AI HW1 - Our Heuristics

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1 MST heuristic

This is the first heuristic we chose to implement, this heuristic is the one we learned in class.

This heuristic is defined as followed:

$$h(v) = w(MST_G)$$

Where MST_G is the Minimum spanning tree (computed according to w) of the graph G, and w is the weight function of the edges of G, meaning $w(MST_G) = \sum_{e \in MST_G} w(e)$.

The rational of using this heuristic is that G is the graph with only our goals and the current vertex v, so using the weight of MST_G, will give some approximation of the path to reach all of our goals, specifically it is an admissible heuristic, since the weight of the MST can me at most the length of the path to pass through all of our goals starting at n since this will be the case if MST_G is a simple path with the lightest edges, Therefore the weight of the MST is the lower bound on the weight of the shortest path through all of the goal vertices.

2 MST + Normalized reward difference

This is the second heuristic that we implemented, it is an extension of the first heuristic.

This heuristic is as followed:

$$h'(v) = w'(MST_G)$$

Where MST_G is the Minimum spanning tree (computed according to w') of the graph G, and w' is the weight function of the edges of G, meaning $w'(MST_G) = \sum_{e \in MST_G} w'(e)$. w' is defined using w the original weight function of G, and $p : V \to \mathbb{N}$ the people count function (returns the number of people to collect at the given vertex), as followed:

$$w'(\{v,u\}) = \frac{w(\{v,u\}) - p(u) - p(v) + p(G)}{w'(G)} = \frac{w(\{v,u\}) - p(u) - p(v) + \sum_{e \in G} p(e)}{\sum_{e \in G} w'(e)}$$

Of course this heuristic is also admissible since all the weights of the edges are $\in (0, 1)$, and $0 \geq h'(v) \leq h(v)$.

The rational behind this heuristic is to give some importance to nodes with more people.