Intro to AI Assignment 2B

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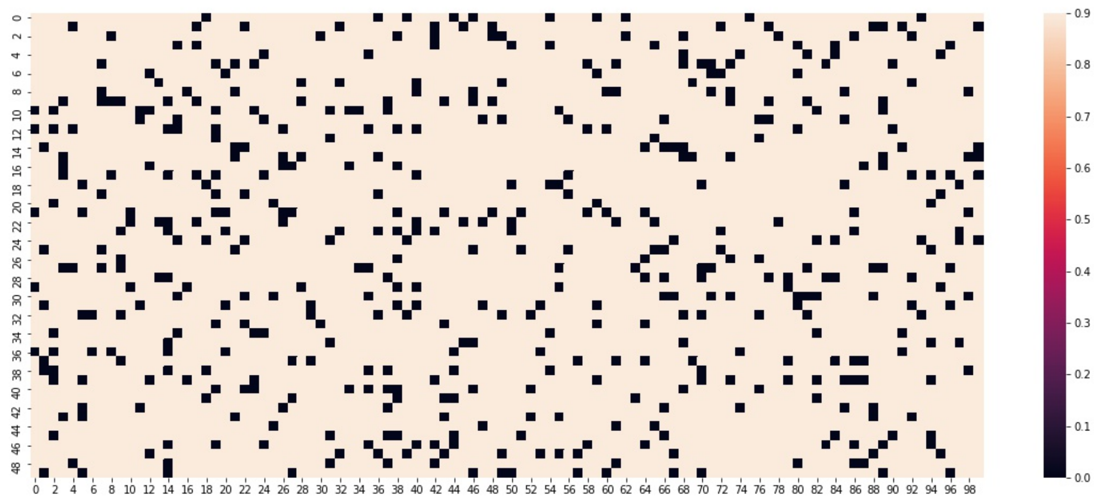
Question 5 - Unknown Cells

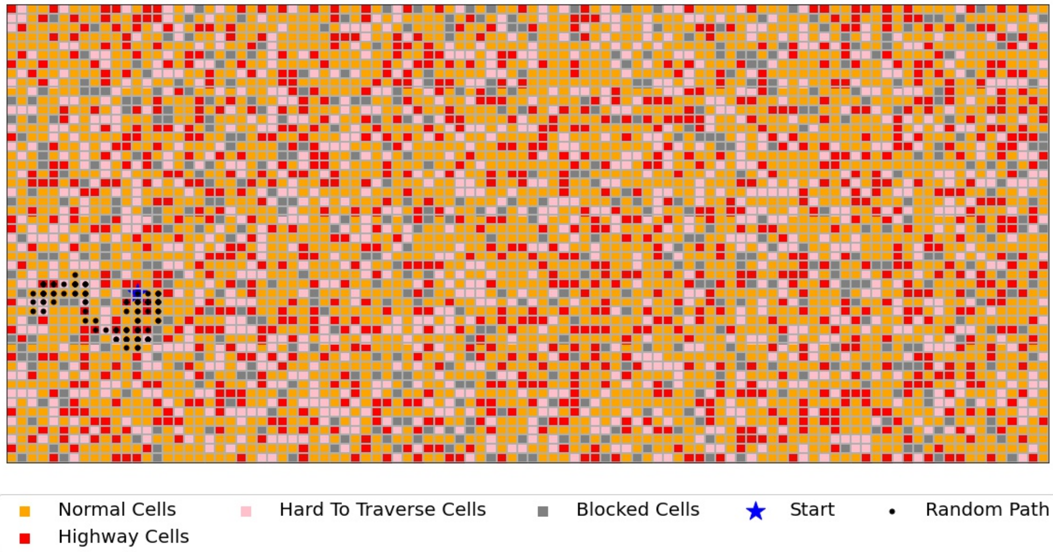
5c) Estimating Positions

Initial Probabilities

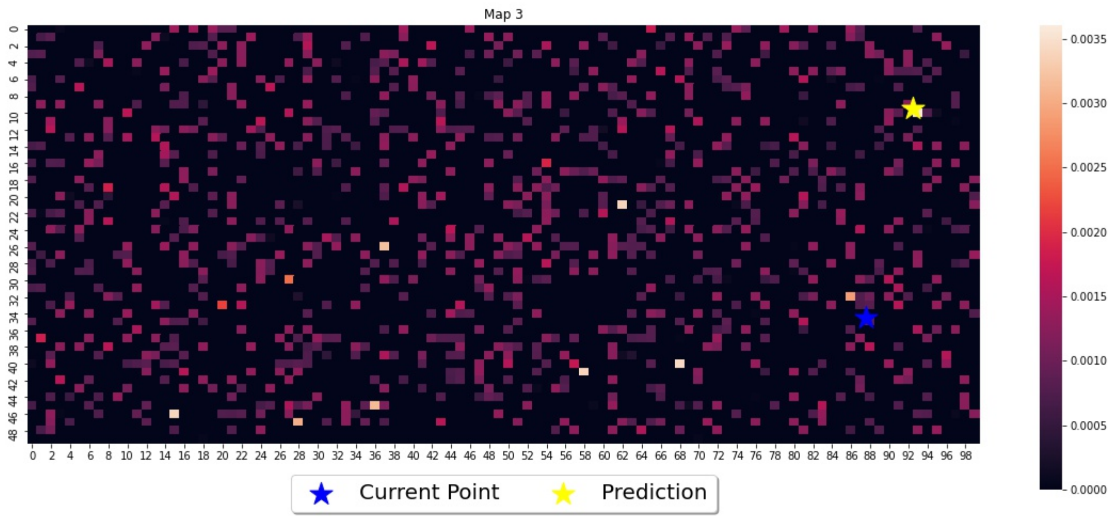
We do not know where our agent is, so there is an equal probability that it could be in each of the unblocked cells. So, our current heat-map looks like this:

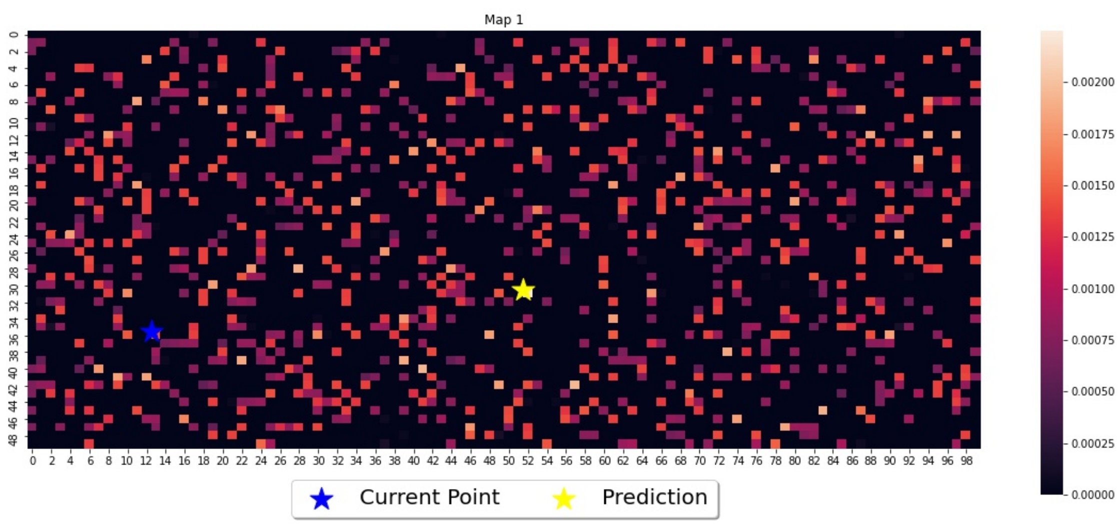


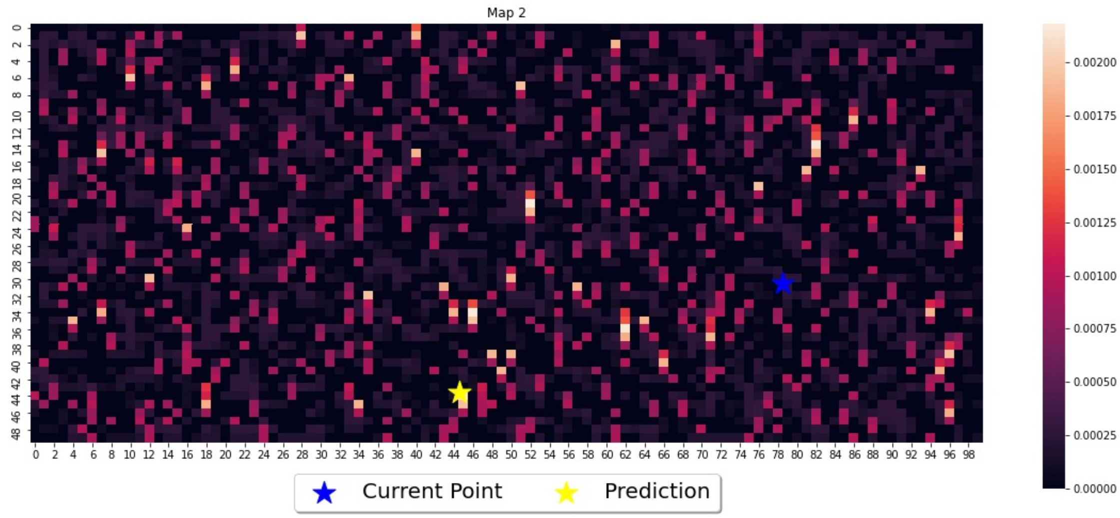
For a map that looks like this:


Normal Cells
Hard To Traverse Cells
Blocked Cells
Start
Random Path
Highway Cells

Example Heat-maps for 10 iterations

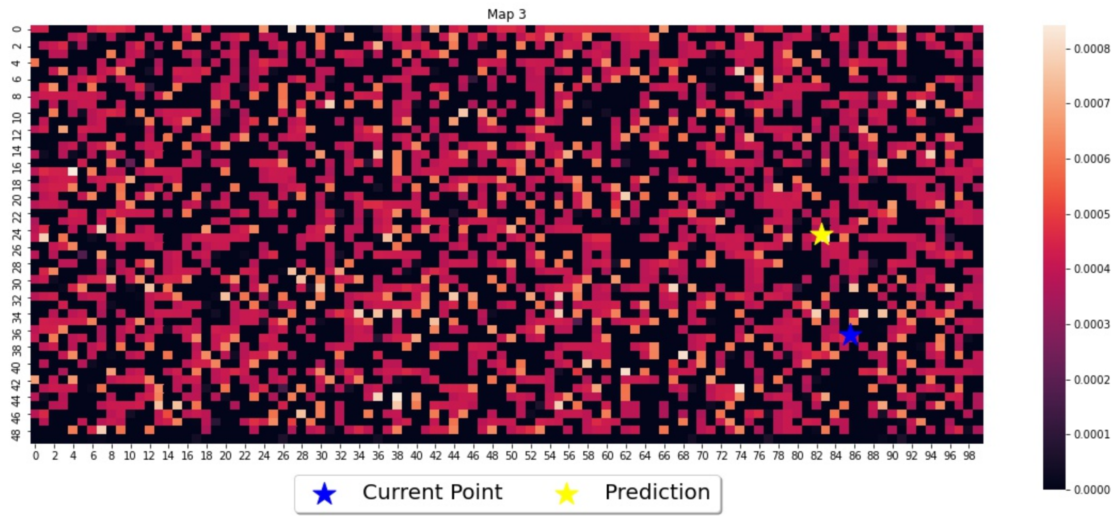


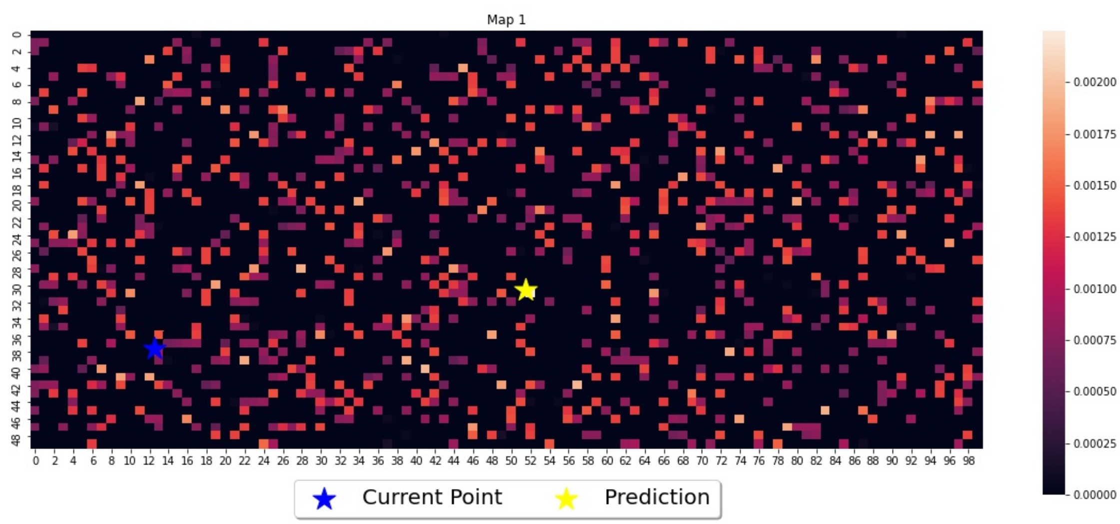


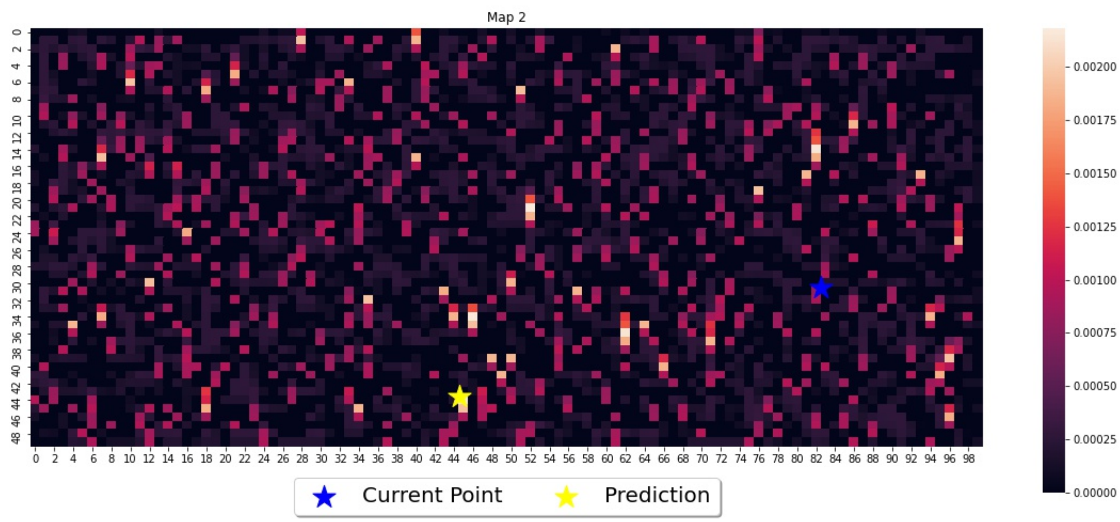


Map 2
Current Point
Prediction

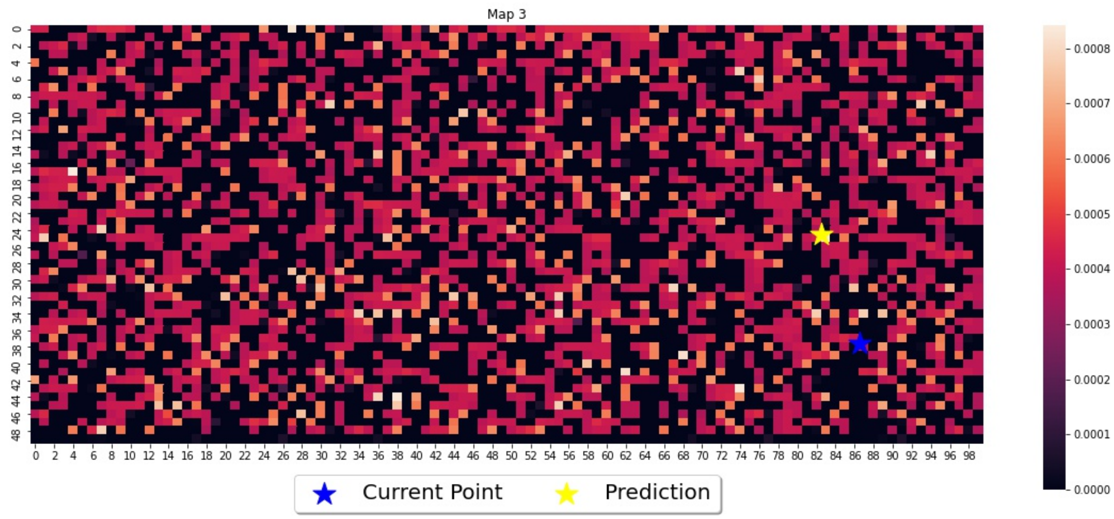
Example Heat-maps for 50 iterations

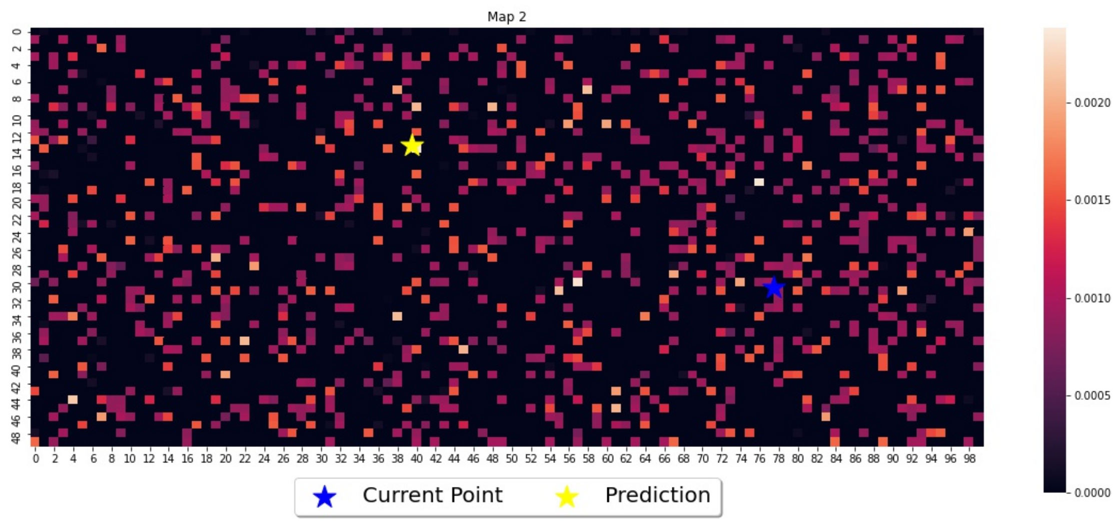


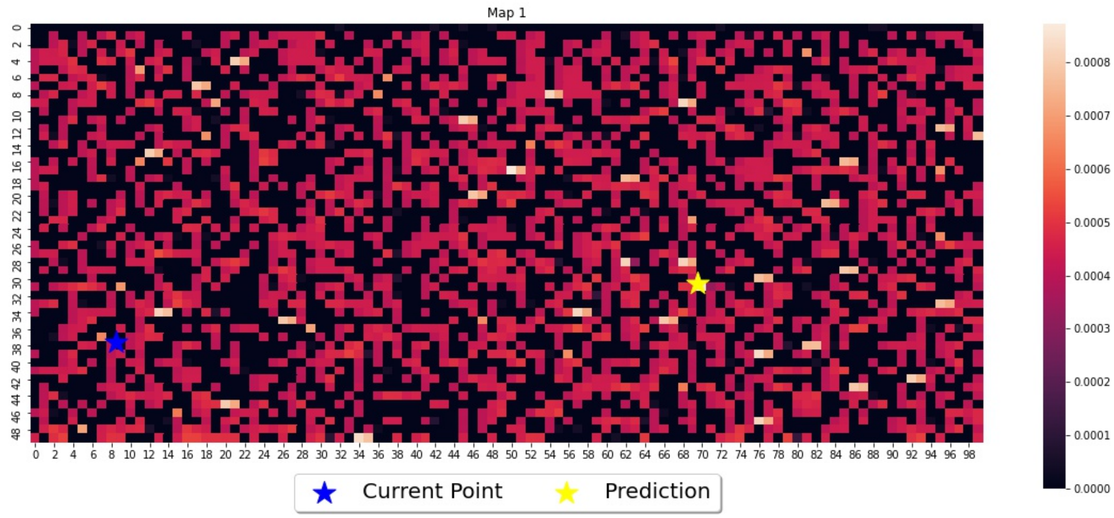



Map 2
Current Point
Prediction

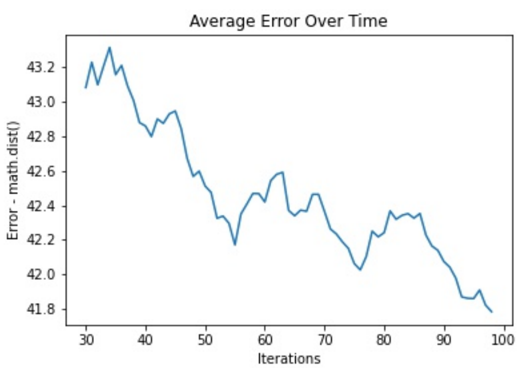
Example Heat-maps for 100 iterations



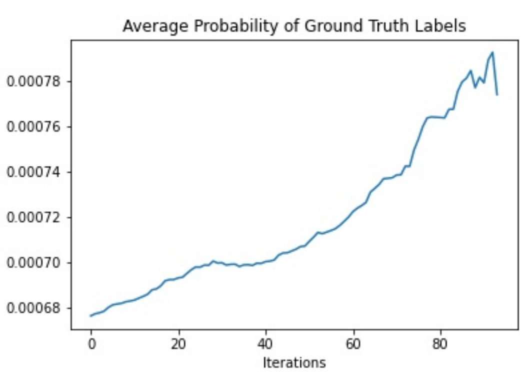




Average Error Over All 100 Experiments



Average Probability of Ground Truth Cells



Extra Features

In addition to all of the computation required to make these graphs we also saved a simulation of all 100 iterations.

To see each iteration you can navigate to the animation folder and find the GIF files to view each experiment.
We have also saved each image in a folder that was used to make these GIFs.
The graph data containing the cell types and the ground truth labels were saved in a folder named data.
We have provided jupyter notebook files with well documented code, so you can see how we implemented the filtering algorithm.
We have also included a .py version of the files as well.
NOTE: The graphs used in this example were not the same graphs from assignment 2B. We generated new graphs for the 100 iterations.

Conclusion

It seems that the less cells covered by the agent gives better results using the filtering algorithm.
When the agent is bounded (in a tight area and does not leave) the filtering algorithm works exceptionally well minimizing the overall error greatly.
This is because it is easier to rule out certain positions in the graph when our sensor reading sequences are relatively similar.

However, when our agent randomly decides to wonder off the filtering algorithm still minimizes error, but is not as accurate.
This is because we have varying sequences of evidence that confuses the filtering algorithm.

Question 6 - The Mechanic

6a) Expected Net Gain From Buying C_1

There is a 70% chance that it is in good shape.
Then, it costs \$3000 to buy and has a \$4000 market value.
This yields a +\$1000 gain.
So, we have that $0.70 * 1000 = 700$.

There is a 30% chance that it is in bad shape.
We have a \$1000 in profit and we need \$1400 in repairs.
So, we have that $0.30 * 400 = 120$.

Our final answer is $\$700 - \$120 = \$580$.
The expected net gain from buying C_1 given no test is \$580.

6b) Bayes' Theorem To Calculate Pass/Fail

Remember that $\frac{P(B|A)P(A)}{P(B)}$. So,

$\text{P}(\text{pass}(c_1)) = \text{P}(\text{pass}(c_1)|q^+(c_1)) * q^+(c_1) + \text{P}(\text{pass}(c_1)|q^-(c_1) * q^-(c_1)$

$P(\text{pass}(c_1)|q^+(c_1)) = 0.80 = \frac{P(q^+(c_1)|pass(c_1))*pass(c_1)}{q^+(c_1)}$

$0.80 = \frac{P(q^+(c_1)|pass(c_1))*pass(c_1)}{0.70}$

$P(pass(c_1)|q^-(c_1)) = 0.35 = \frac{P(q^-(c_1)|pass(c_1))pass(c_1)}{q^-(c_1)}$

$0.35 = \frac{P(q^-(c_1)|pass(c_1))pass(c_1)}{0.30}$

Our answers are below:

$P(q^+(c_1)|pass(c_1)) = \frac{P(pass(c_1)|q^+(c_1))P(q^+(c_1))}{P(pass(c_1))}$
$= \frac{0.80*0.70}{0.80*0.70+0.35*0.30} = 0.84$

$P(q^-(c_1)|pass(c_1)) = \frac{P(pass(c_1)|q^-(c_1))P(q^-(c_1))}{P(pass(c_1))}$
$= \frac{0.35*0.30}{0.80*0.70+0.35*0.30} = 0.158$

$P(q^+(c_1)|\neg pass(c_1)) = \frac{p(\neg pass(c_1)|q^+(c_1))P(q^+(c_1))}{P(\neg pass(c_1))}$
$= \frac{(1-0.80)*(0.70)}{1-10.8*0.70+0.35*0.30} = 0.418$

$P(q^-(c_1)|\neg pass(c_1))) = \frac{P(\neg pass(c_1)|q^-(c_1))P(q^-(c_1)}{P(\neg pass(c_1))}$
$= \frac{(1-0.35)*0.30}{1-(0.80*0.70+0.35*0.30)} = 0.58$

6c) Best Decision and Expected Utility

Given that the car passes the mechanic's test the best decision is to buy the car since there is an 84% chance that is it in good condition and since the expected utility is positive

Expected Utility:

$0.84 * (\$4000 - \$3000) + 0.16(\$4000 - \$3000 - \$1400) - \$100$
$= \$840 - \$64 - \$100$
$= \$676$
Given that the car fails the mechanic's test, the best decision is to buy the car because even though it is only 41.80% that the car is in good shape, the expected utility is still positive

Expected Utility:

$0.418 * (\$4000 - \$3000) + 0.582(\$4000 - \$3000 - \$1400) - \$100$
$= \$418 - \$232.80 - \$100$
$= \$85.20$

6d) The Value of Optimal Information for the Mechanic's Test

Value of Optimal Information = Utility with Mechanic - Utility without Mechanic
Value of Optimal Information = $\$676 - \$580 = \$96$

It is worth going to the mechanic because the value of optimal information is positive even with the $100 paid for the test accounted for in the utility equations.

Question 7 - Markov Decision Process

Original Utilities

Five Intermediate Results

Final Results

Convergence Criterion

Computation Time and Number of Iterations

Code Implementation