# Practical Exercise 7

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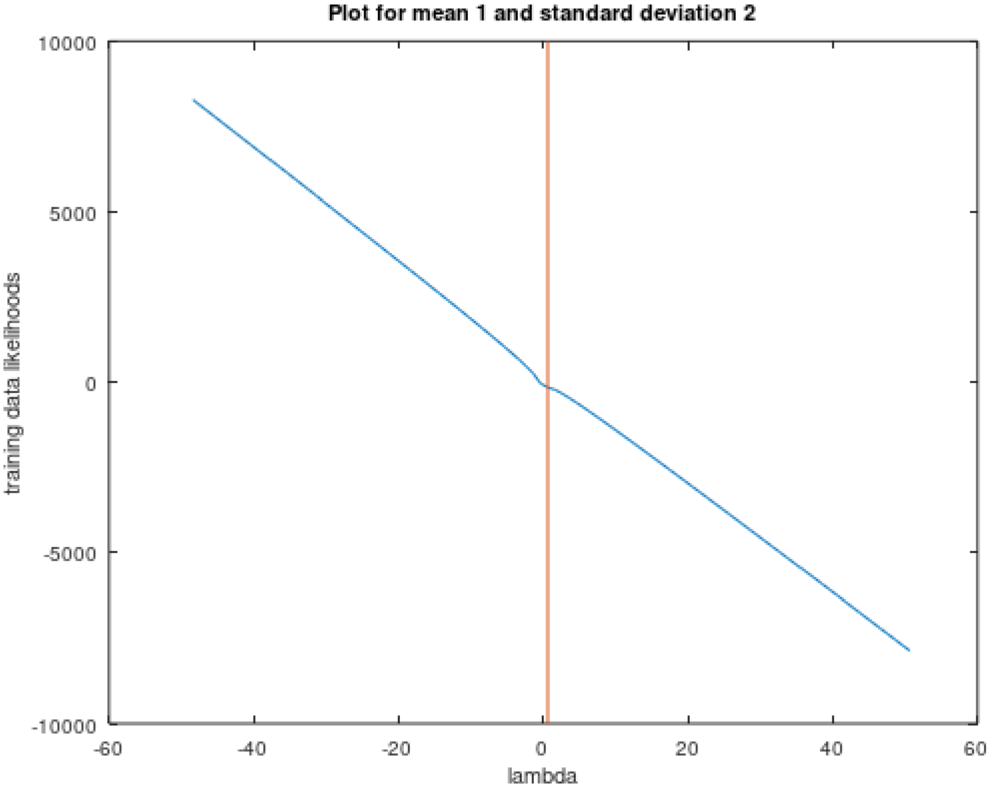
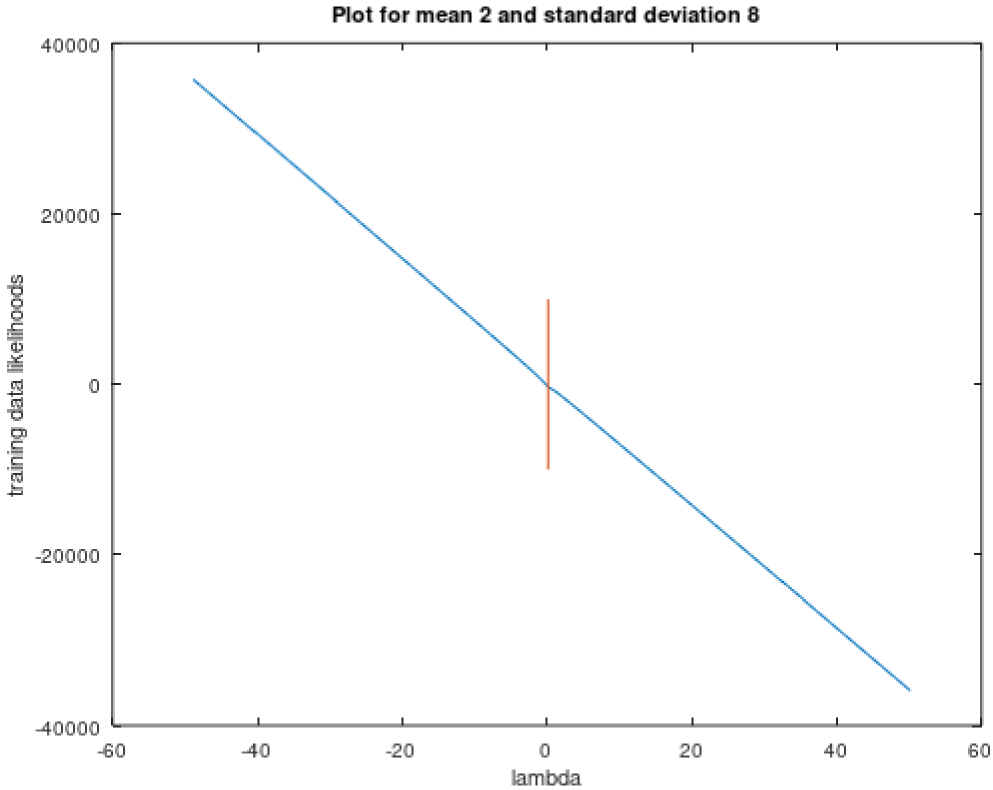
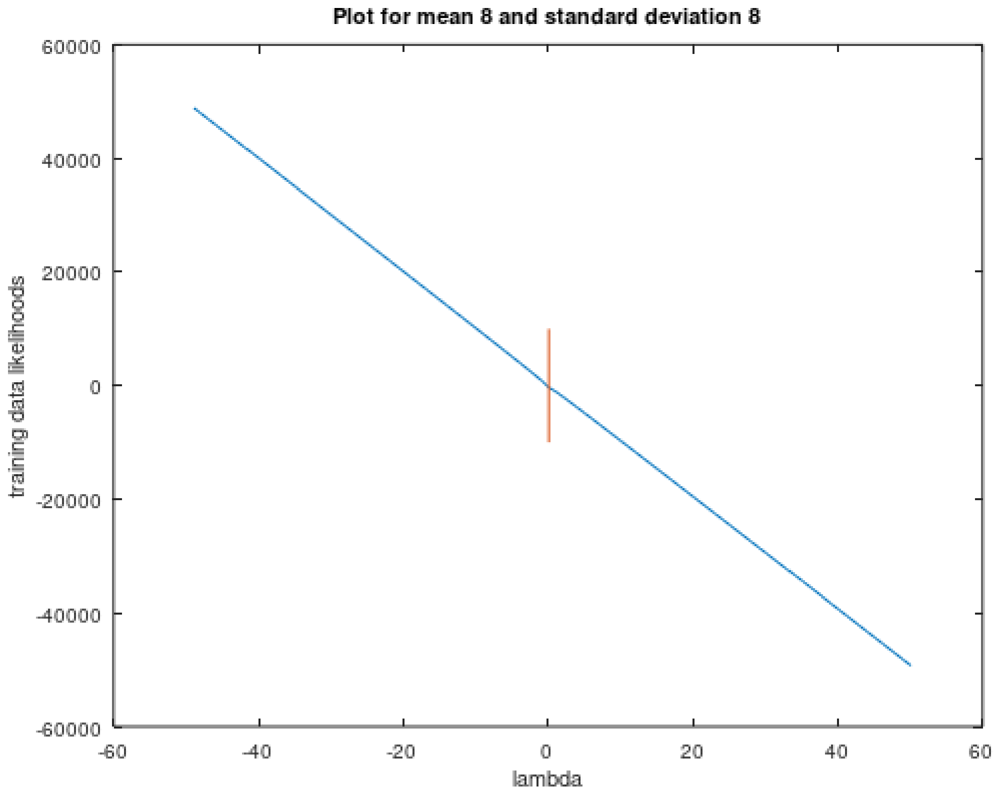
## Code

```
axis ([-60 60 -10000 10000]);
fig = 1;
X = [];
Maxlies = [];
Logli = [];
#Different means and standdev
for mean = 1:8
  for standdev = 1:8
    #Get a 10x10 matrix with random numbers which are normally distributed
    #with mean and standard deviation (standdev)
    m = mean + standdev * randn(10)
    #Make one vector out of the 100 entrys of the matrix
    m = reshape(m,1,[])
    #No negative samples
    m = abs(m)
    #Maximum-likelihood estimate following the theory sheet
    maxlies = 100 * (1/sum(m))
    #Computing log-likelihood function
    logli = 100 * log(maxlies) - (maxlies * (sum(m)))
    #Vector with 100 settings around maxlies
    vec = []
    for dif = -49:50
      vec(end+1) = maxlies + dif
    endfor
    #Compute log-likelihood function on vec
    for i = 1:100
      vec(i) = 100 * log(vec(i)) - (vec(i) * (sum(m)))
    endfor
    #Show result
    figure(fig);
    x = 1:100;
    plot (maxlies - 50 + x,vec(x));
    hold on;
    #the line at the maximum-likelihood estimate
    plot([maxlies,maxlies],[-10000,10000]);
    xlabel ("lambda");
    ylabel ("training data likelihoods");
    tit = cstrcat("Plot for mean ",num2str(mean)," and standard deviation ", num2str(standdev));
    title (tit);
    hold off;

    fig = fig + 1;
    #Put the new values into the matrix X, Maxlies and Logli
    X = vertcat(X,x)
    Maxlies = vertcat(Maxlies,maxlies)
    Logli = vertcat(Logli,logli)
  endfor
endfor
```


Plot for mean 1 and standard deviation 2
10000
5000
0
-5000
-10000
training data likelihoods
-60
-40
-20
0
20
40
60
lambda


Plot for mean 2 and standard deviation 8
40000
20000
0
-20000
-40000
training data likelihoods
-60
-40
-20
0
20
40
60
lambda




**Comment on the results**

In the graphs above we clearly see the intersection of the estimated lambda (the vertical red line marks it) and the likelihoods of the training data (blue line) for given lamda. Intersection is the value of the estimated likelihood.

Furthemore we notice that the function of likelihoods is almost a linear function for all data sets. That was to be expected because the likelihood-function is a linear function in relation to lambda (see theory sheet 5).

Also we see as expected that the estimated lambda values for the different models differ quite drastically.