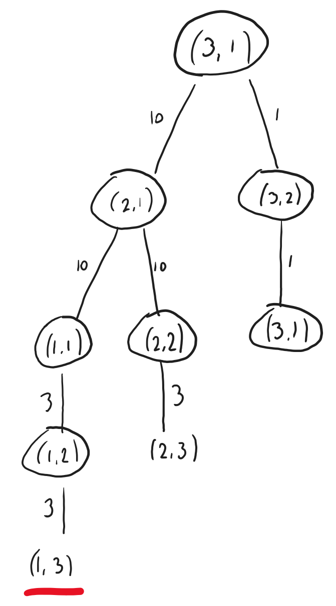
AI 2019 Paper

1.a/



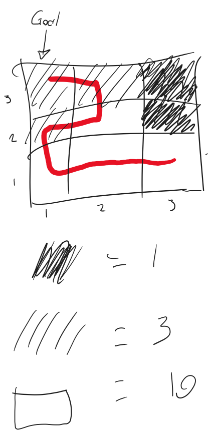
indicates a visit

The frontier when terminating: {(1,3), (2,3)}

Sequence of nodes visited: (3,1), (2,1), (3,2), (1,1), (2,2), (3,1), (1,2)

Path by BFS: (3,1), (2,1), (1,1), (1,2), (1,3)

Solution by BFS: left, left, up, up



b/ BFS is complete, but non-optimal as our cost function is not non-decreasing in terms of depth. We can trivially see a better solution, (3,1), (3,2), (3,3), (2,3), (1,3), with far less cost. This problem is not suited for BFS, but formulating this as an optimization problem would yeild better results

c/ Design Variable : $\mathbf{V}$ is a vector, comprising of states in the graph (x,y) where $1 \le x \le 3$, $1 \le y \le 3$. No infeasible solutions exist as we have limited the design variable to only contain states that exist. Two example feasible solutions are:

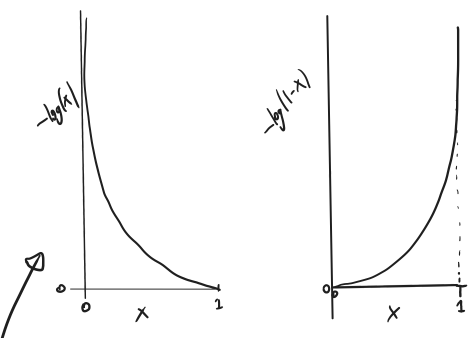
$$\mathbf{V} = \begin{pmatrix} (2,1) \\ (1,1) \\ (1,2) \end{pmatrix} \quad \text{and} \quad \mathbf{V} = \begin{pmatrix} (3,1) \\ (2,1) \\ (2,2) \\ (2,3) \\ (1,3) \end{pmatrix}$$

Q2 out of spec

Q3/a/ x when $z^2 - 12z + 2$ is min is 6

b/

$$Cost(h(\mathbf{x};w), y) = \begin{cases} -\log(h_w(x)) & \text{s.t. } y = 1 \\ -\log(1 - h_w(x)) & \text{s.t. } y = 0 \end{cases}$$



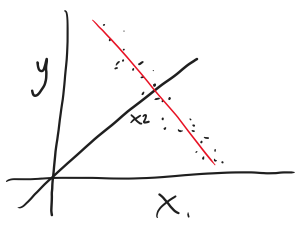
These are two graphs for each function. If the actual y-value is zero, then we want our cost function to have zero cost at $x=0$, but high cost at closer to 1, which we see here. The opposite is true if $y=1$, we want $x=1$ to have zero cost, and closer to 0 to be more and more penalised, as we see here. This means that the cost function appropriately penalises wrong answers, and is reasonable.

c/ i/ Hypothesis Func: $h(\mathbf{x};\mathbf{w}) = w_0 + w_1 x_1 + w_2 x_2$

Cost Func: $\sum_{n=1}^{N} \left(y^{(n)} - (w_0 + w_1 x_1 + w_2 x_2)\right)^2$

The hypothesis function is comprised of the weights, w_0, w_1, w_2, which are free parameters that are learnt in the training phase, and independant variables, x_1, x_2, that represent the input data we are using to try and predict an output. The hypothesis function represents a line that we are trying to closely fit to the input vs output graph.

Like so



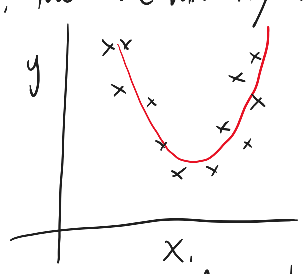
is the $h(x;w)$

The cost function finds the difference between the actual y value and the predicted y-value, and squares it. This error is summed over all examples N to find the total error.

ii/ Hypothesis Func: $h(\mathbf{x};\mathbf{w}) = w_0 + w_1 x_1 + w_2 x_1^2$

Cost Func: $\sum_{n=1}^{N} \left(y^{(n)} - (w_0 + w_1 x_1 + w_2 x_1^2)\right)^2$

The hypothesis function is a quadratic, that we will try to fit closely to the input vs output graph like so:



is the $h(x;w)$

The cost function does the same as described above.