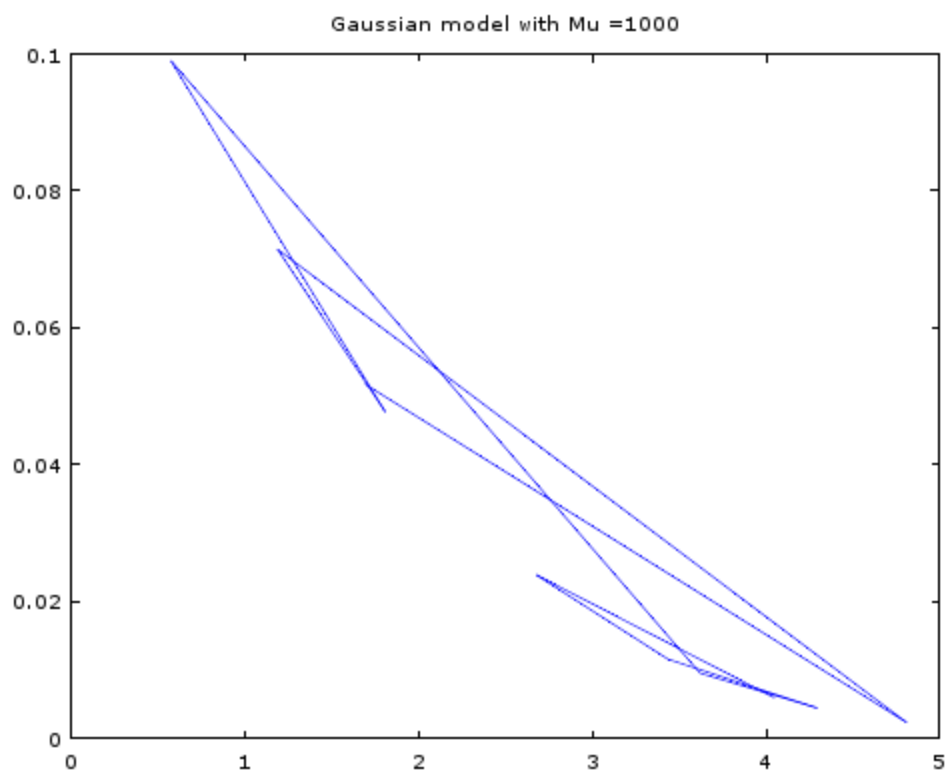
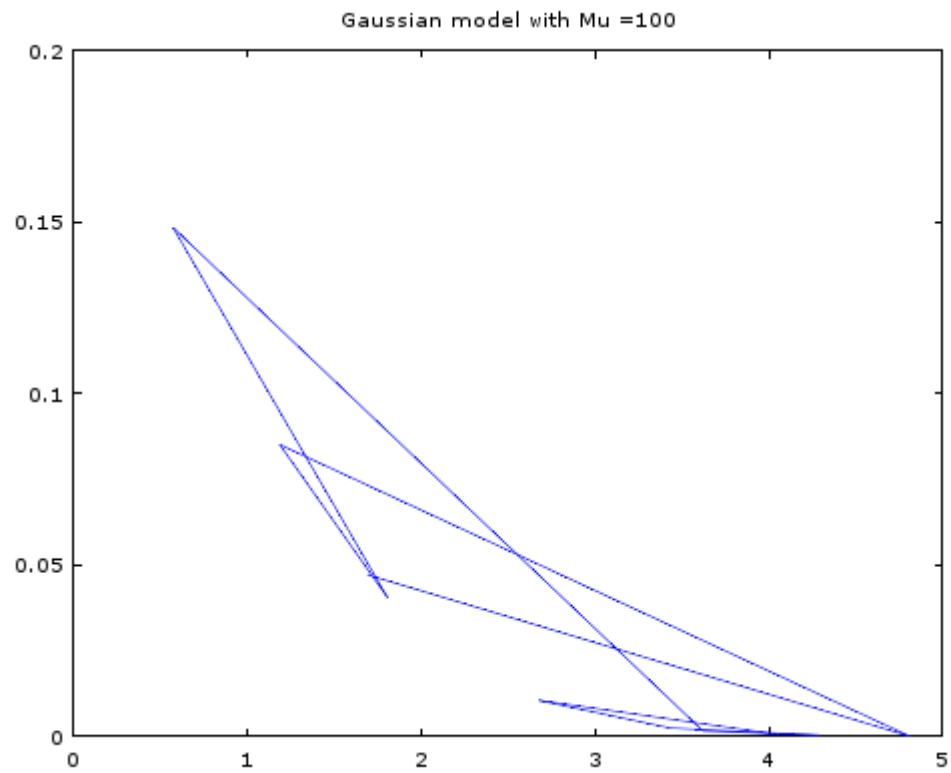
----The hyperparameter doesn't seem to influence the graph at all for large μ , but has somewhat of an influence at lower μ and great influence at $\mu = 1$. It appears to impact the solution to the problem by determining how much spread the solution has – of course, this is only for the cases where small μ is used as mentioned just now. For large μ , it seems to not affect the solution at all.

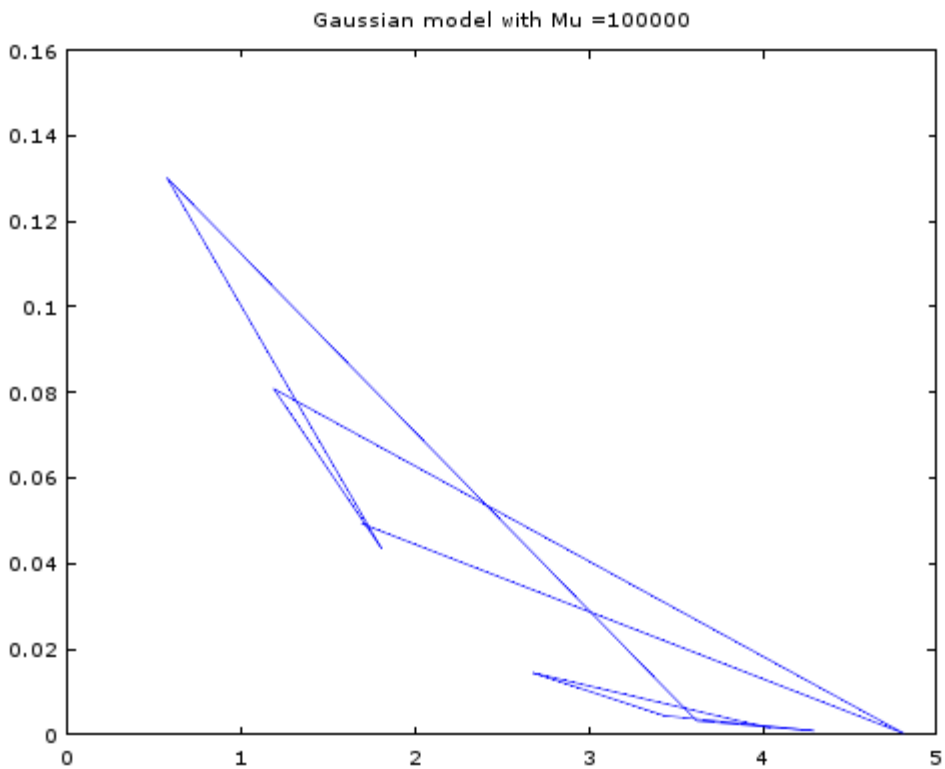
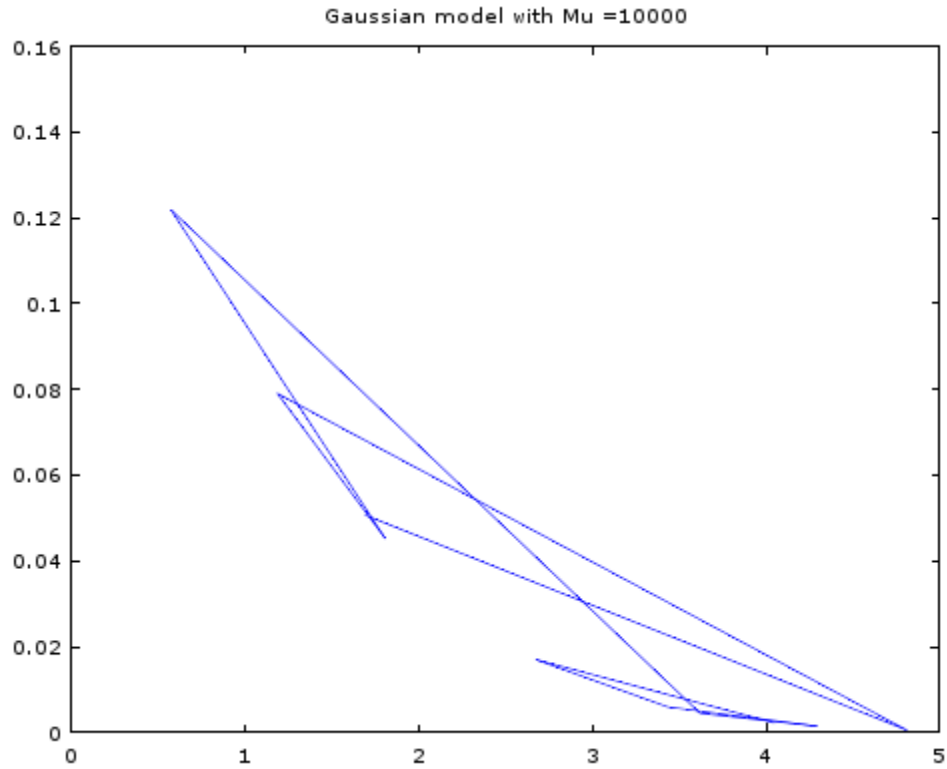
5. (2) Train the model with $M = 10$ Gaussian basis functions and $\mu = 10^5$, then plot and turn in the learned model evaluated (the function fitted to the data) on the interval $[0; 2_+]$.

--- shown below (6) with the rest of the graphs

6. As before, explore other values of the hyperparameter such as $\mu = 10$ and $\mu = 1$.



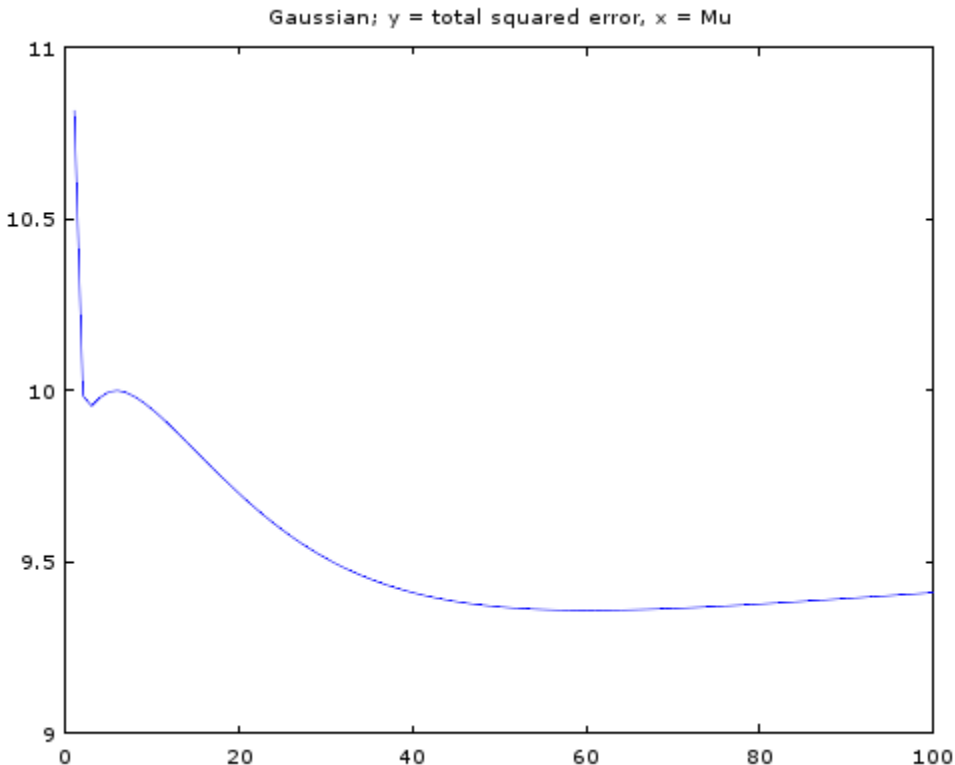




7. (2) What, if anything, is the hyperparameter controlling in this case? How does the dependence of the solution on the hyperparameter differ for this basis when compared to the hat basis?

---- The hyperparameter also seems to be influencing the spread in this case – for larger μ , the spread of the solution has more verticality in general, while at smaller μ , the solution is constrained to less values on the bottom side of the vertical y spectrum. The solution here seems to be considerably more dependent on the hyperparameter, as it affects how far the solution can go vertically at all levels of μ , while for the hat basis it only affected it for the small μ .

8. (4) Fit the model with values of μ in the range $[1; 100]$ and using a Gaussian basis of ten elements on the data in `simple.mat`. For each model, calculate the squared error for the observations in `test.mat` (therefore testing the model). Generate and turn in a plot with μ on the x-axis and the total squared model error on the test data along the y-axis.



9. (2) What value of μ , when trained on the data in `simple.mat`, performs best on the data in `test.mat`? How do you know? Explain the shape of the plot you generated in the previous step.

---- I found that $\mu = 60$ performs best on the data in `test.mat`. I know this because as we plot μ against the total squared error, the minimum squared error occurs when $\mu = 60$. This error is approximately around 9.385. The shape of the graph takes on massive error for small μ ; this might be because the solution has less positive values to center about on each side where μ is. As μ increases, the solution has more positive values to spread about on both sides of μ , allowing the error to decrease suddenly and then level out.

10. (4) Repeat the process now fixing μ to be the optimal value you found and varying the number of basis elements from 1 to 100. Generate and turn in a plot with the number of basis elements on the x-axis and the error for the test data on the y-axis.

