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# Solving Eikonal Equations using Dijkstra's algorithm

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Srivatsa Srinivas

## 1 The Hamilton-Jacobi-Bellman equation

The purpose of this section is to define the Hamilton-Jacobi-Bellman equation. The Hamilton-Jacobi-Bellman (HJB for short) equation describes the way to choose the next “direction” that an agent must go in order to minimize a “loss-function”. We will introduce the data required to define the HJB equation. We will use conventions from the document [Cal24], mixed with our own.

**Definition 1** (HJB triple). *An HJB triple is a triple  $(L, U, g)$  where  $U \subset \mathbb{R}^n$  is open and bounded,  $g$  is a continuous function on  $\partial U$  and  $L : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$  is a continuous function such that*

1. (1-Positive Homogeneity): *We have for all  $\alpha > 0$  that  $L(\alpha x, y) = \alpha L(x, y)$*

2. (1-Positivity): *We have that for all  $p, x \in \mathbb{R}^n$  that if  $p \neq 0$  then  $L(p, x) > 0$ .*

**Definition 2** (Cost and Value functions). *Let  $(L, U, g)$  be an HJB triple*

1. (Cost Function). *For any  $x, y \in \mathbb{R}^n$  we define*

$$\text{Cost}(x, y) := \inf_w \int_0^1 L(w'(t), w(t)) dt$$

where  $w : [0, 1] \rightarrow \mathbb{R}^n$  ranges over all continuous functions from  $[0, 1]$  to  $\mathbb{R}^n$  such that  $w(0) = x, w(1) = y$ .

2. (Value function). *For any  $x \in \mathbb{R}^n$  we define*

$$u(x) := \inf_{y \in \partial U} (g(y) + \text{Cost}(y, x))$$

3. (Compatibility). *We say that  $(L, U, g)$  is compatible if for every  $x, y \in \partial U$  we have that*

$$g(y) - g(x) \leq \text{Cost}(y, x)$$

From this point of the document onwards, we **assume** that every HJB triple is compatible

**Example 1** (Distance Function). *If  $L : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$  is defined by*

$$L(x, y) := \|\pi_L(x, y)\|_2 = \|x\|_2$$

and  $U \subset \mathbb{R}^n$  is bounded, and  $g : \partial U \rightarrow \mathbb{R}$  is just the 0 function i.e,  $g(x) = 0(x) = 0$ , then we have that  $(L, U, 0)$  is an HJB triple with cost function

$$\text{Cost}(x, y) = \|x - y\|_2$$

and value function

$$u(x) = d_{\partial U}(x)$$

where  $d_A(x)$  is the minimum distance of  $x$  from the set  $A$ .

The following lemma is similar to Lemma 4.3 and 4.4 in [Cal24]

**Lemma 1** (Locality and Locally Lipschitz properties of value function). *Let  $(L, U, g)$  be an HJB triple*

25 1. (Locally Lipschitz). We have that the value function  $u : \mathbb{R}^n \rightarrow \mathbb{R}$  is Locally Lipschitz.

26 2. (Locality). We have that for all  $x \in \mathbb{R}^n, r > 0$  that

$$u(x) = \inf_{y \in B(x,r) \setminus \{x\}} u(y) + \text{Cost}(y, x)$$

27 The above lemma tells us that if the value function,  $u$ , of an HJB triple  $(L, U, g)$  is differentiable at  
28 a point  $x_0$  then we have that

$$0 = \sup_{\|a\|_2=1} (-\nabla u \cdot a - L(a, x))$$

29 **Definition 3** (HJB equation). Let  $(L, U, g)$  be an HJB triple

30 1. (Hamiltonian). Given a point  $x_0 \in \mathbb{R}^n$  and a function  $\phi$  that is differentiable at  $x_0$  we  
31 define the Hamiltonian,  $H$  to be

$$H(\phi, x_0) := \sup_{\|a\|_2=1} (-\nabla \phi \cdot a - L(a, x))$$

32 2. (HJB equation). We say that a function  $\phi$  which is continous and piecewise differentiable  
33 on  $\mathbb{R}^n$  satisfies the HJB equation if for all points  $x$  at which it is differentiable we have that

$$H(\phi, x) = 0$$

34 and for all  $x_0 \in \partial U$  we have that

$$\phi(x_0) = g(x_0)$$

35 Thus, we can now ask the question: Is it possible to recover the value function by finding a solution  
36 to the HJB equation of a triple? Let us look at the example of the HJB triple  $(L(x, y), (0, 1), 0)$ ,  
37 with  $L(x, y) = 1$ . The value function,  $u$ , of this triple should be the function  $d_{\{0,1\}} : \mathbb{R} \rightarrow \mathbb{R}$ , ie the  
38 minimum distance from the set  $\{0, 1\}$ . This satisfies the equation

$$|du/dx|^2 - 1 = 0$$

39 and  $u(0) = u(1) = 0$ . But there are infinitely many solutions to the above equation which are  
40 piecewise differentiable. Is there a way to recover the value function from the above equation? In  
41 order to answer this, we need the notion of a viscosity solution.

42 **Definition 4** (Viscosity Solution). Let  $(L, U, g)$  be an HJB triple with hamiltonian  $H$ . Let  $V \subset \mathbb{R}^n$   
43 be an open subset

44 1. (Viscosity Subsolution). We say that a function  $v : V \rightarrow \mathbb{R}^n$  is a viscosity subsolution to  $H$   
45 at a point  $x_0 \in V$  if for all  $\phi \in C^\infty(\mathbb{R}^n)$  such that  $\phi(x_0) - v(x_0) = 0$  is a local maximum  
46 of  $\phi - v$  we have that

$$H(\phi, x_0) \leq 0$$

47  $v$  is a viscosity subsolution to  $H$  on  $V$  if it is a viscosity subsolution to  $H$  for all  $x_0 \in V$ .

48 2. (Viscosity Supersolution). We say that a function  $v : V \rightarrow \mathbb{R}^n$  is a viscosity supersolution  
49 to  $H$  at a point  $x_0 \in V$  if for all  $\phi \in C^\infty(\mathbb{R}^n)$  such that  $\phi(x_0) - v(x_0) = 0$  is a local  
50 minimum of  $\phi - v$  we have that

$$H(\phi, x_0) \geq 0$$

51  $v$  is a viscosity supersolution to  $H$  on  $V$  if it is a viscosity supersolution to  $H$  for all  $x_0 \in V$ .

52 3. (Viscosity Solution). A function  $v : V \rightarrow \mathbb{R}$  is a viscosity solution to  $H$  if it is both a  
53 viscosity supersolution and subsolution to  $H$  on  $V$

54 The following theorem appears as Theorem 4.6 in [Cal24].

55 **Theorem 1** (Recovering the value function). Given an HJB triple  $(L, U, g)$  with hamiltonian  $H$ ,  
56 there is a unique function  $v$  such that  $v$  is a viscosity solution to  $H$  on  $\mathbb{R}^n \setminus \partial U$  and is equal to  $g$  on  
57  $\partial U$ . This function  $v$  is equal to the value function of the HJB triple,  $u$ . We say that  $u$  is the viscosity  
58 solution to the HJB equation of the triple  $(L, U, g)$

59 Thus we know that if we find the viscosity solution to an HJB equation, we find it's value function.  
60 But is there a way we can do this efficiently? The rest of this article is dedicated to using the  
61 "Generalized Dijkstra's algorithm" to efficiently estimate the value function of special HJB triples  
62 on a box  $[a_1, b_1] \times \dots \times [a_n, b_n]$

## 63 2 The generalized Dijkstra's algorithm

64 For this section we will define  $\mathbb{K} := \mathbb{R} \cup \{\infty\}$ . Also given, a graph  $G = (V, E)$ , we define the  
 65 neighbor function  $N : V \rightarrow 2^V$  by

$$N(v) := \{w \mid \{w, v\} \in E\}$$

66 The degree function  $d : V \rightarrow \mathbb{N}$  is defined by

$$d(v) := |N(v)|$$

67 **Definition 5.** Given a graph  $G = (V, E)$  we say that a function  $\Phi : (v : V) \rightarrow \mathbb{K} \times \mathbb{K}^{N(v)} \rightarrow \mathbb{K}$  is  
 68 a **monotone local constraint** we have that following hold:

- 69 • *Monotonocity:* For all  $v \in V$  we have that  $\Phi(v)$  is continous, piecewise differentiable and

$$\partial \Phi(v)(t_0, r_1, \dots, r_{d(v)}) / \partial t \geq 0$$

70 and for all  $n_i \in N(v)$  we have that

$$\partial \Phi(v)(t_0, r_1, \dots, n_{d(v)}) / \partial n_i \leq 0$$

71 for every  $(t_0, r_1, \dots, r_{d(v)}) \in \mathbb{R} \times \mathbb{R}^{N(v)}$  at which the corresponding partial derivatives  
 72 exist, where  $(t, n_1, \dots, n_{d(v)})$  are the corresponding co-ordinates in  $\mathbb{K} \times \mathbb{K}^{N(v)}$ .

- 73 • *Causality:* For all  $v \in V$  we have that if

$$\Phi(v)(t_0, r_1, \dots, r_{d(v)}) = 0$$

74 Then for all  $1 \leq i \leq d(v)$  such that  $r_i > t_0$  we have that

$$\Phi(v)(t_0, \underbrace{r_1, \dots, r_i}_{i}, \dots, r_{d(v)}) = 0$$

75 where  $a \geq t_0$ .

- 76 • *Solvability:* For any  $v \in V$  if one of  $r_1, \dots, r_{d(v)}$  is not equal to  $\infty$  then we have that there  
 77 exists a unique  $t_0 \in \mathbb{R}$  such that

$$\Phi(v)(t_0, r_1, \dots, r_{d(v)}) = 0$$

78 **Definition 6** (Update function). Given a graph  $G = (V, E)$  and a monotne local constraint  $\Phi$  we  
 79 define the update function to be a function  $\text{Upd}_\Phi : (V \rightarrow \mathbb{K}) \rightarrow (V \rightarrow \mathbb{K})$  defined by

$$\text{Upd}_\Phi(f)(v) := \begin{cases} \min\{f(v), t_0\} & \exists 1 \leq i \leq d(v). f(n_i) < \infty \\ \infty & \text{else} \end{cases}$$

80 where  $N(v) = \{n_1, \dots, n_{d(v)}\}$  and  $\Phi(v)(t_0, f(n_1), \dots, f(n_{d(v)})) = 0$

81 **Definition 7** (Fixed Points). Given a graph  $G = (V, E)$ , monotone local update  $\Phi$  and a function  
 82  $f : V \rightarrow \mathbb{K}$  we define

$$\text{Fix}(f) = \{v \in V \mid \text{Upd}_\Phi^{(n)}(f)(v) = f(v) \text{ for all } n \in \mathbb{N}\}$$

83 where for any function  $g : A \rightarrow A$  we define  $g^{(0)} = \text{id}_A$ ,  $g^{(n)} = g \circ g^{(n-1)}$ .

84 **Lemma 2** (Adding fixed points). Given a graph  $G = (V, E)$ , a monotone local update  $\Phi$ , and a  
 85 function  $f : V \rightarrow \mathbb{K}$ , let  $A = \text{Fix}(f)$  and  $B = V \setminus \text{Fix}(f)$ . Define  $g_k = \text{Upd}_\Phi^{(k+1)}(f)$ . Let  $b^* \in B$   
 86 be such that

$$s = g_0(b^*) = \min\{g_0(b) \mid b \in B\}$$

87 Then we have that  $v \in \text{Fix}(g_0)$ .

88 *Proof.* We first prove the following claim

89 **Claim.** For all  $k \in \mathbb{N}$ ,  $b \in B$  we have that  $g_k(b) \geq s$

90 *Proof.* The claim is definitionally true when  $k = 0$ . Thus we may assume that  $k > 0$  and that the  
 91 result holds for  $0 \leq k' < k$ . Suppose that there exists a  $b_0 \in B$  such that  $g_k(b_0) < s$ . Then since  
 92  $g_{k-1}(b_0) \geq s$  we must have that  $g_k(b_0) = \min\{g_{k-1}(b_0), t_0\} = t_0$  where

$$\Phi(b_0)(t_0, g_{k-1}(a_1), \dots, g_{k-1}(a_m), g_{k-1}(b_1), \dots, g_{k-1}(b_n)) = 0$$

93 where the  $a_i, b_j$  are the neighbors of  $b_0$  that are in  $A$  and  $B$  respectively. Since  $t_0 < s \leq$   
 94  $g_0(b_1), g_{k-1}(b_1), \dots, g_0(b_n), g_{k-1}(b_n)$ , we have by causality and the fact that  $a_i \in \text{Fix}(f)$

$$\Phi(b_0)(t_0, f(a_1), \dots, f(a_m), g_0(b_1), \dots, g_0(b_n)) = 0$$

95 Since  $\text{Upd}_\Phi(h)(w) \leq h(w)$  for all  $\Phi, h, w$  we know that  $t_0 < g_0(b_i) \leq f(b_i)$ . Applying causality  
 96 again we get that

$$\Phi(b_0)(t_0, f(a_1), \dots, f(a_m), f(b_1), \dots, f(b_n)) = 0$$

97 Thus we have that  $g_0(b_0) = \min\{f(b_0), t_0\} = t_0 < s$ , a contradiction by the definition of  $s$ . This  
 98 proves the claim.  $\square$

99 By the claim we have that for all  $k \in \mathbb{N}, b \in B$ , we have that  $\text{Upd}_\Phi^{(k)}(g_0)(b) \geq s$ . Thus we have that  
 100  $s \leq \text{Upd}_\Phi^{(k)}(g_0)(b^*) \leq s$  and we have finished the proof.  $\square$

101 **Definition 8** (Priority Queue). A priority queue is a data structure that stores  $n$  points of the form  
 102  $(v, r)$  where  $r$  belongs to a type that is orderable. A priority queue is required to have a time  
 103 complexity of  $O(1)$  to return a point of the form  $(v_0, r_0)$  where  $r_0$  is minimal amongst all the  $r$   
 104 such that there exists a  $(v, r)$  in the priority queue. A priority queue is also required to have a time  
 105 complexity of  $O(\log n)$  for inserting a new element  $(v, r)$  into the priority queue.

106 **Lemma 3** (Dijkstra's algorithm). Let  $G = (V, E)$  be a finite graph with monotone local constraint  
 107  $\Phi$ . The following algorithm has a time complexity of  $O(|V| \log |V|)$  that takes in a function  $f : V \rightarrow$   
 108  $\mathbb{K}$  and returns a function  $f_\infty : V \rightarrow \mathbb{K}$  such that  $\text{Upd}_\Phi(f_\infty) = f_\infty = \text{Upd}_\Phi^{(|V|+1)}(f)$

```
#vals is a hash map from vertices to values supplied by the user
#that represents a function on vertices. upd is the update function
def djikstra(vals, upd):
    #pq is a priority queue that stores pairs of the form (vertex, value)
    pq = empty;
    pair_min = (argmin vals, min vals);
    pq.insert(pair_min);
    #solved_points is a set that contains the points which have
    #been popped from the priority queue
    solved_points = empty;
    while (not(pq.is_empty()))
        min_vertex, min_val = pq.pop();
        vals.update(min_vertex, min_val);
        solved_points.insert(min_vertex);
        for v in neighbors(min_vertex):
            if not(solved_points.contains(x)):
                new_val = upd(vals)(v);
                vals.update(v, new_val);
                pq.insert(v, new_val);

    return vals;
```

### 109 3 Using Dijkstra's algorithm to numerically solve Eikonal equations

110 **Definition 9.** Given an HJB triple  $(L, U, g)$  we say that it is an Eikonal triple if  $L(x, y) =$   
 111  $F(y)\|x\|_2$ , where  $\forall y \in \mathbb{R}^n, F(y) > 0$  and  $F$  is continous on  $\mathbb{R}^n$ .

112 Thus if  $(L, U, g)$  is an Eikonal triple we have that the Hamiltonian of this triple is

$$H(\phi, x_0) = \|\nabla \phi\|_2^2 - F(x_0)$$

113 We will now define a graph and a local monotone update which will help us numerically solve an  
 114 eikonal equation.

115 **Definition 10** (Discretization). *Given a  $K \in \mathbb{N}$  and a box  $B = [a_1, b_1] \times [a_n, b_n] \subset \mathbb{R}^n$  we define*  
 116 *the  $K$ -discretization of  $B$  as the graph  $G_{K,B} = (V_{K,B}, E_{K,B})$*

$$V_{K,B} = \{(a_1 + (i_1 + 1/2)\delta_i, \dots, a_n + (i_n + 1/2)\delta_n) \mid 0 \leq i_j \leq K - 1\}$$

117

$$E_{K,B} = \{ \{(a_1 + (i_1 + 1/2)\delta_i, \dots, a_n + (i_n + 1/2)\delta_n), \\ (a_1 + (i_1 + 1/2 \pm 1)\delta_1, \dots, a_n + (i_n + 1/2 \pm 1)\delta_n)\} \\ \mid 0 \leq i_j \leq K - 1\} \cap (V_{K,B} \times V_{K,B})$$

118 *where*

$$\delta_i = (b_i - a_i)/K$$

119 Basically, it is the grid of points obtained by dividing  $B$  into  $K^n$  boxes, taking the vertices to be  
 120 the centers of the boxes and taking the edges to be those which connect a center to another adjacent  
 121 center.

122 **Definition 11** (Eikonal constraint). *Given an Eikonal triple  $(L, U, g)$  with  $L(x, y) = \|x\|_2 F(y)$  and*  
 123 *a discretization  $G_{K,B}$  we define the eikonal constraint to be*

$$\Phi_{F,K,B} : (v : V_{K,B}) \rightarrow \mathbb{K} \times \mathbb{K}^{N(v)} \rightarrow \mathbb{K}$$

124

$$\Phi(v)(t, n_1, \dots, n_{d(v)}) = (e_1/\delta_1)^2 + \dots + (e_n/\delta_n)^2 - F(v)^2$$

125 *where*

$$e_i = \max\{\{0\} \cup \{t - v' \mid v' \in (\{v \pm \delta_i(\underbrace{0, \dots, 1}_{i}, \dots, 0)\} \cap V_{K,B})\}\}$$

126 So for example, if  $n = 2$ , and the Eikonal triple is  $(L, U, 0)$  with  $L(x, y) = \|x\|_2$  and  $v \in V_K$  is not  
 127 on the “boundary” of the grid then

$$\Phi(v)(t, r_{x,+}, r_{x,-}, r_{y,+}, r_{y,-}) = \delta_x^{-2} \max\{t - r_{x,+}, t - r_{x,-}, 0\}^2 \\ + \delta_y^{-2} \max\{t - r_{y,+}, t - r_{y,-}, 0\}^2 - 1$$

128 where  $r_{x,\pm}$  correspond to the horizontal neighbors  $v \pm (\delta_x, 0)$  and  $r_{y,\pm}$  correspond to the vertical  
 129 neighbors  $v \pm (0, \delta_y)$ . Proving the following lemma would cause the document to exceed the page  
 130 limit, but it is not too bad.

131 **Lemma 4** (Eikonal Update). *Given an Eikonal triple  $(L, U, g)$  and a discretization  $G_{K,B}$  the*  
 132 *Eikonal constraint  $\Phi_{F,K,B}$  is a monotone local constraint. The function  $\text{Upd}_{\Phi_{F,K,B}}$  is called the*  
 133 *Eikonal update.*

134 We now note how discretization can help us approximate the viscosity solutions to Eikonal triples.  
 135 This corresponds to Theorem 9.17 in [Cal24].

136 **Lemma 5.** *Given an Eikonal triple  $(L, U, g)$  and a box  $B \subset \mathbb{R}^n$ , define  $g_{B,K} : V_{K,B} \rightarrow \mathbb{K}$  by*

$$g_{B,K}(v) := \begin{cases} \min_{x \in B_v} g(x) & \text{if } \partial U \cap B_v \neq \emptyset \\ \infty & \text{else} \end{cases}$$

137 *where  $B_v$  is the box  $[v_1 - \delta_1/2, v_1 + \delta_1/2] \times \dots \times [v_n - \delta_n/2, v_n + \delta_n/2]$  and  $v_i$  is the  $i^{\text{th}}$  component*  
 138 *of  $v$ .*

139 *Then there exists a constant depending on the Eikonal triple and the box such that*

$$|g_{B,K,\infty}(v) - u(v)| \leq C \sqrt{1/K}$$

140 *for all  $v \in V_{K,B}$ , where  $u$  is the viscosity solution to the HJB equation of the triple  $(L, U, g)$  and*

$$141 \quad g_{B,K,\infty} = \text{Upd}_{\Phi_{L,K,B}}^{(|V_{K,B}|+1)}(g_{B,K})$$

142 Thus we have connected Djikstra’s algorithm to numerically approximating the viscosity solution of  
 143 an HJB equation corresponding to an Eikonal triple  $(L, U, g)$ . This results in an algorithm known as  
 144 the “Fast Marching Method” introduced by James Sethian; [KS98] provides a good explanation and  
 145 history of this technique.

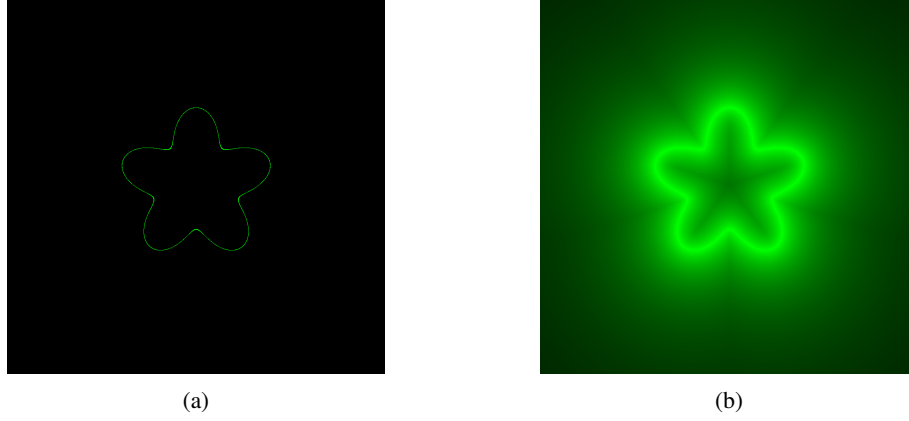


Figure 1: The input and output of generalized Dijkstra's algorithm

## 146 4 Implementation

147 We implement Dijkstra's algorithm to solve eikonal equations in the programming language Rust.  
 148 As an exercise, we implement the special case where we try to approximate the distance from a set  
 149 given by the form  $G(x, y) = 0$  where  $G : \mathbb{R}^2 \rightarrow \mathbb{R}$ . We do so by using Dijkstra's algorithm on  
 150 the Eikonal triple  $(L, U, 0)$ , with  $L(x, y) = \|x\|_2$  and  $U = G^{-1}(-\infty, 0)$ . Figure 1 visually depicts  
 151 approximating the distance from  $G(x, y) = 0$ , where

$$G(x, y) = x^2 + y^2 - 0.5(2 + \sin(5 \arctan(y/x)))$$

152 Let  $B = [-3, 3] \times [3, 3]$ . Each plot in Figure 1 represents a function on  $f : V_{1024, B} \rightarrow \mathbb{R}_{\geq 0}$ ; At a  
 153 vertex  $v$  we plot the color green with intensity  $1/(1 + 0.01f(v))$ . Figure 1a represents  $g_{1024, B}$ , the  
 154 input into the generalized Dijkstra's algorithm. Figure 1b represents  $\text{Upd}_{\Phi_{L, 1024, B}}^{(1025)}(g_{B, K})$ , the output  
 155 of the generalized Dijkstra's algorithm. Note that Figure 1a approximates the indicator function  $\mathbb{1}_{\partial U}$   
 156 and that Figure 1b approximates the function

$$f(x, y) = \frac{1}{1 + 0.01d_{\partial U}(x, y)}$$

## 157 References

- 158 [Cal24] Jeff Calder. *Lecture notes on viscosity solutions*. 2024. URL: [https://www-users.cse.umn.edu/~jwcalder/8590F18/viscosity\\_solutions.pdf](https://www-users.cse.umn.edu/~jwcalder/8590F18/viscosity_solutions.pdf).  
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