



# Potential fields for navigation

EECS 367  
Intro. to Autonomous Robotics

ROB 320  
Robot Operating Systems

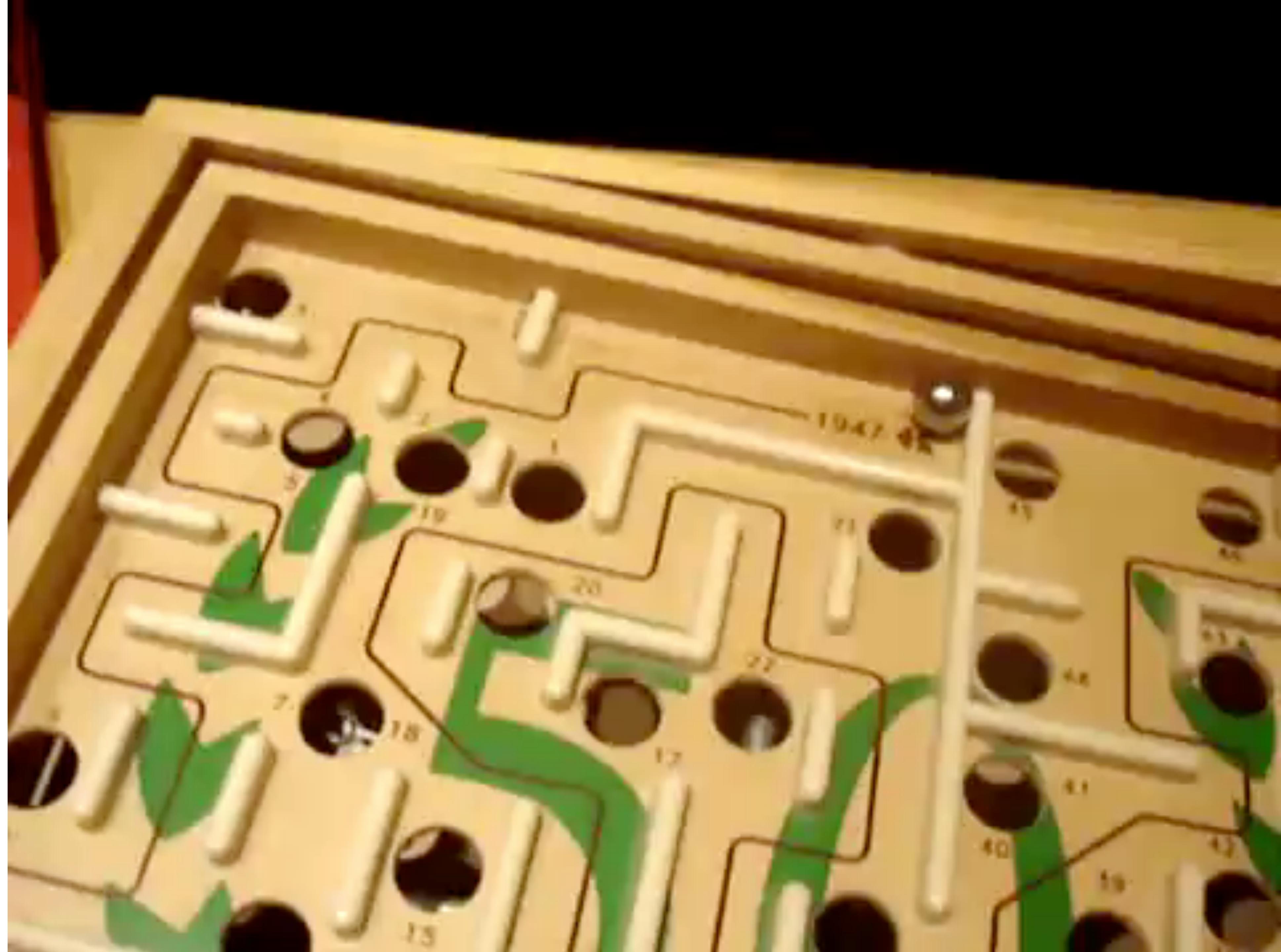
Winter 2022

[autorob.org](http://autorob.org)

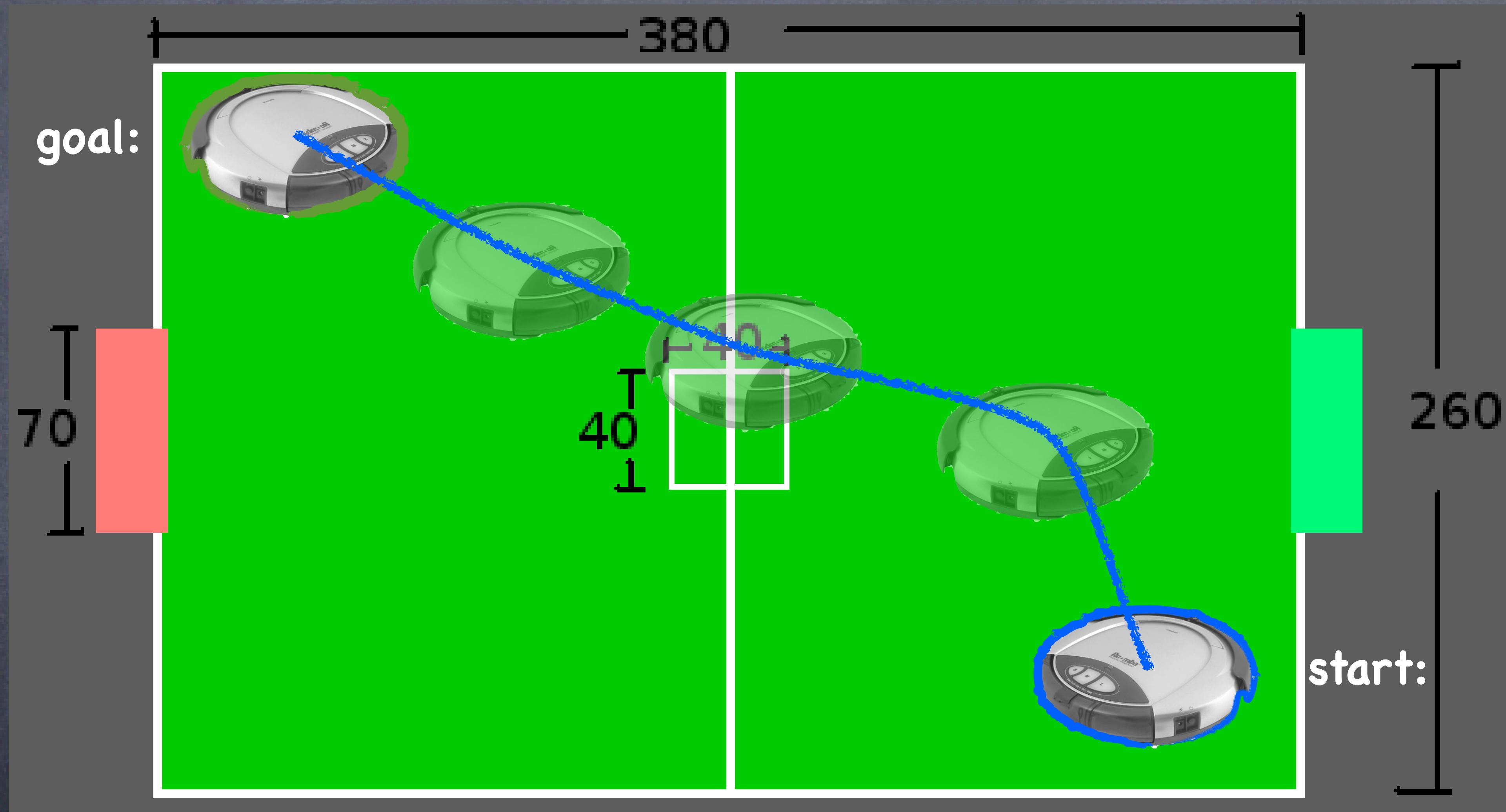
# Approaches to motion planning

- Bug algorithms: Bug[0-2], Tangent Bug
- Graph Search (fixed graph)
  - Depth-first, Breadth-first, Dijkstra, A-star, Greedy best-first
- Sampling-based Search (build graph):
  - Probabilistic Road Maps, Rapidly-exploring Random Trees
- **Optimization and local search:**
  - **Gradient descent, Potential fields, Simulated annealing, Wavefront**



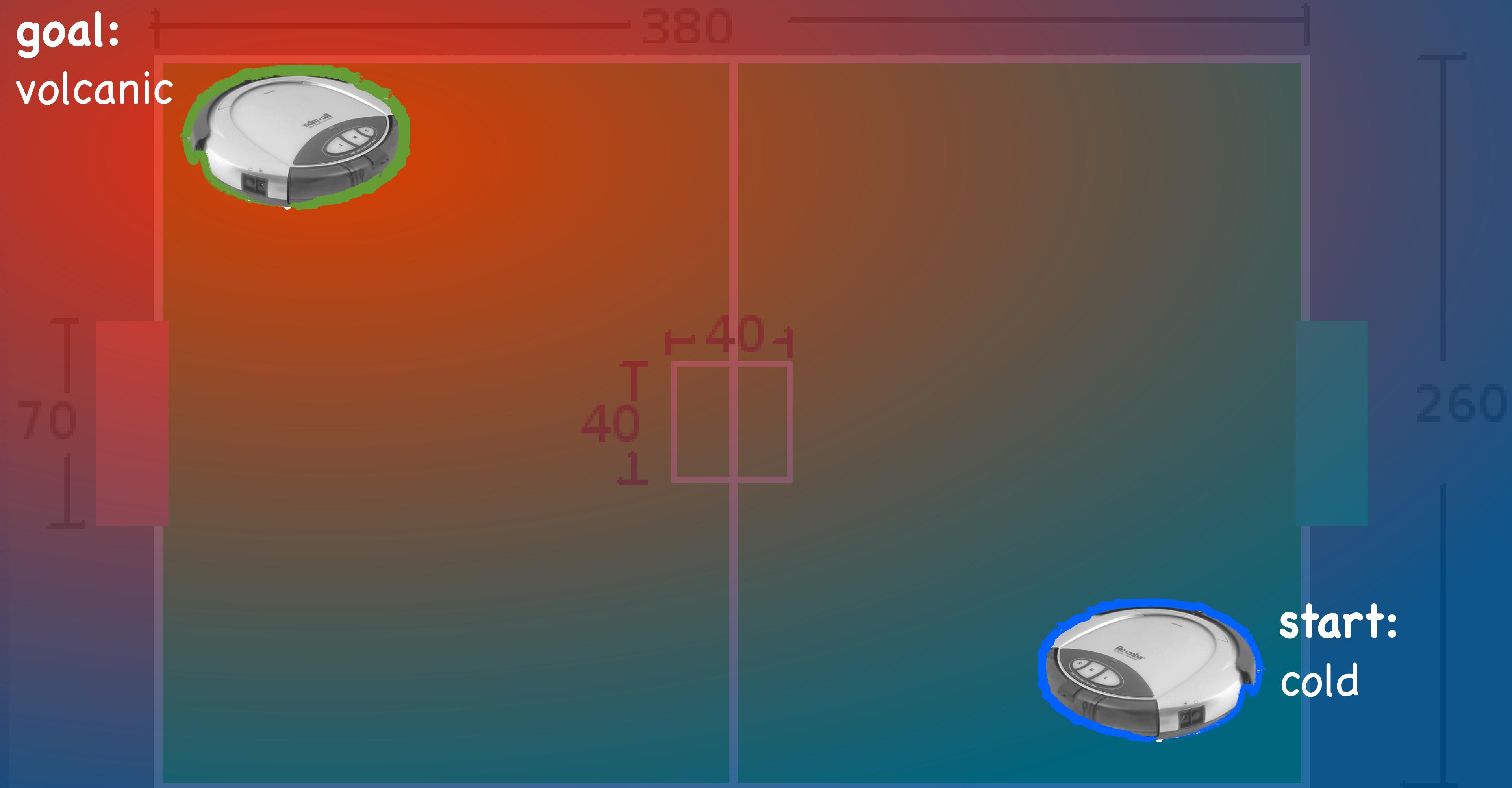


# Navigation (again)



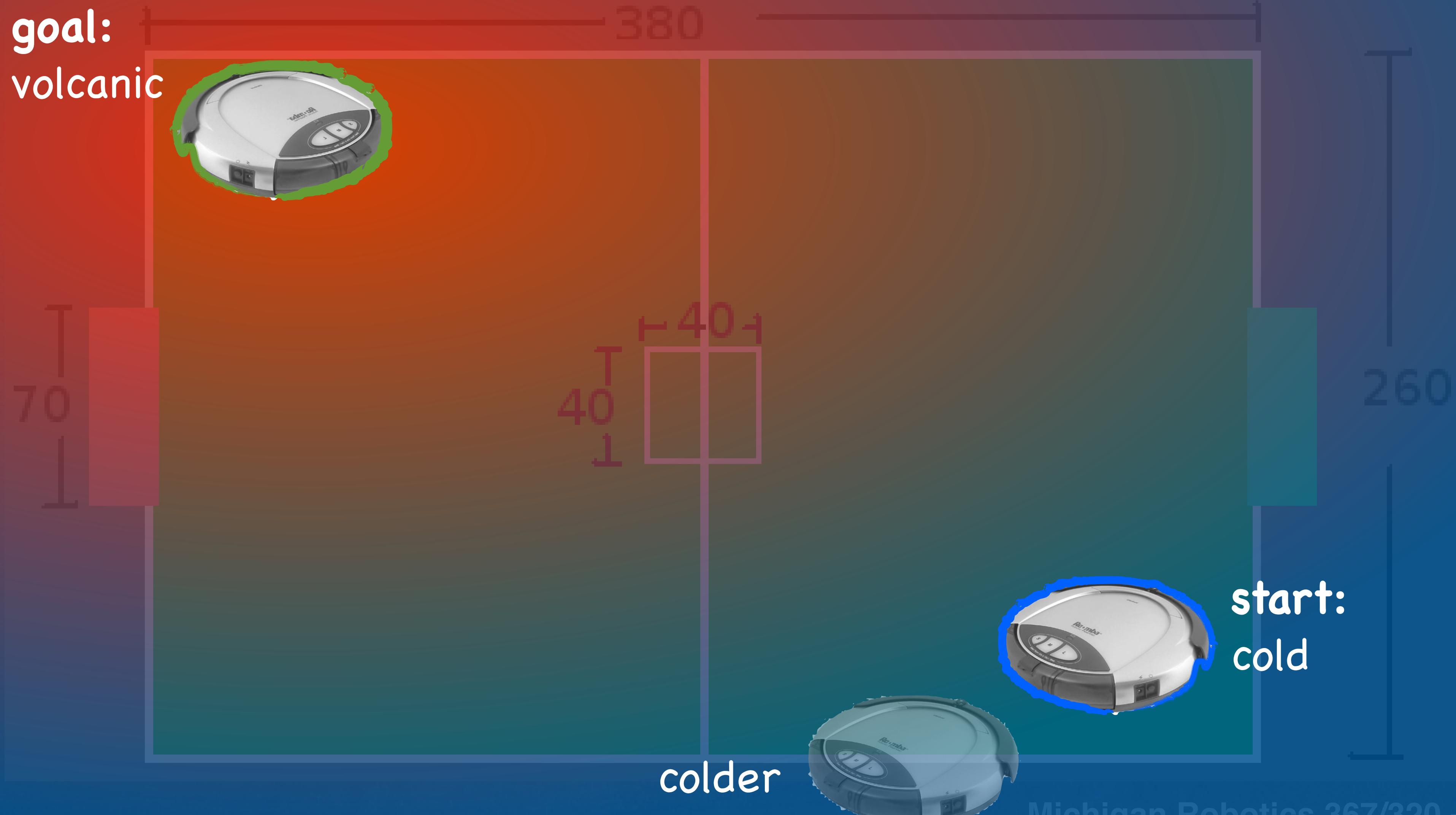
# Potential field

(like a game of “warmer-colder”)



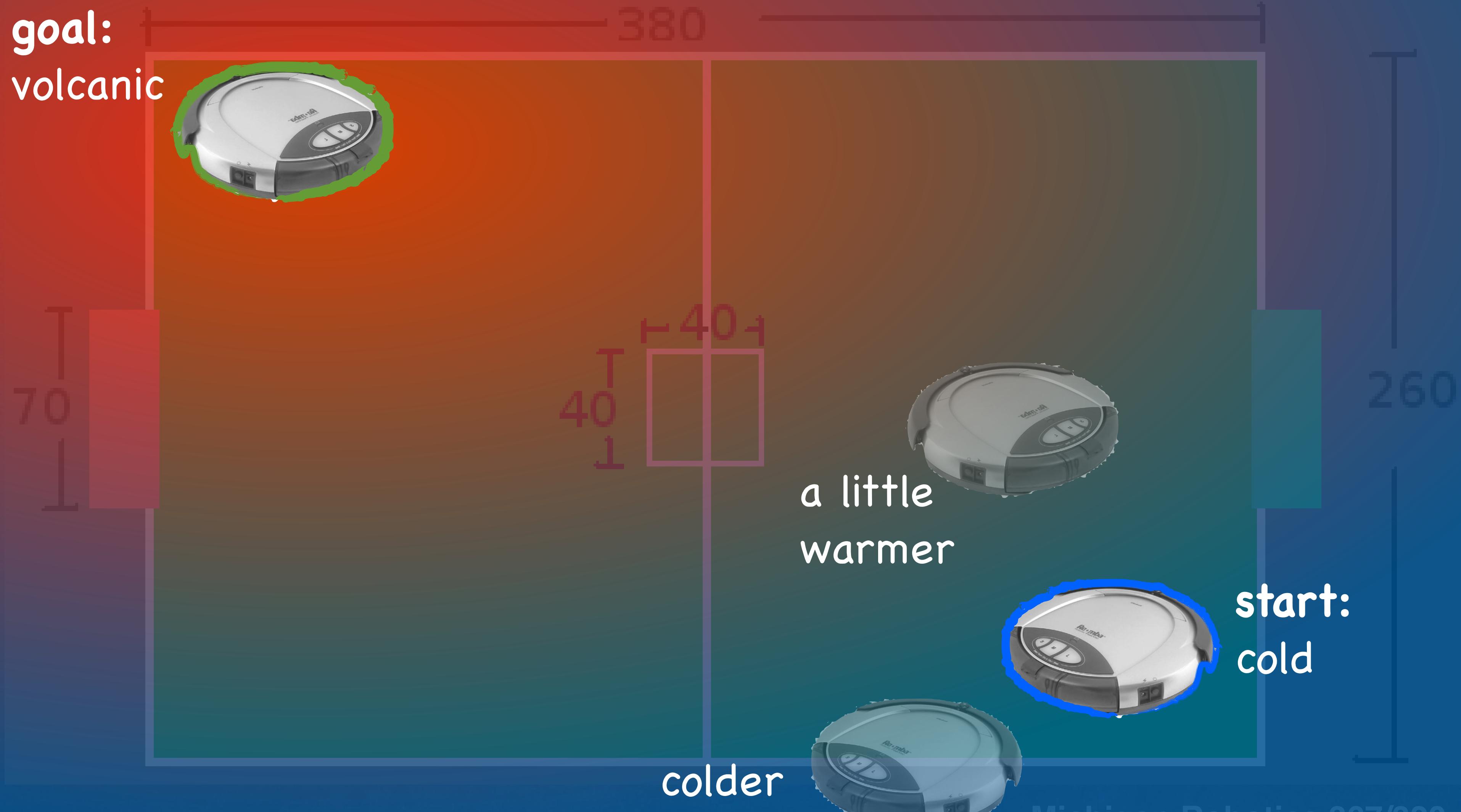
# Potential field

(like a game of “warmer-colder”)



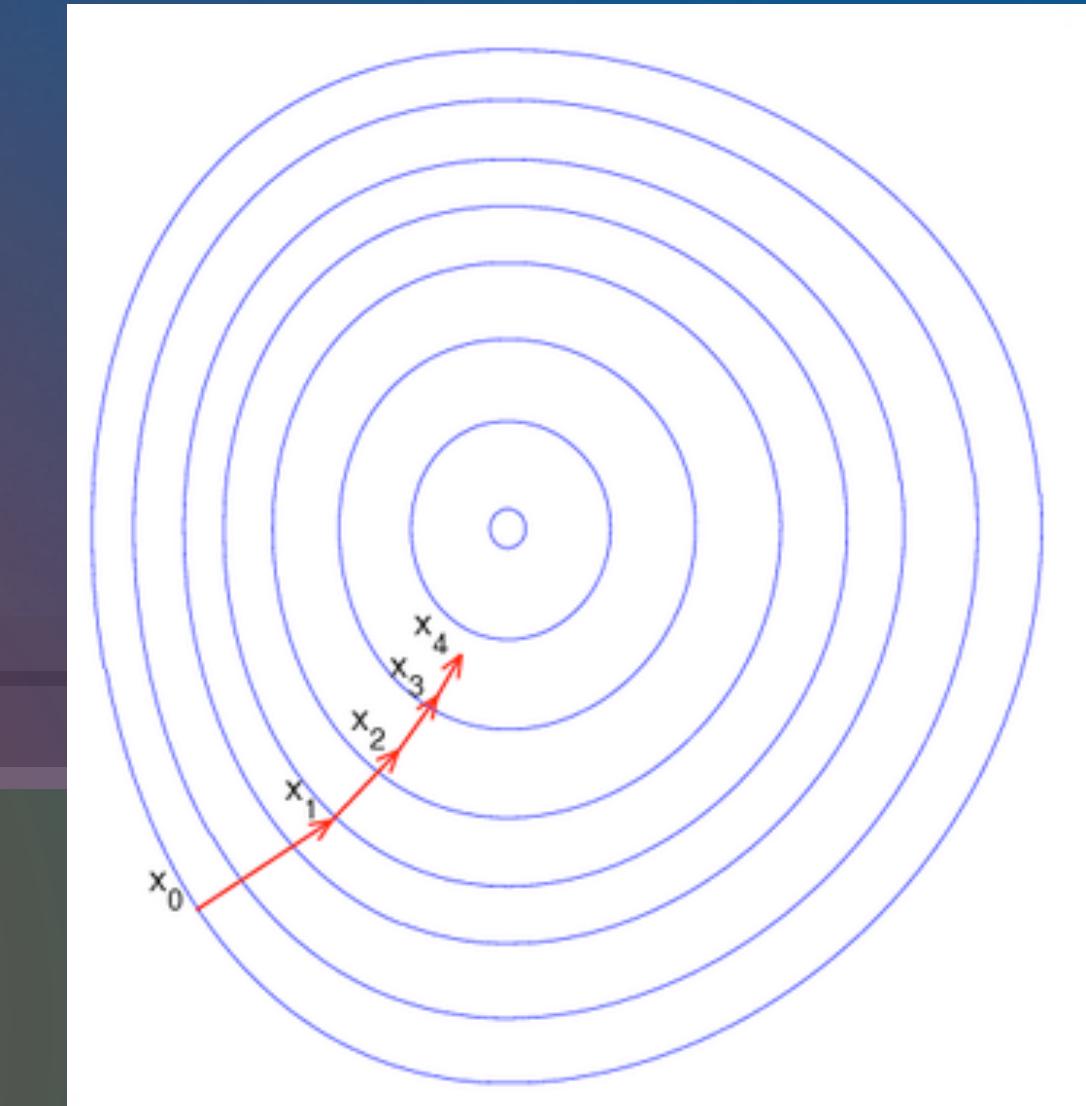
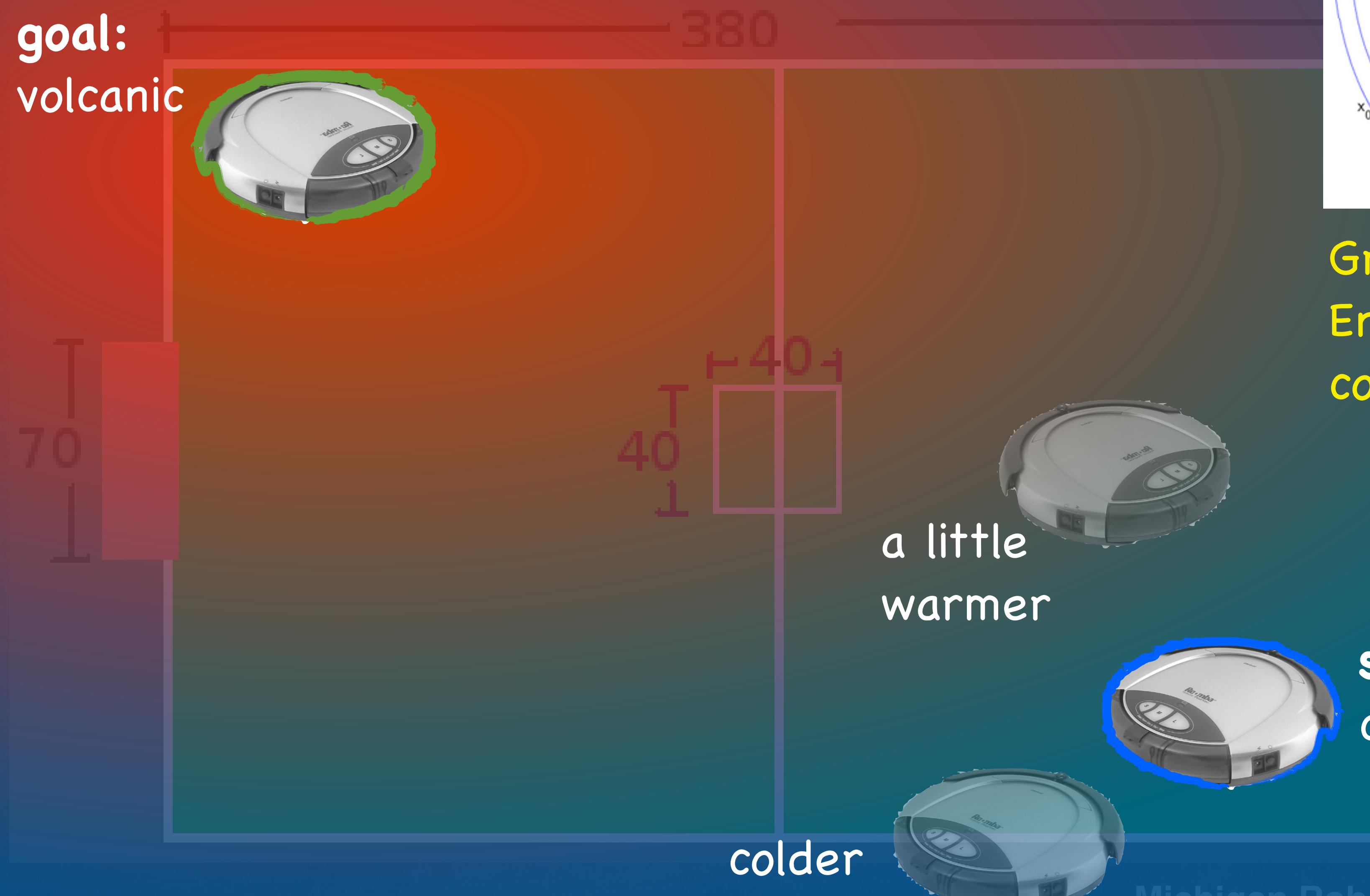
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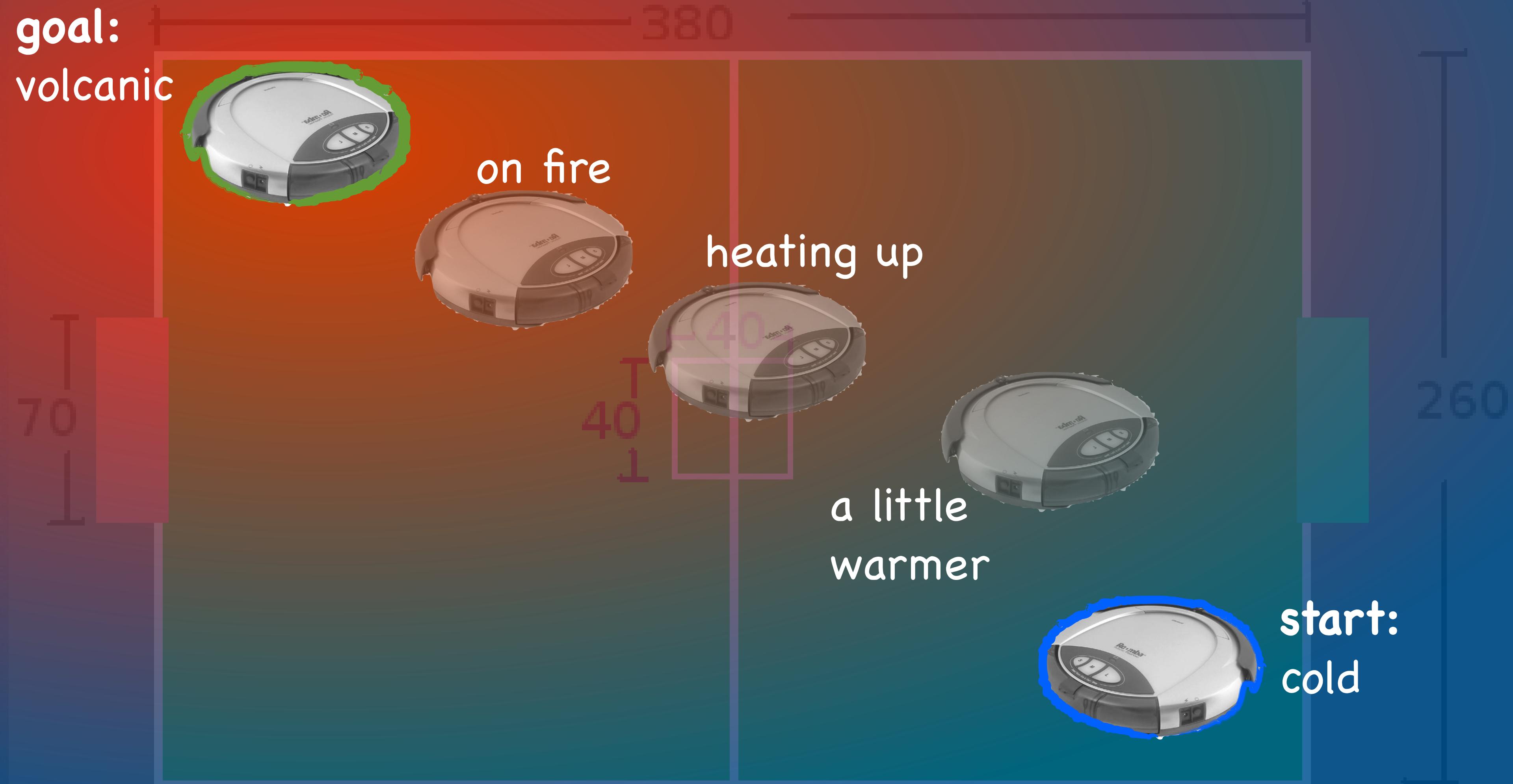


# Gradient descent: Energy potential converges at goal

start:  
cold

# Potential field

(like a game of “warmer-colder”)



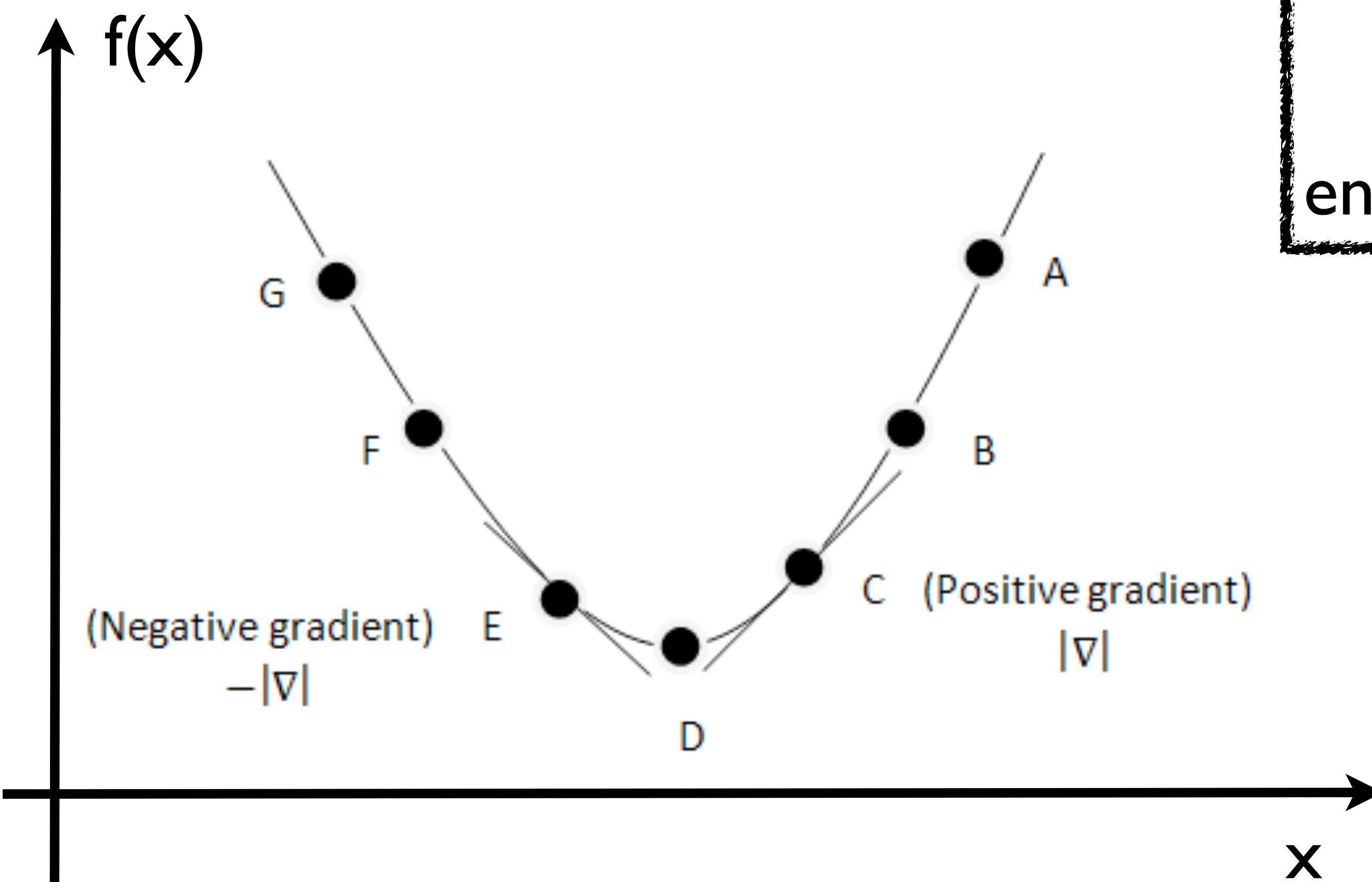
How do we define a  
potential field?

# Potential Field

- A potential field is a differentiable function  $U(q)$  that maps configurations to scalar “energy” value
- At any  $q$ , gradient  $\nabla U(q)$  is the vector that maximally increases  $U$
- At goal  $q_{goal}$ , energy is minimized such that  $\nabla U(q_{goal}) = 0$
- Navigation by descending field -  $\nabla U(q)$  to goal

## Gradient Descent Algorithm:

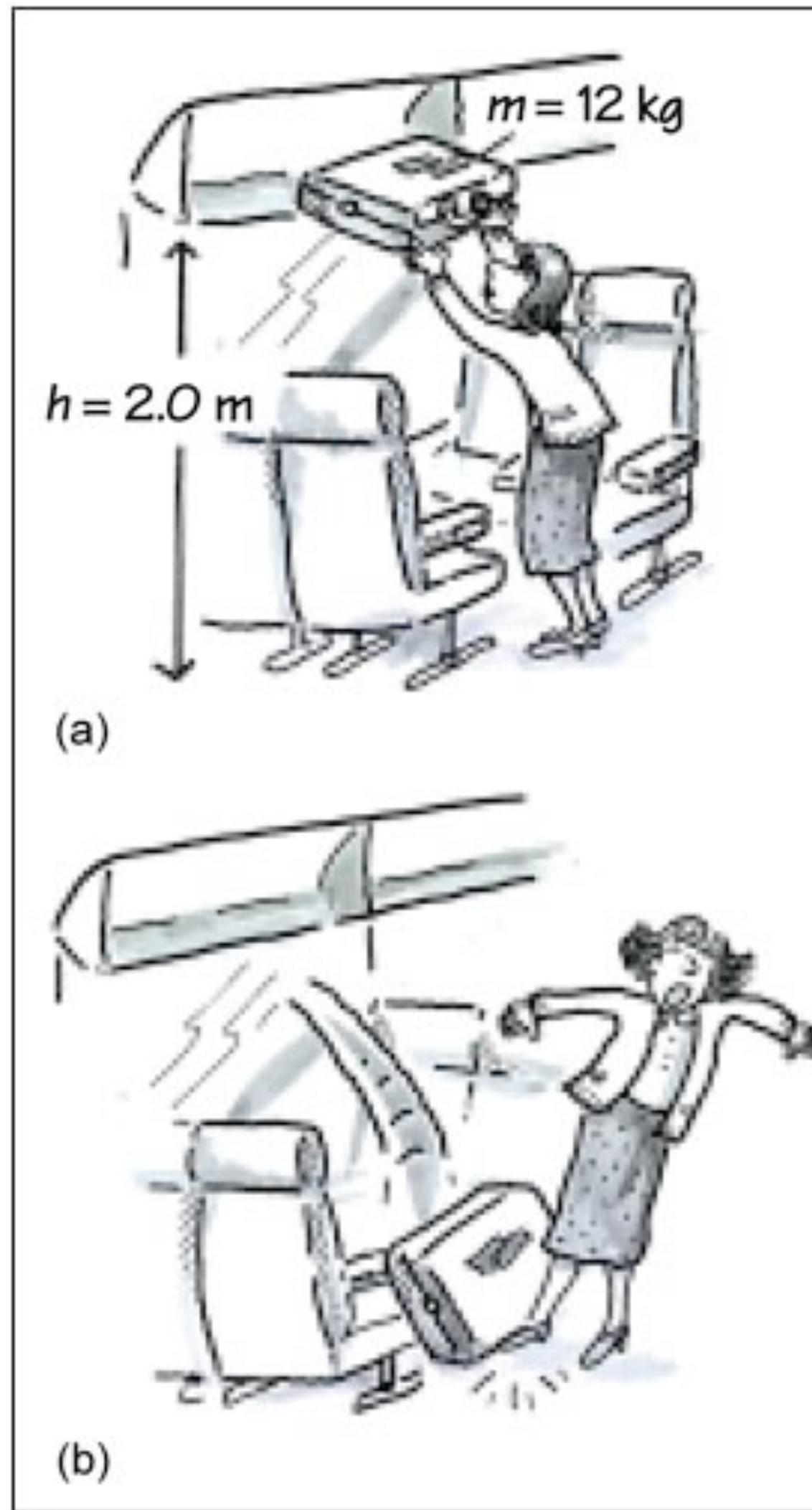
```
qpath[0] ← qstart
i ← 0
while (|| ∇U(q[i]) || > ε)
    qpath[i+1] ← qpath[i] - a ∇U(qpath[i])
    i ← i+1
end
```



Derivative assumed to be direction  
of steepest ascent away from goal

$$\mathbf{x}_{n+1} = \mathbf{x}_n - \gamma_n \boxed{\nabla F(\mathbf{x}_n)}$$

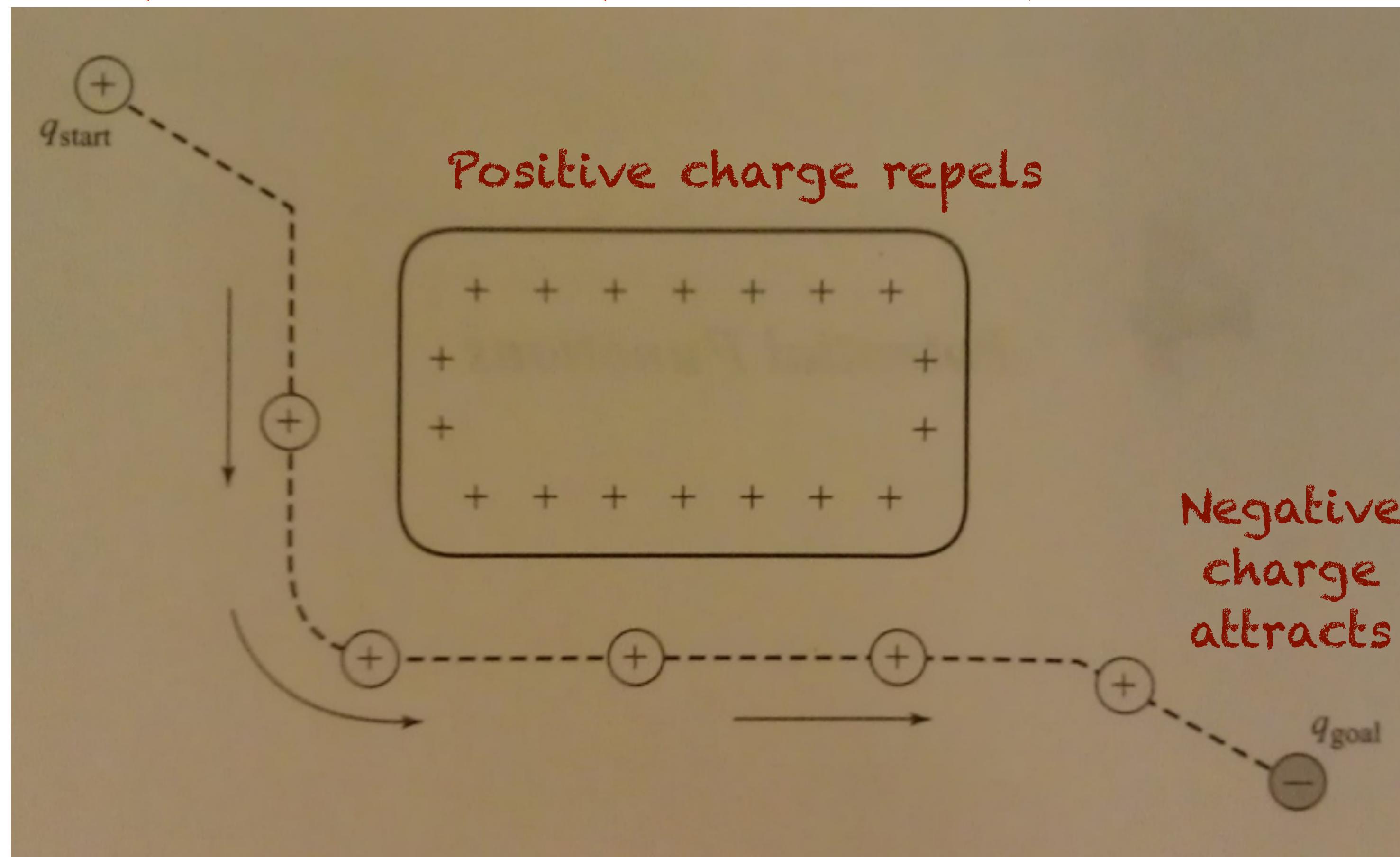
# Potential Energy



- Energy stored in a physical system
- Kinetic motion caused by system moving to lower energy state
- For objects acting only w.r.t. gravity
- $\text{potential\_energy} = \text{mass} * \text{height} * \text{gravity}$

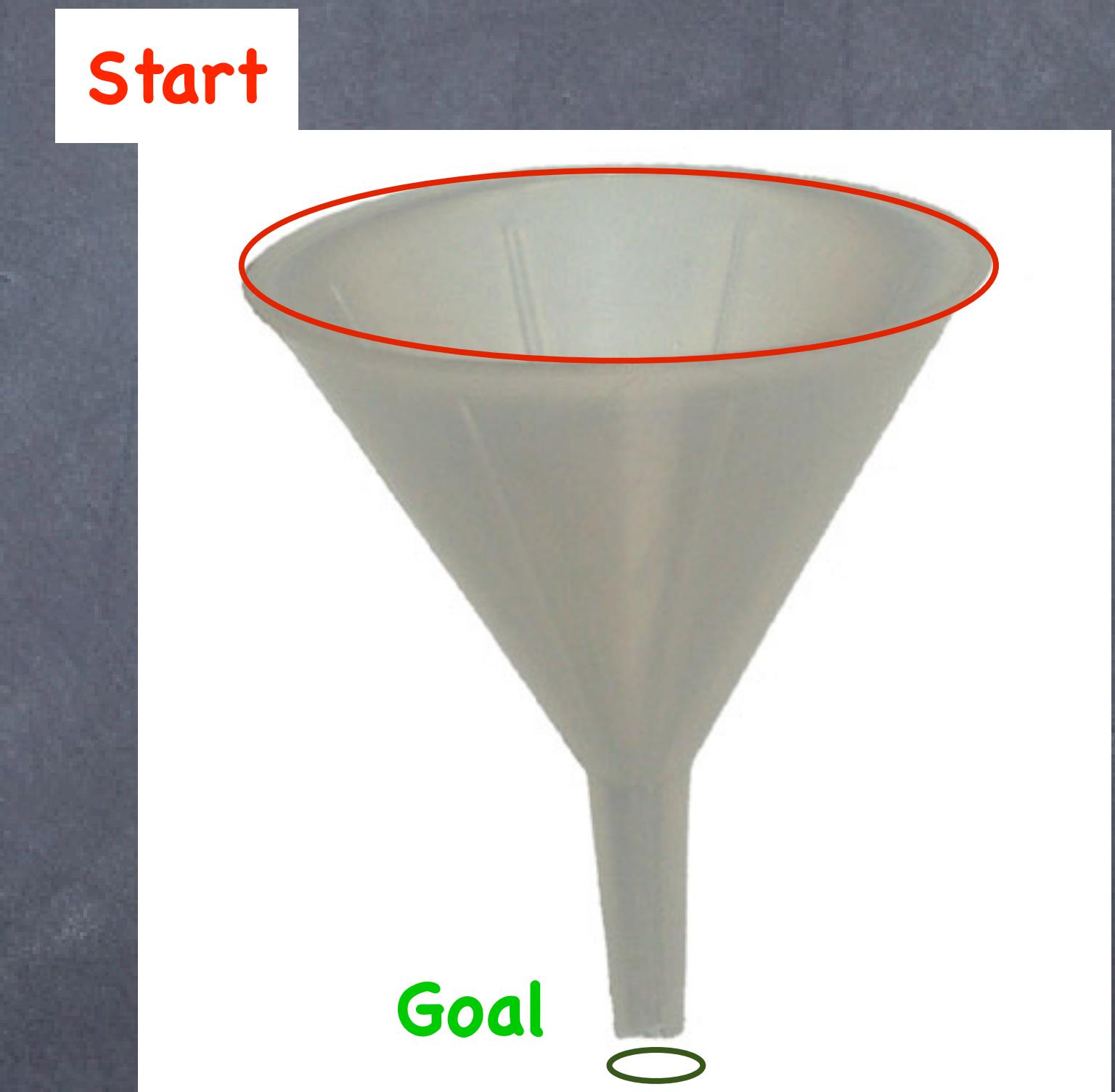
# Charged Particle Example

Positively charged particle follows potential energy to goal



# Convergent Potentials

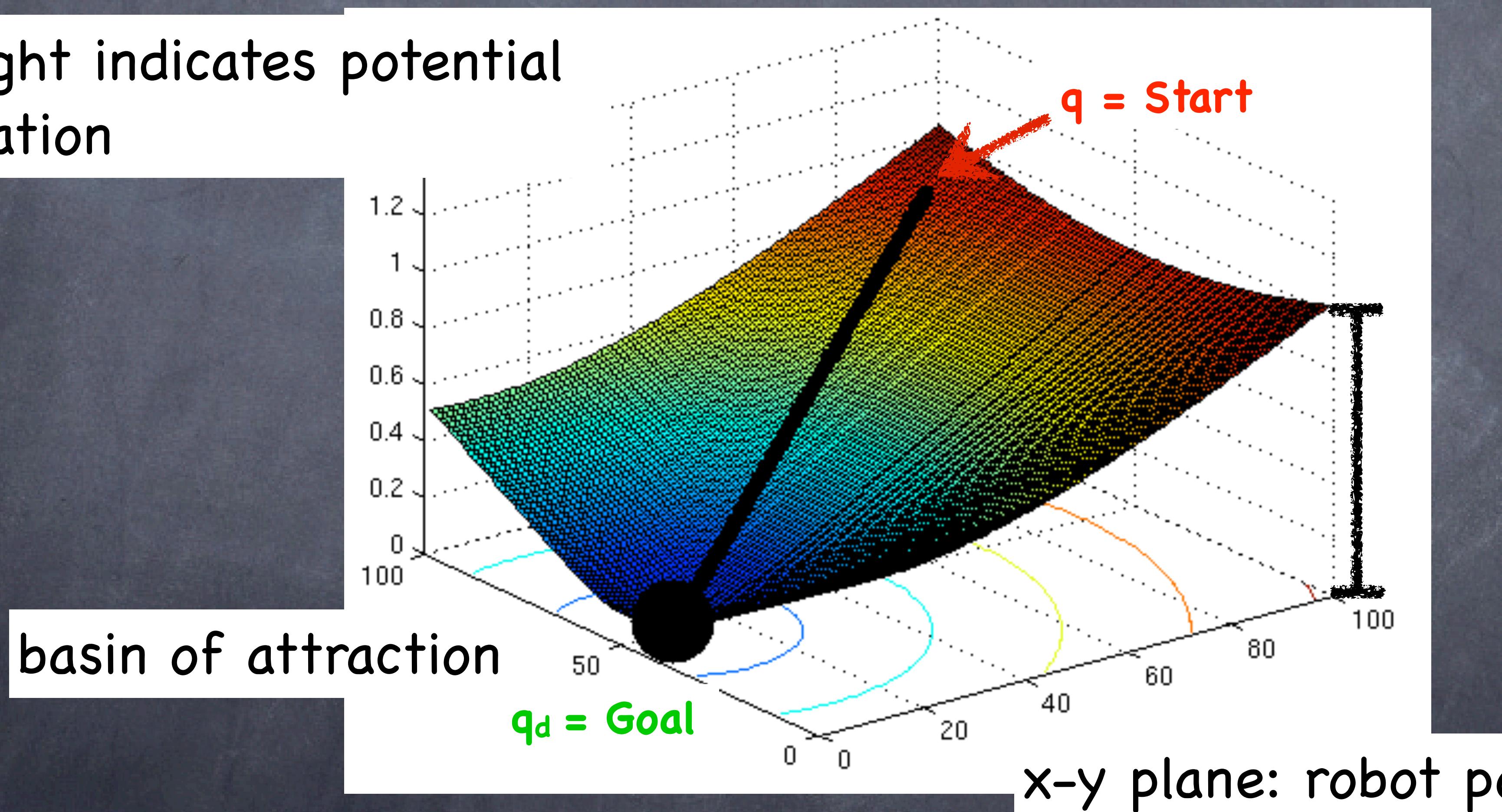
let's call these "attractor landscapes"



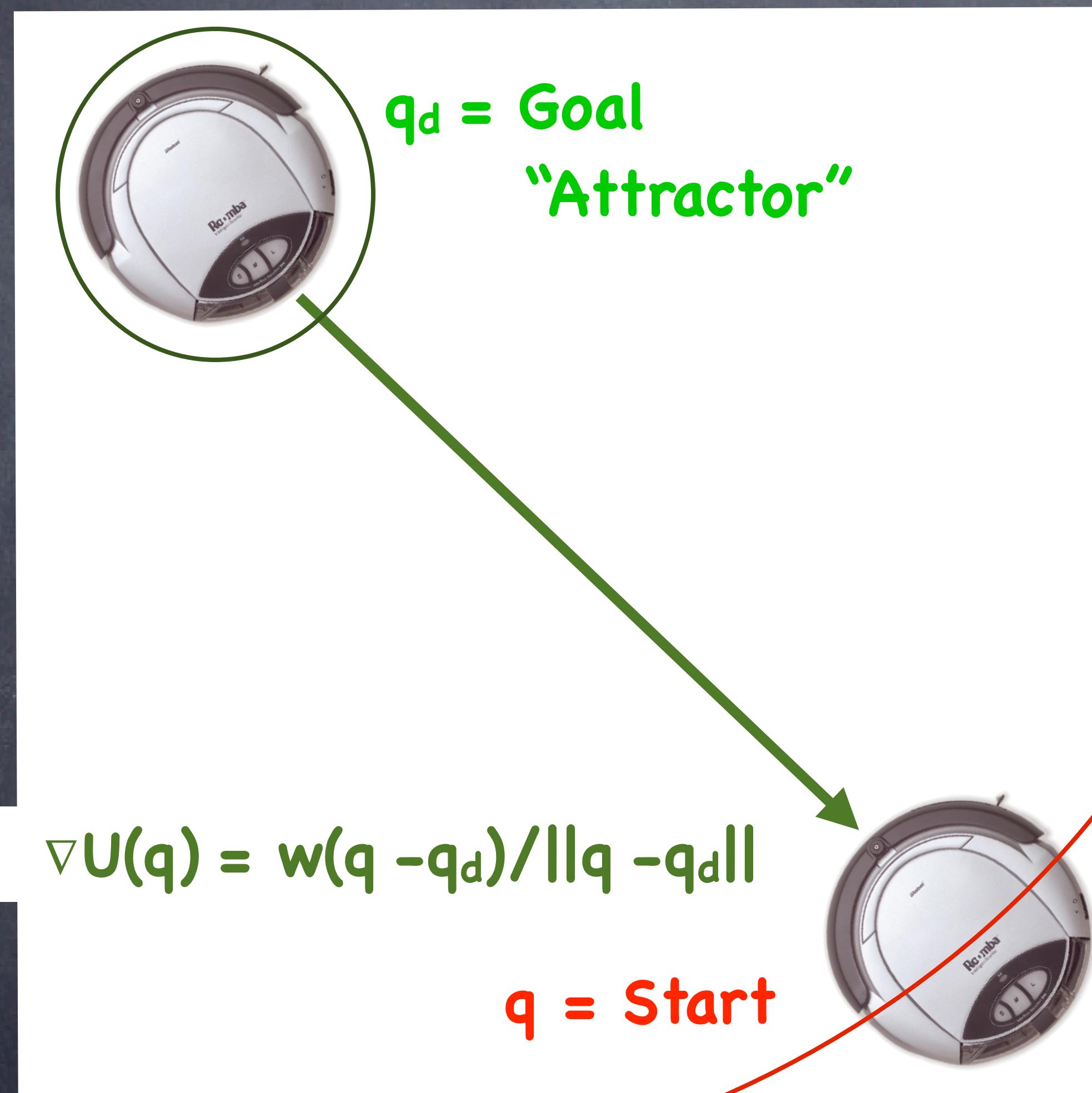
basin of attraction

# 2D potential navigation

$z$ : height indicates potential at location



# “Cone” Attractor



top view

Start

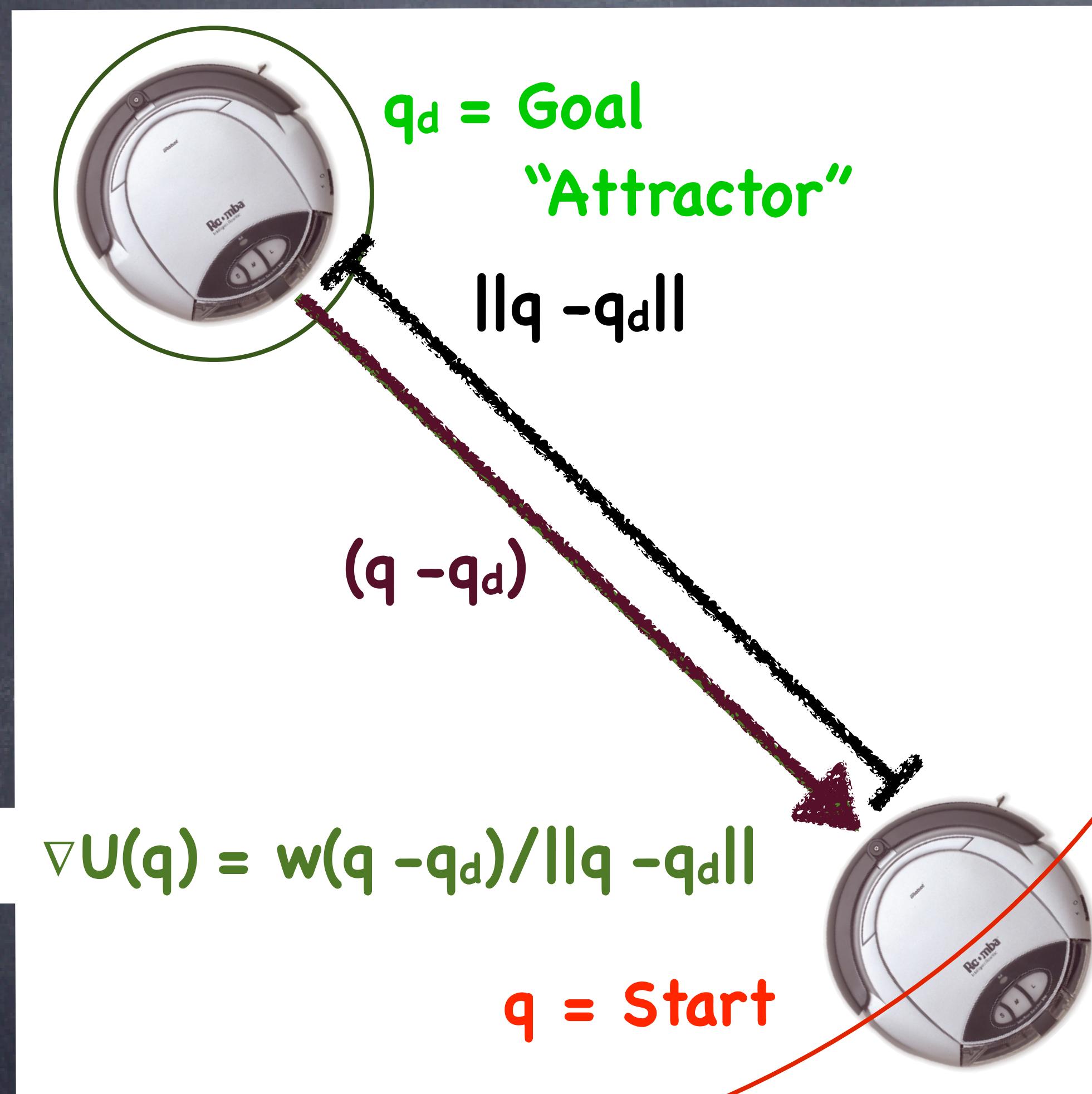
Goal

w: weight  
 $(q - q_d)$ : direction  
 $\|q - q_d\|$ : distance

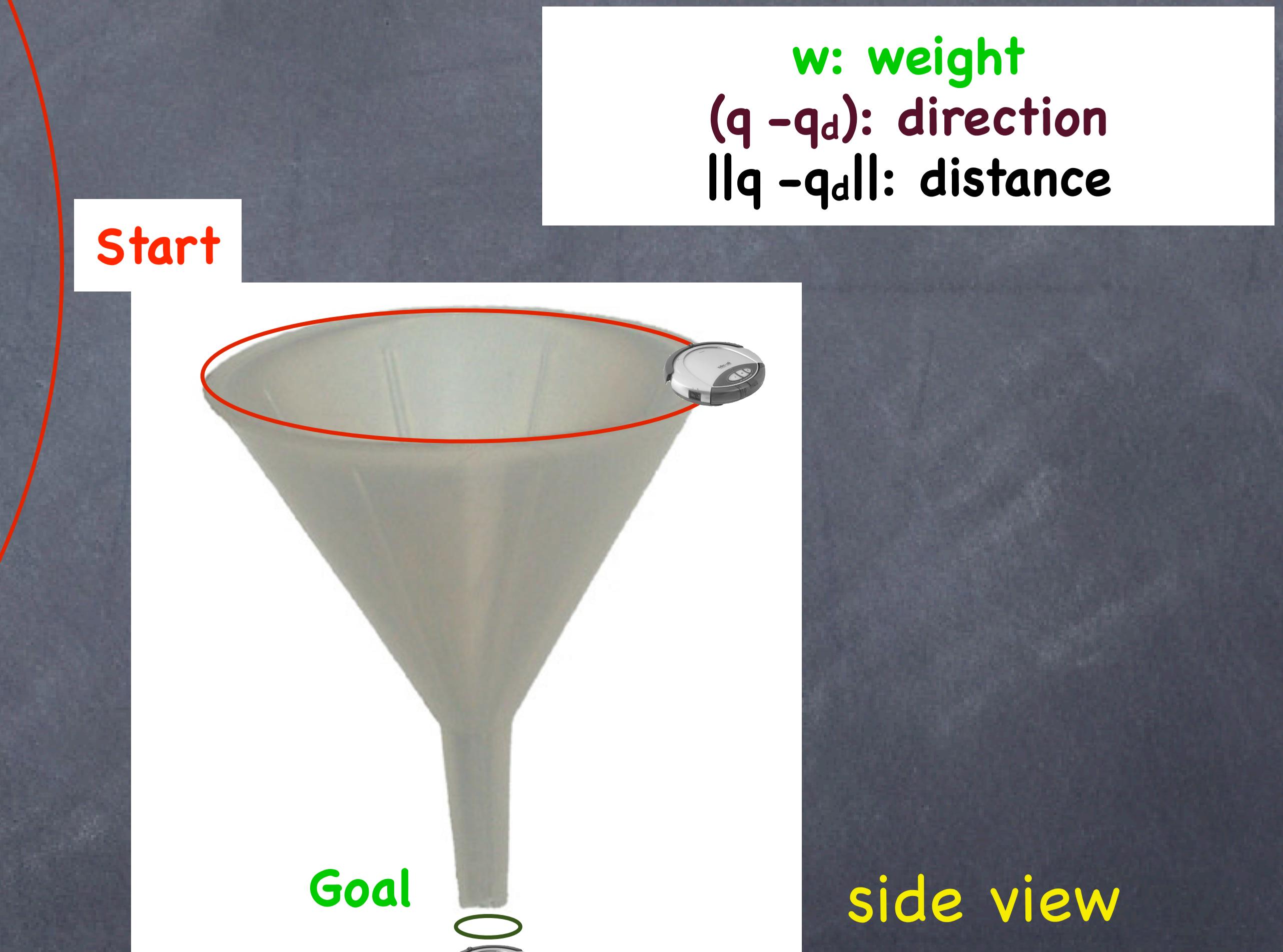


side view

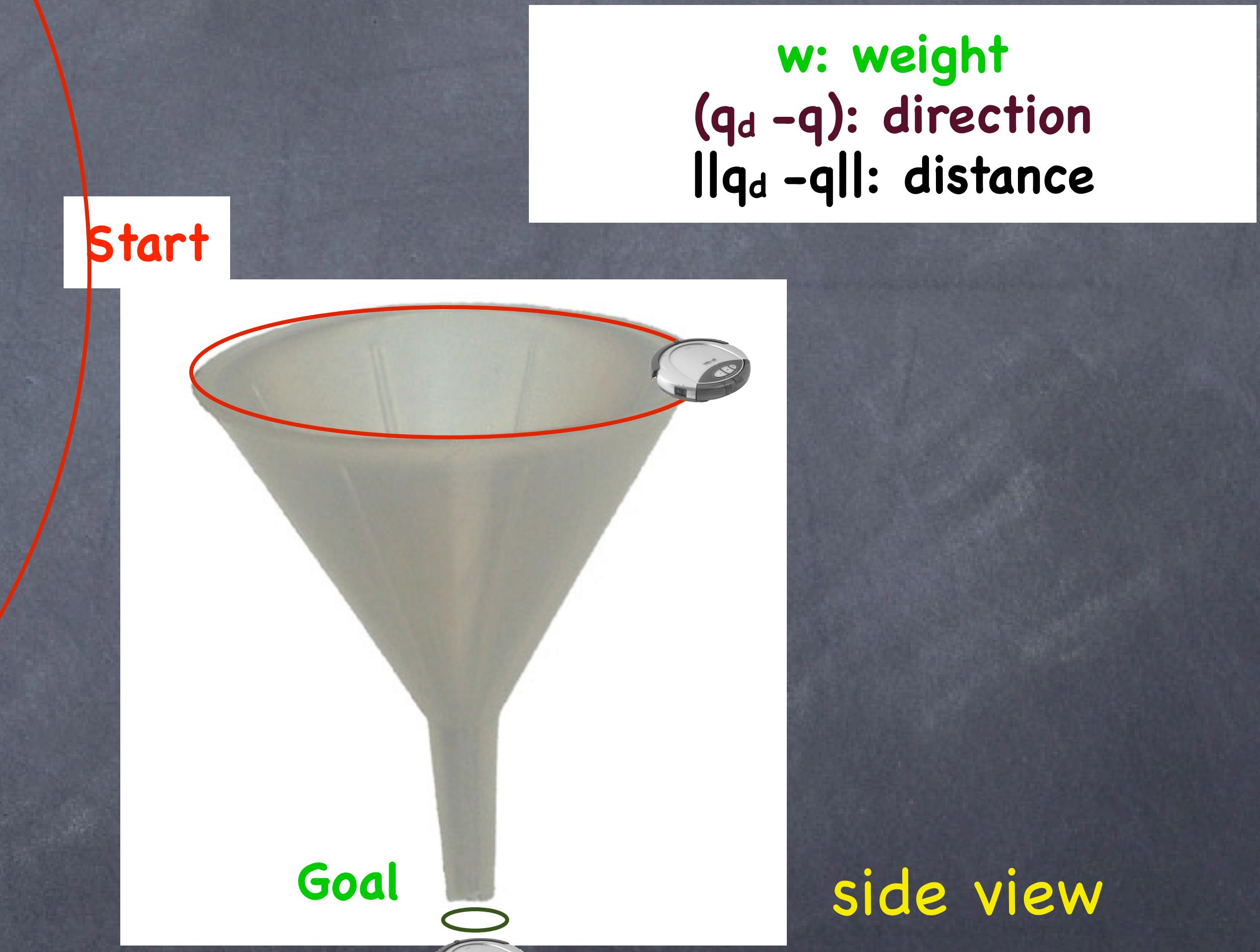
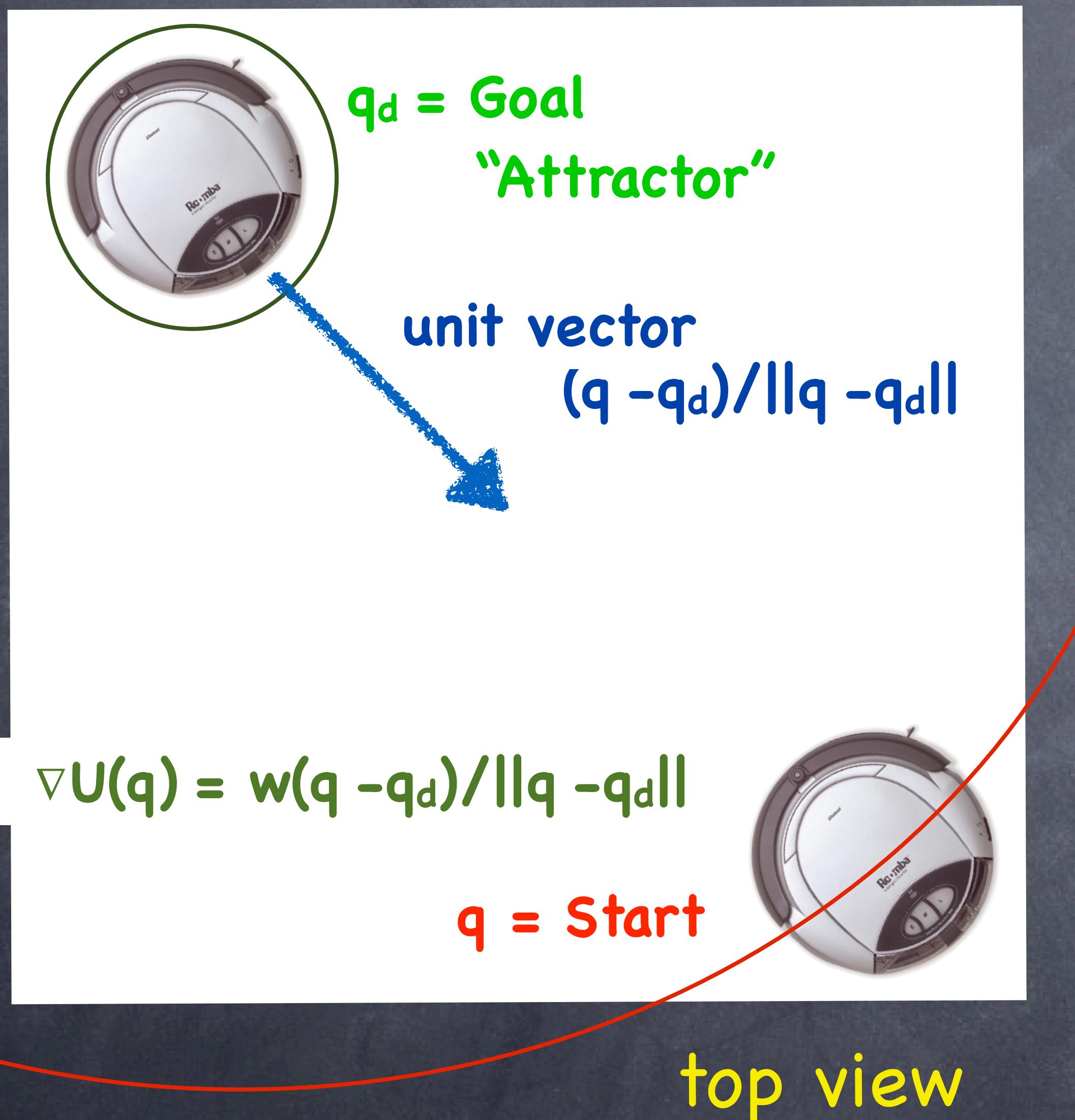
# “Cone” Attractor



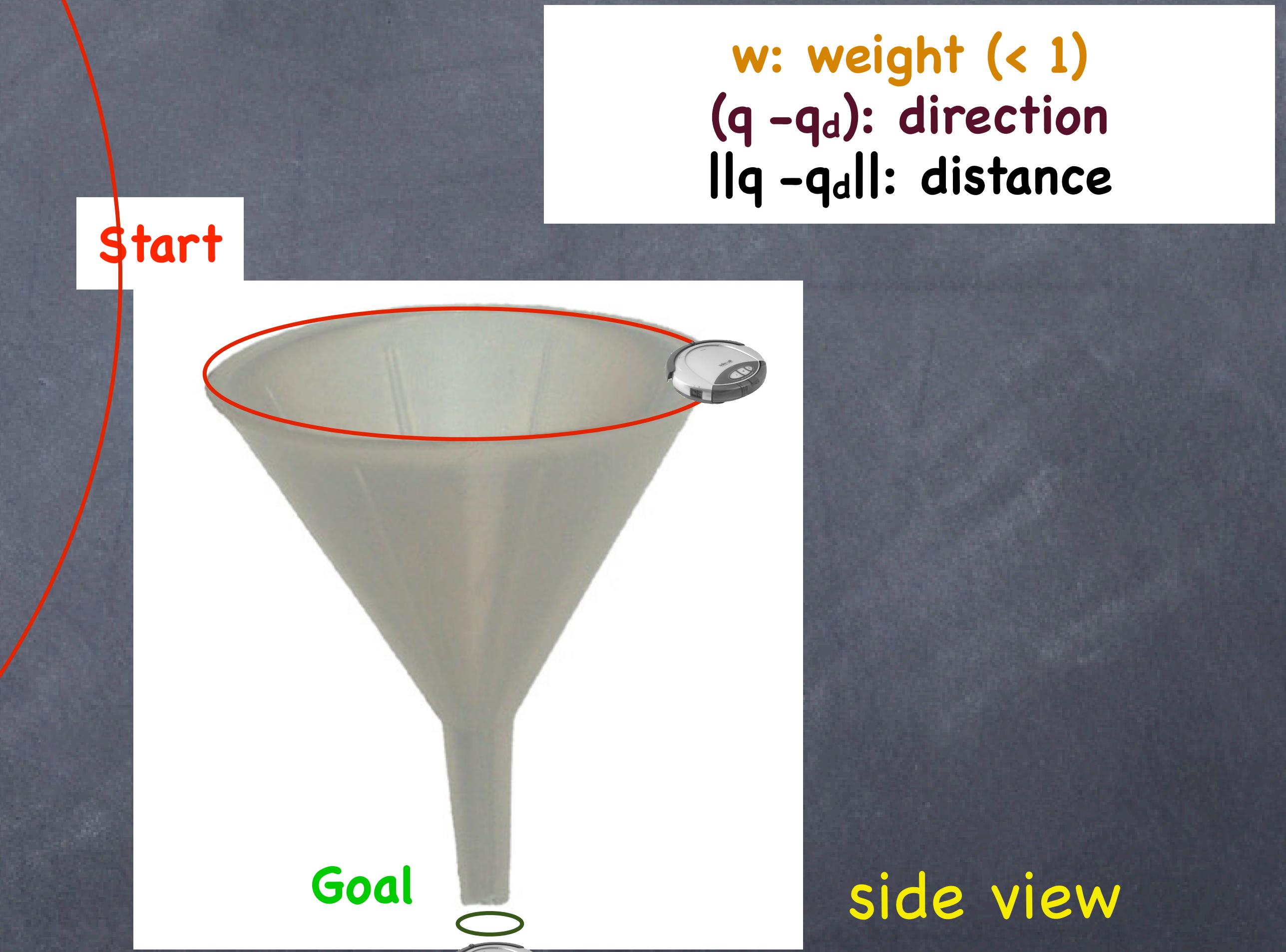
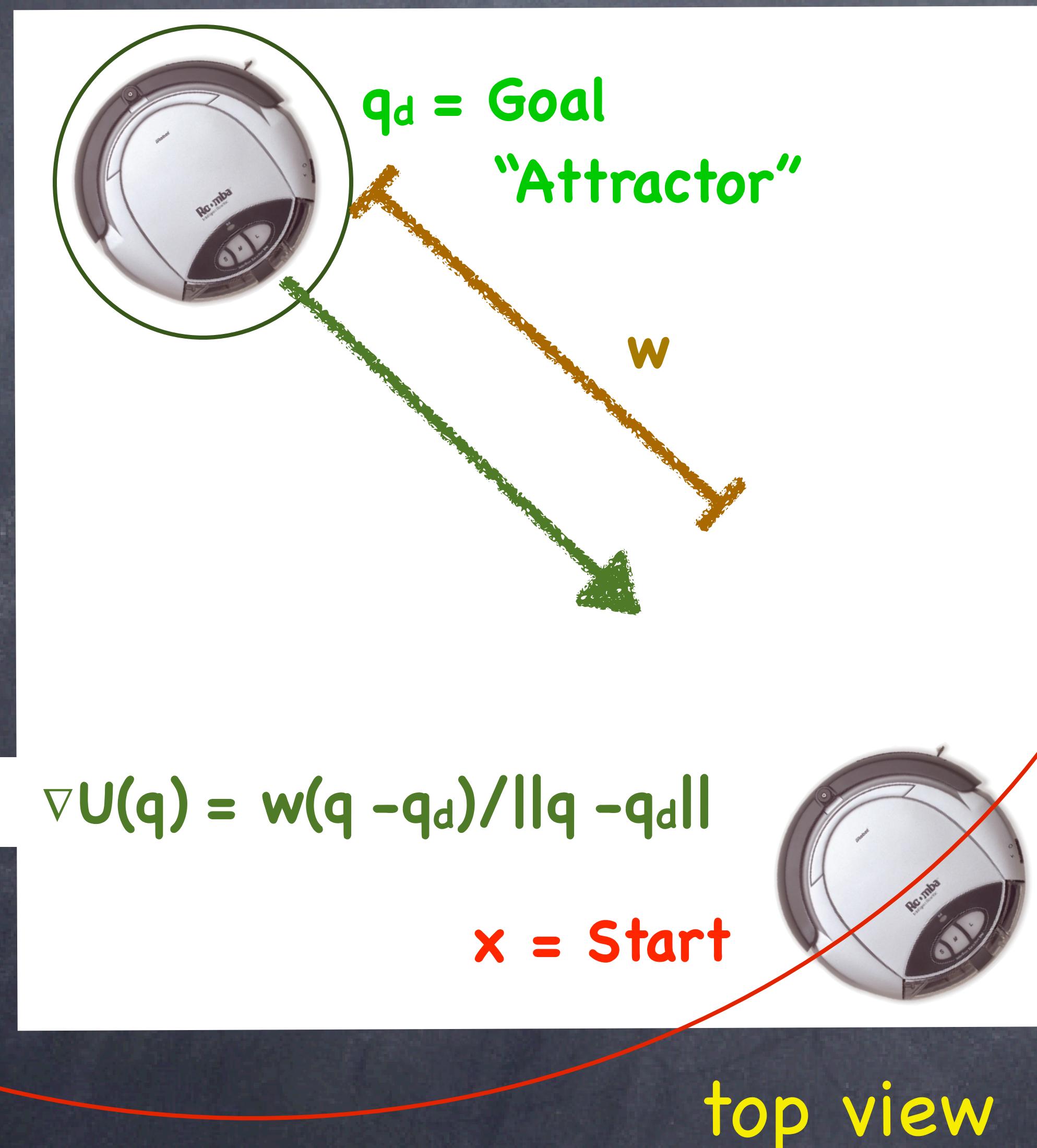
top view



# “Cone” Attractor

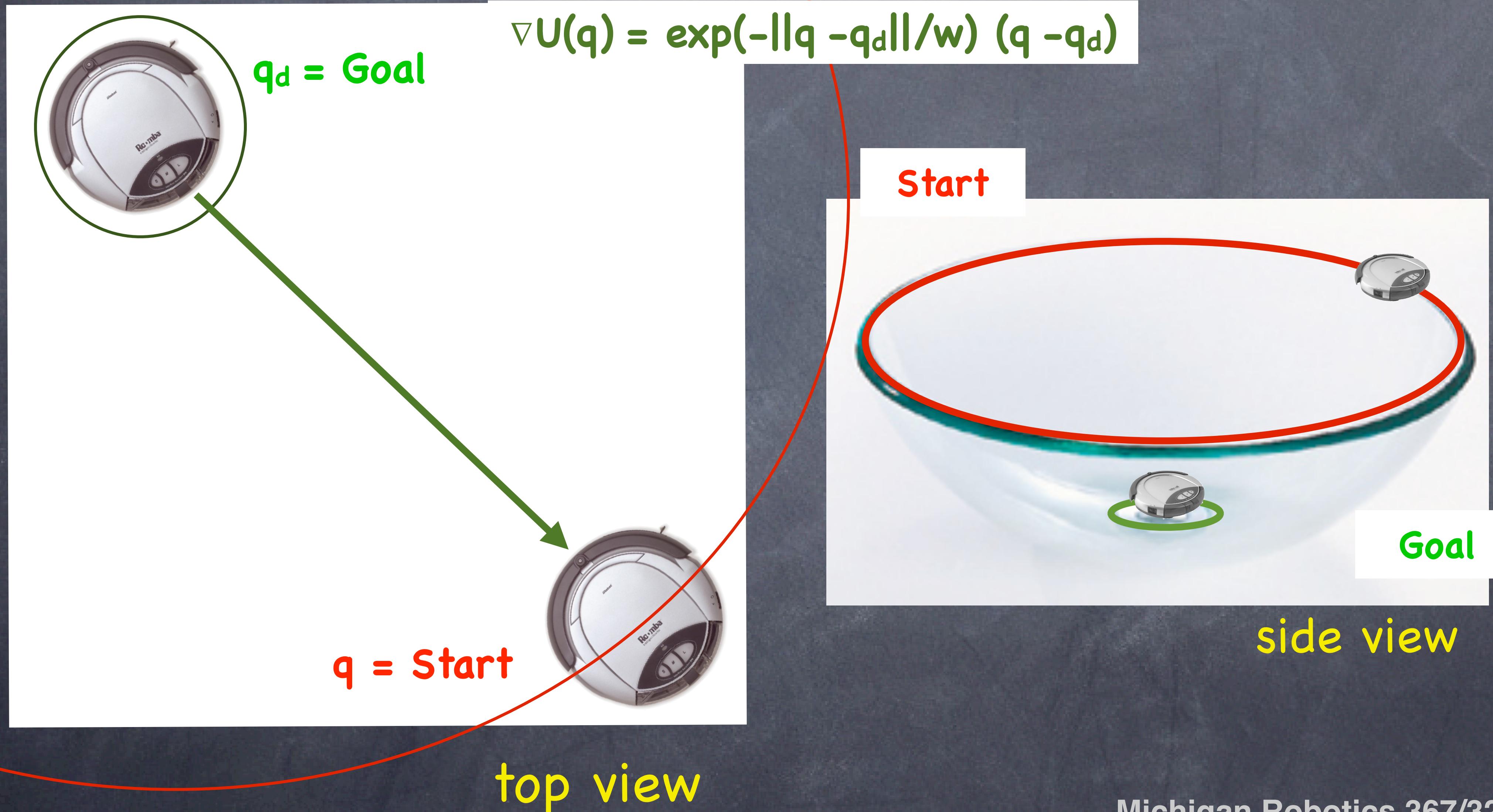


# “Cone” Attractor



Can we modulate the  
range of a potential field?

# "Bowl" Attractor

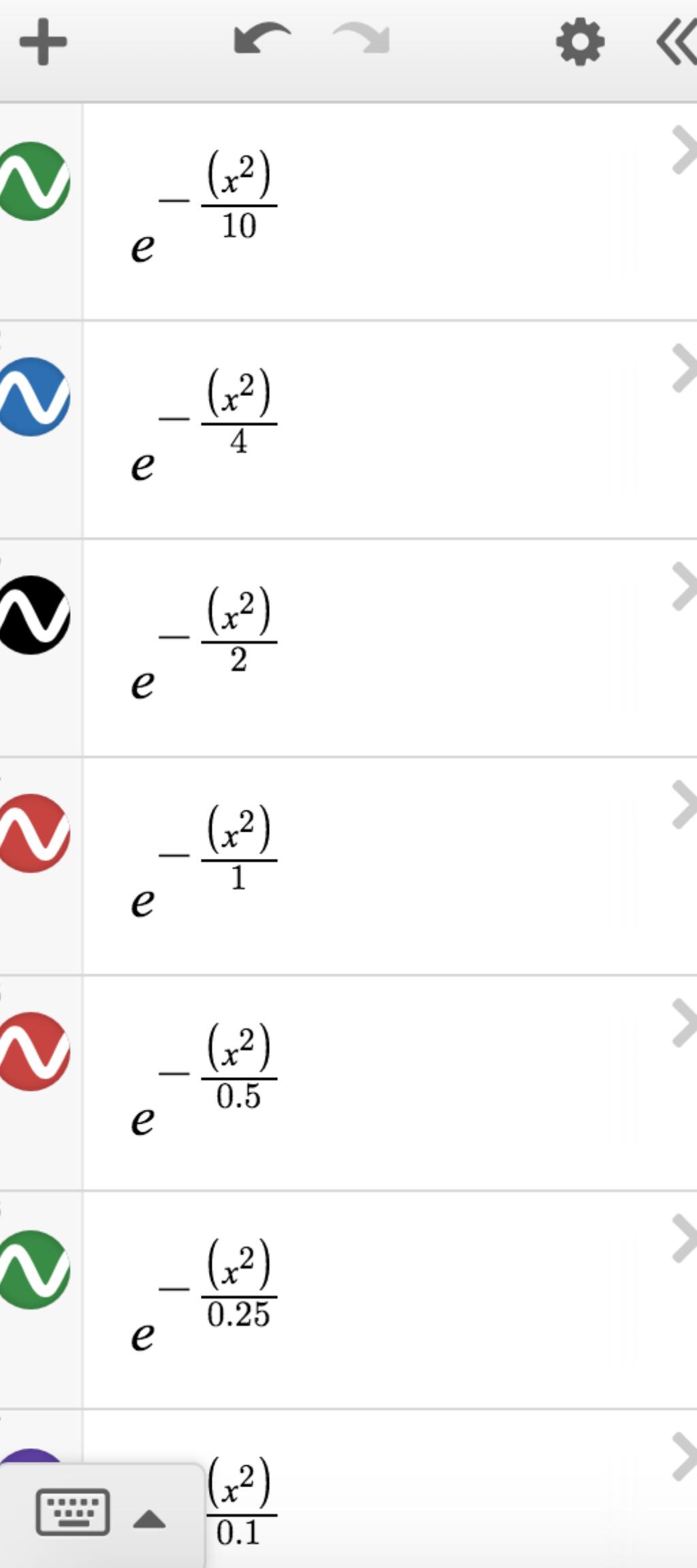


## Untitled Graph

desmos

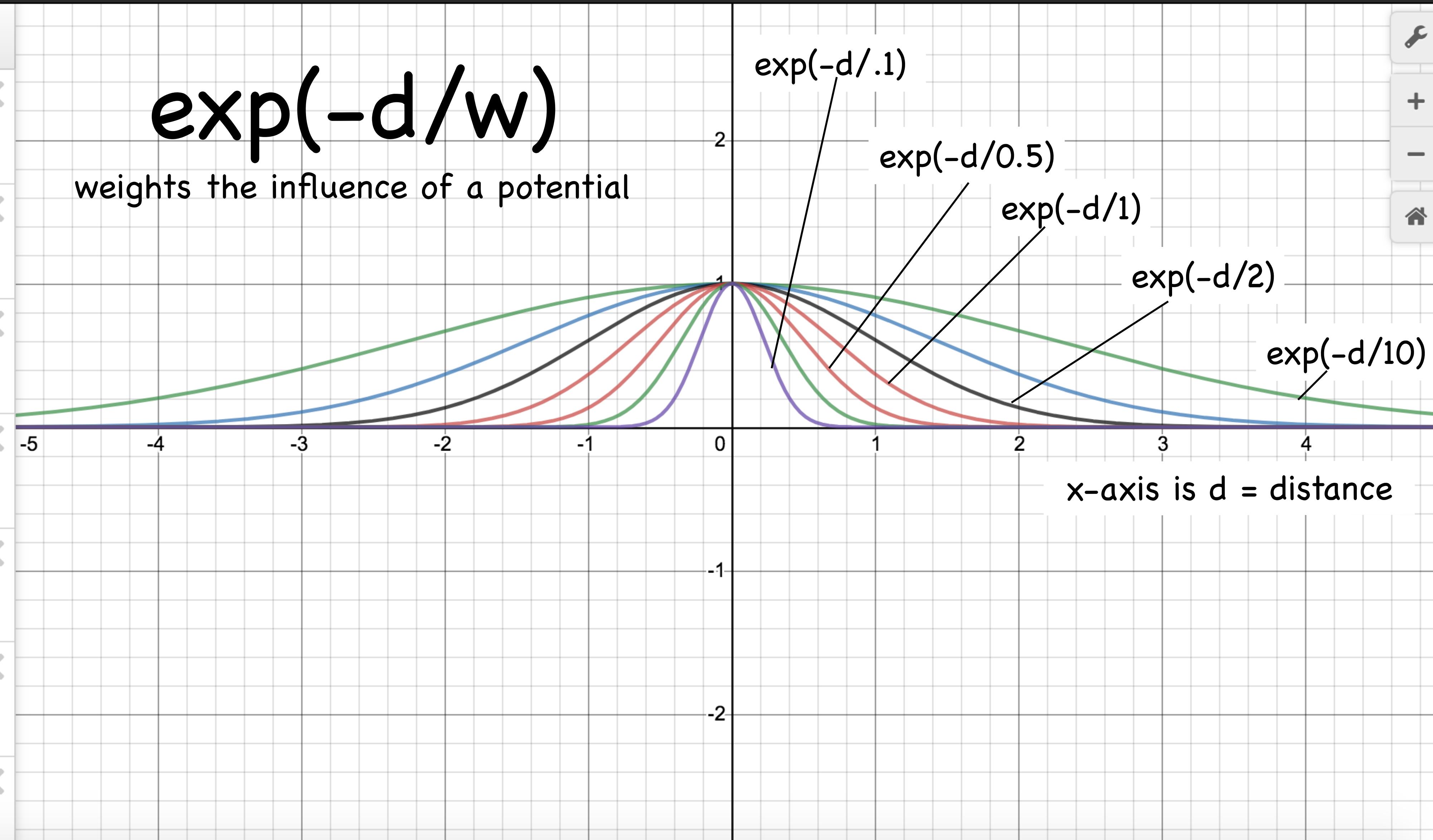
Create Account

or Sign In



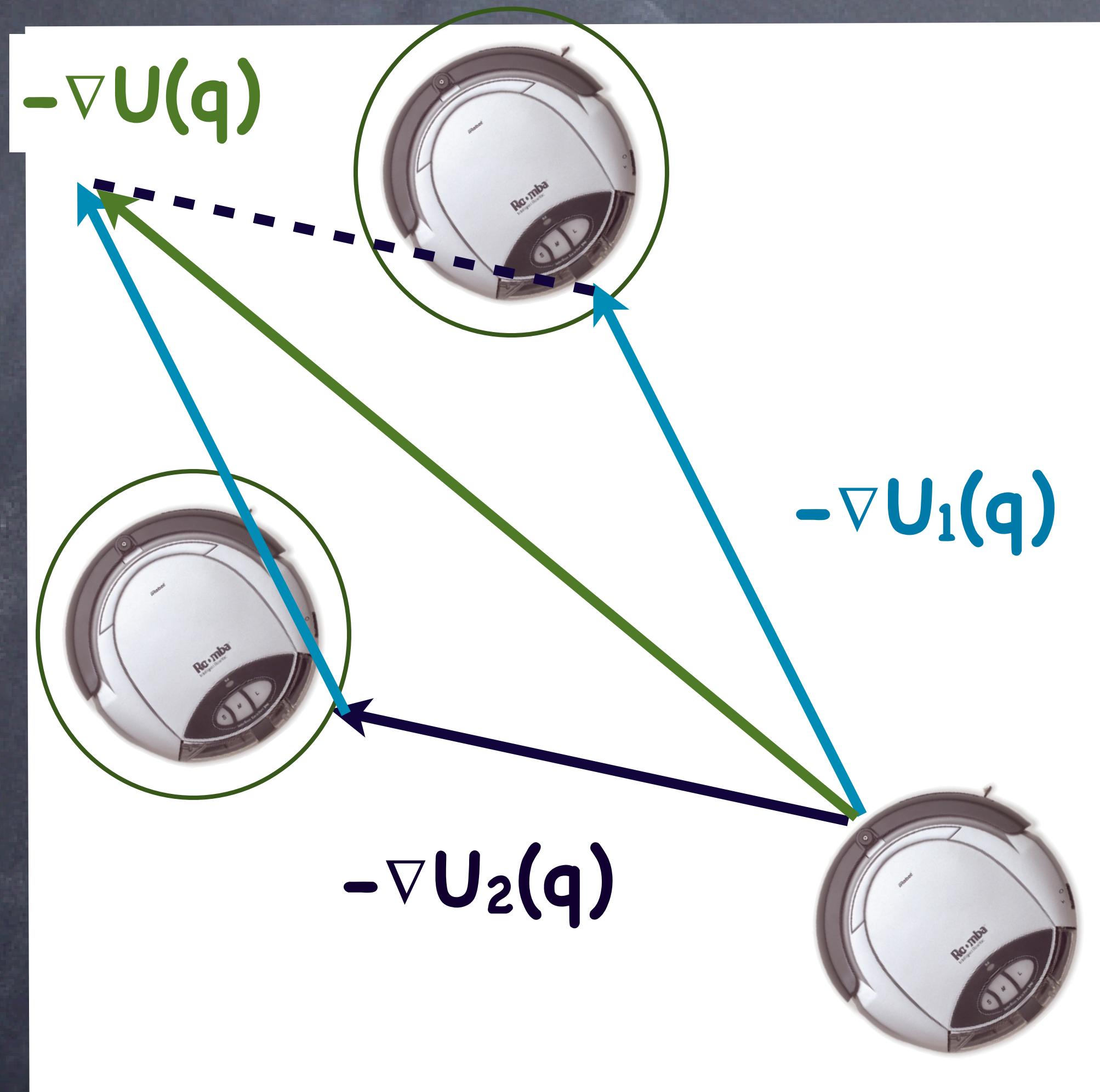
# $\exp(-d/w)$

weights the influence of a potential



Can we combine  
multiple potentials?

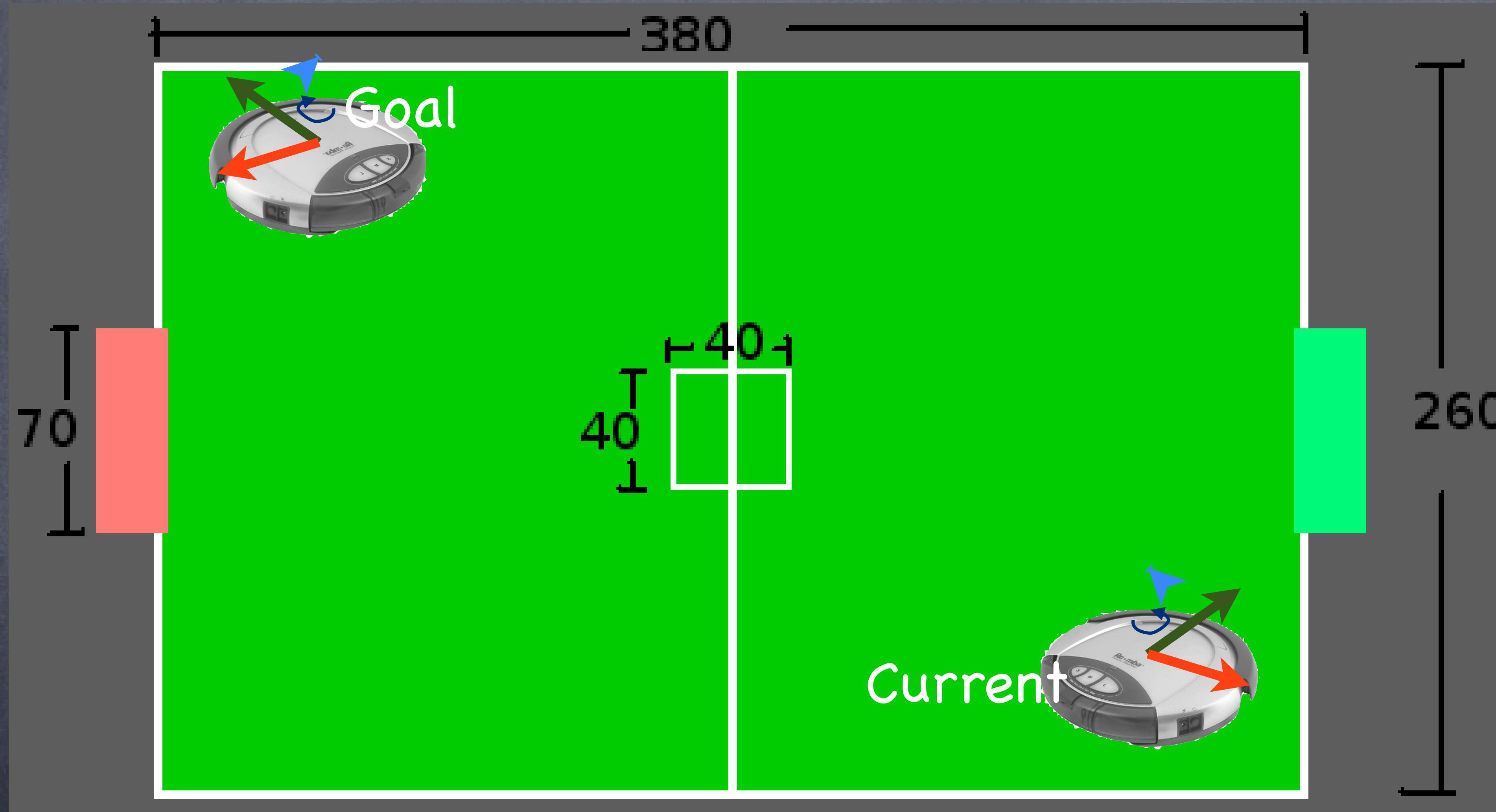
# Multiple potentials



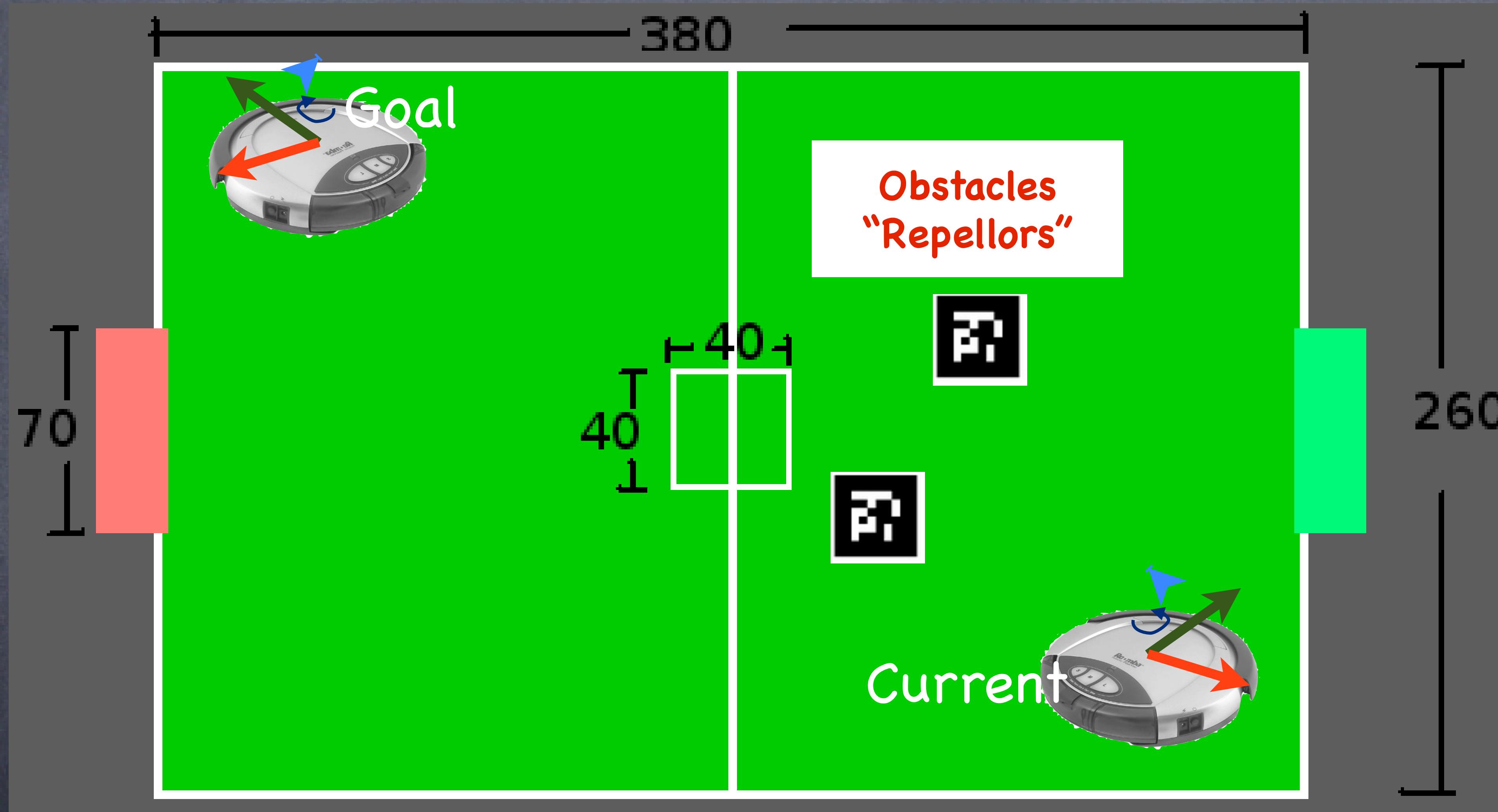
- ⦿ Output of potential field is a vector
- ⦿ Combine multiple potentials through vector summation

$$U(q) = \sum_i U_i(q)$$

describe performance for this case

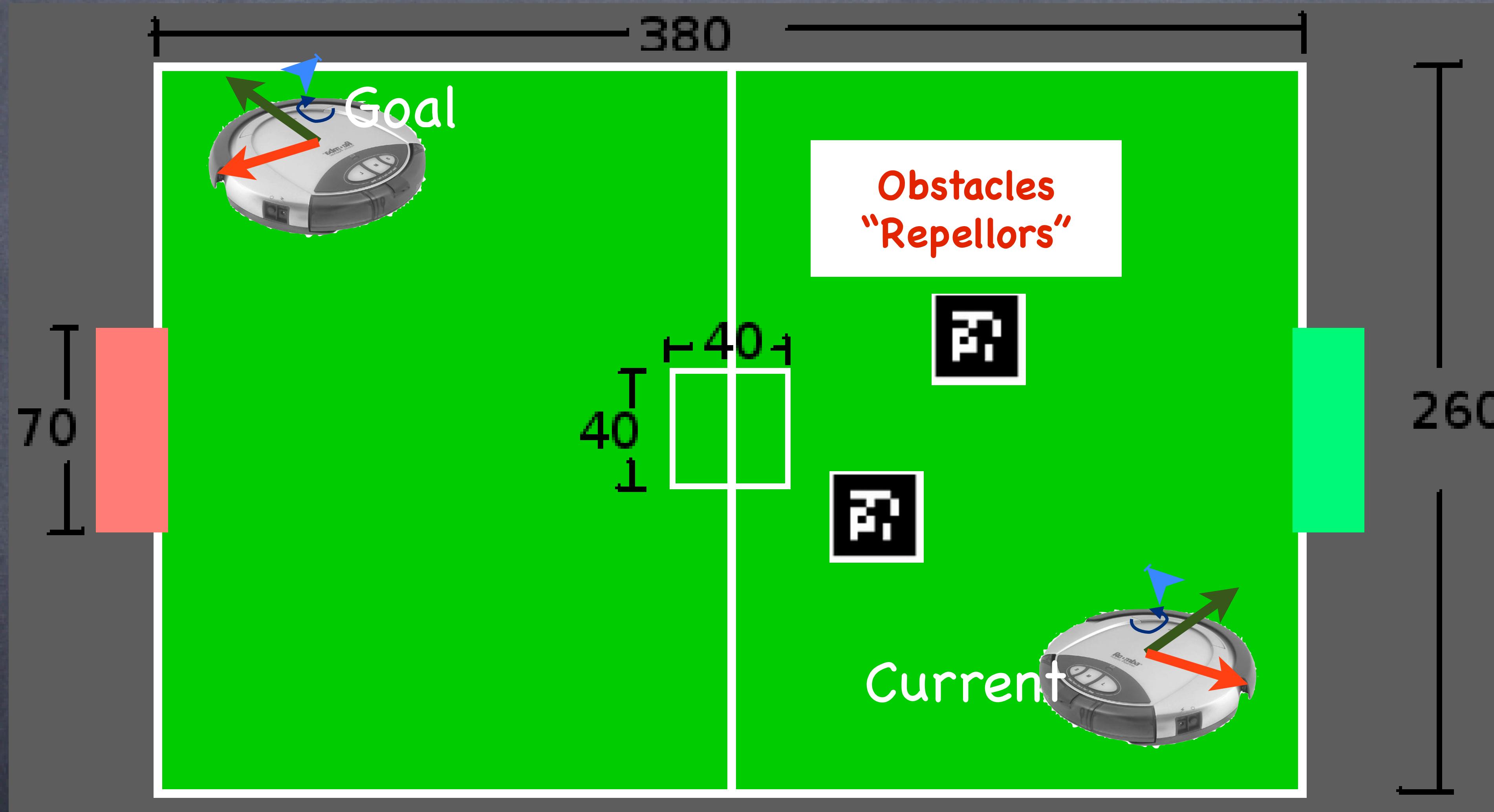


describe performance for this case



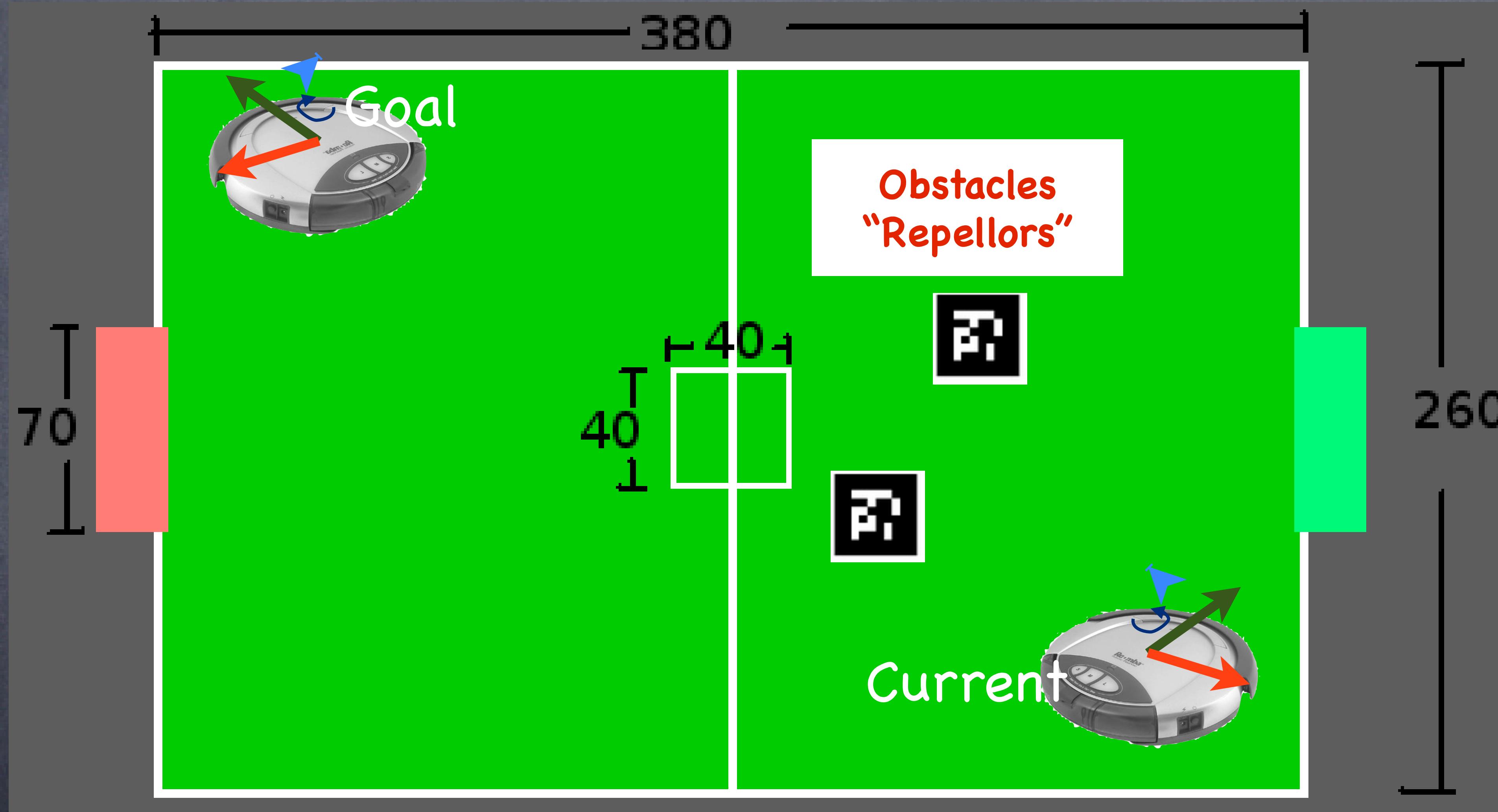
describe performance for this case

how do we deal with repellors?



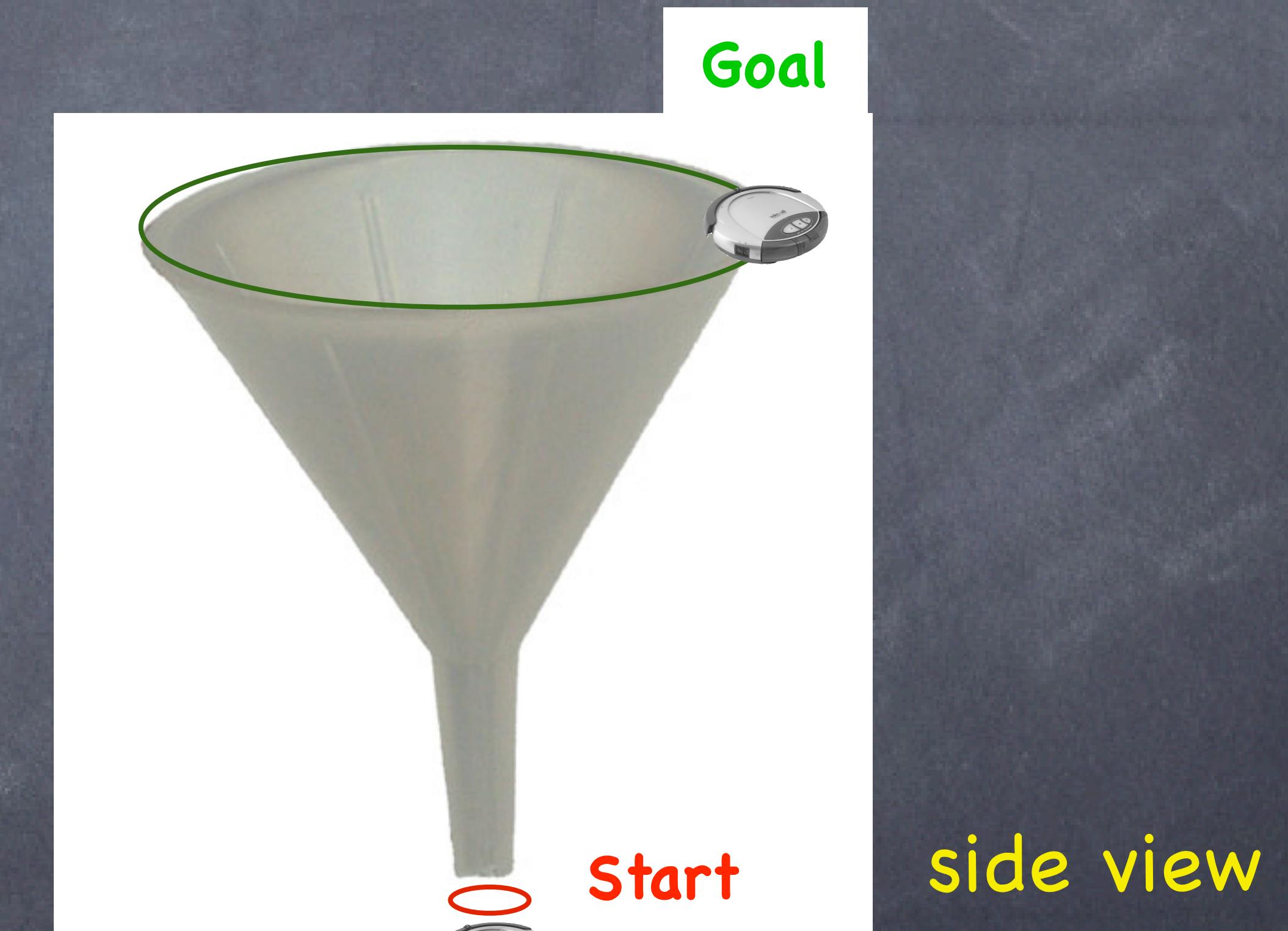
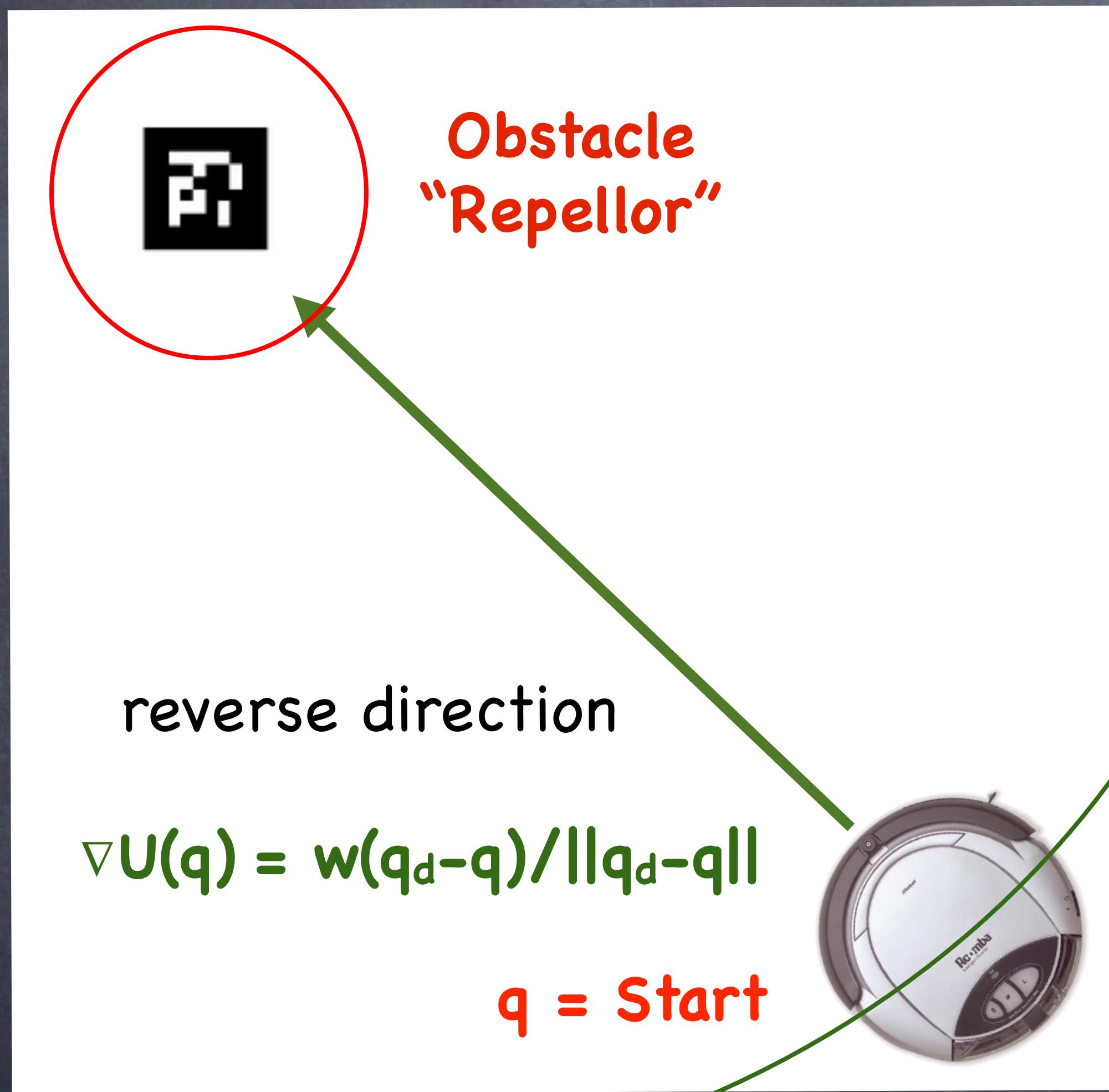
add sum of repulsive potentials

$$U(q) = U_{\text{attracts}}(q) + U_{\text{repellors}}(q)$$

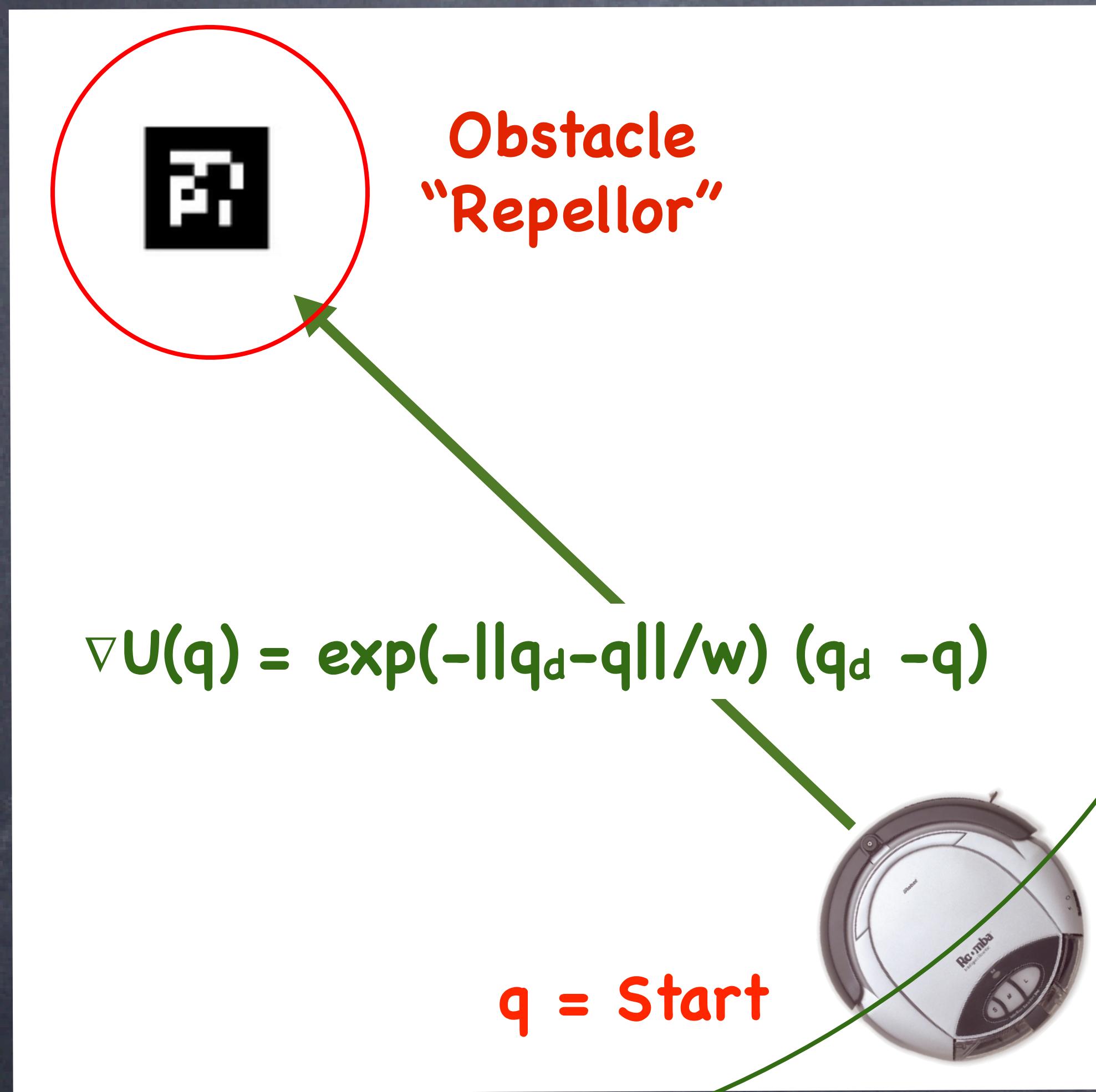


# "Cone" Repellor

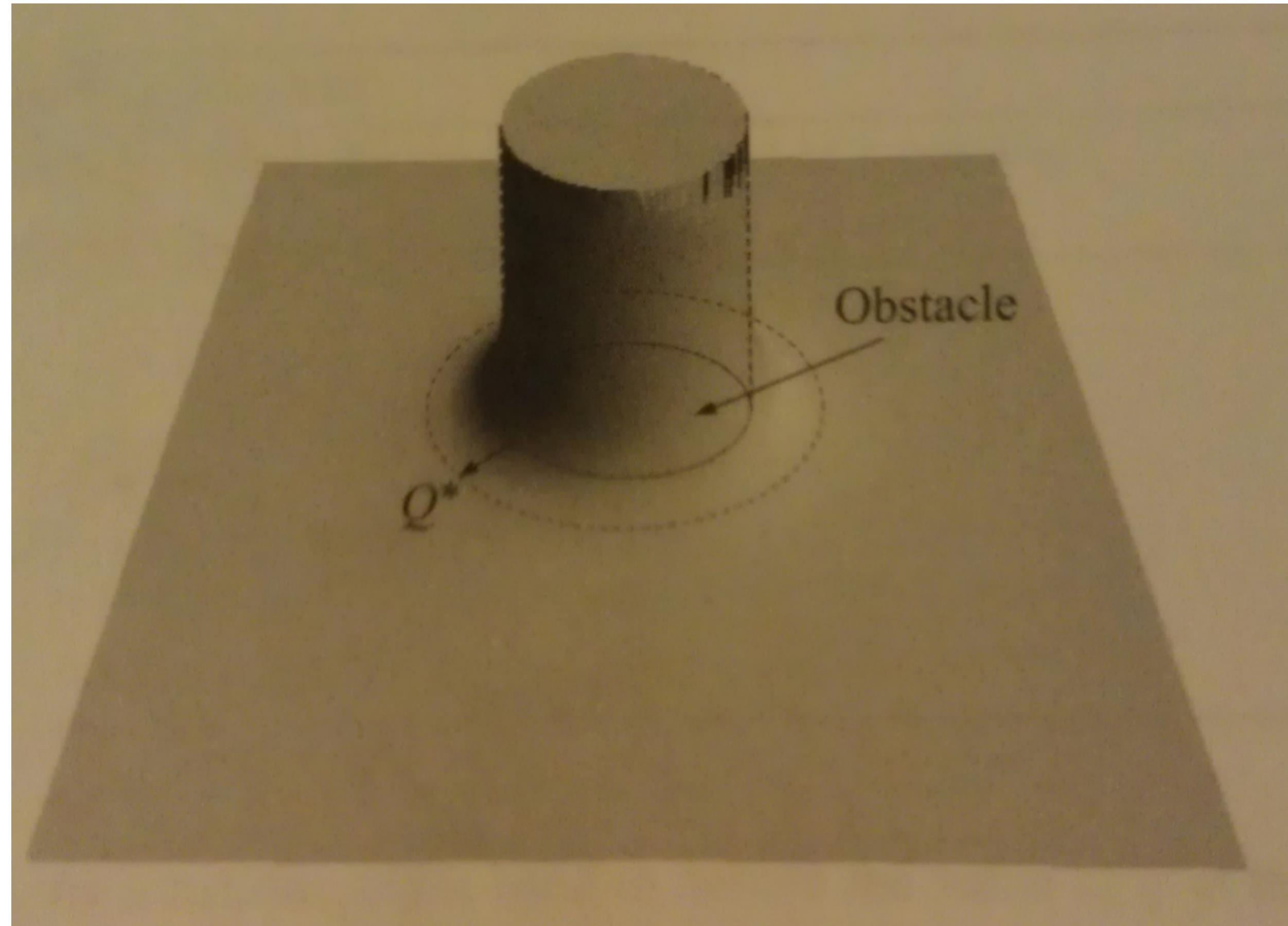
potential problems?



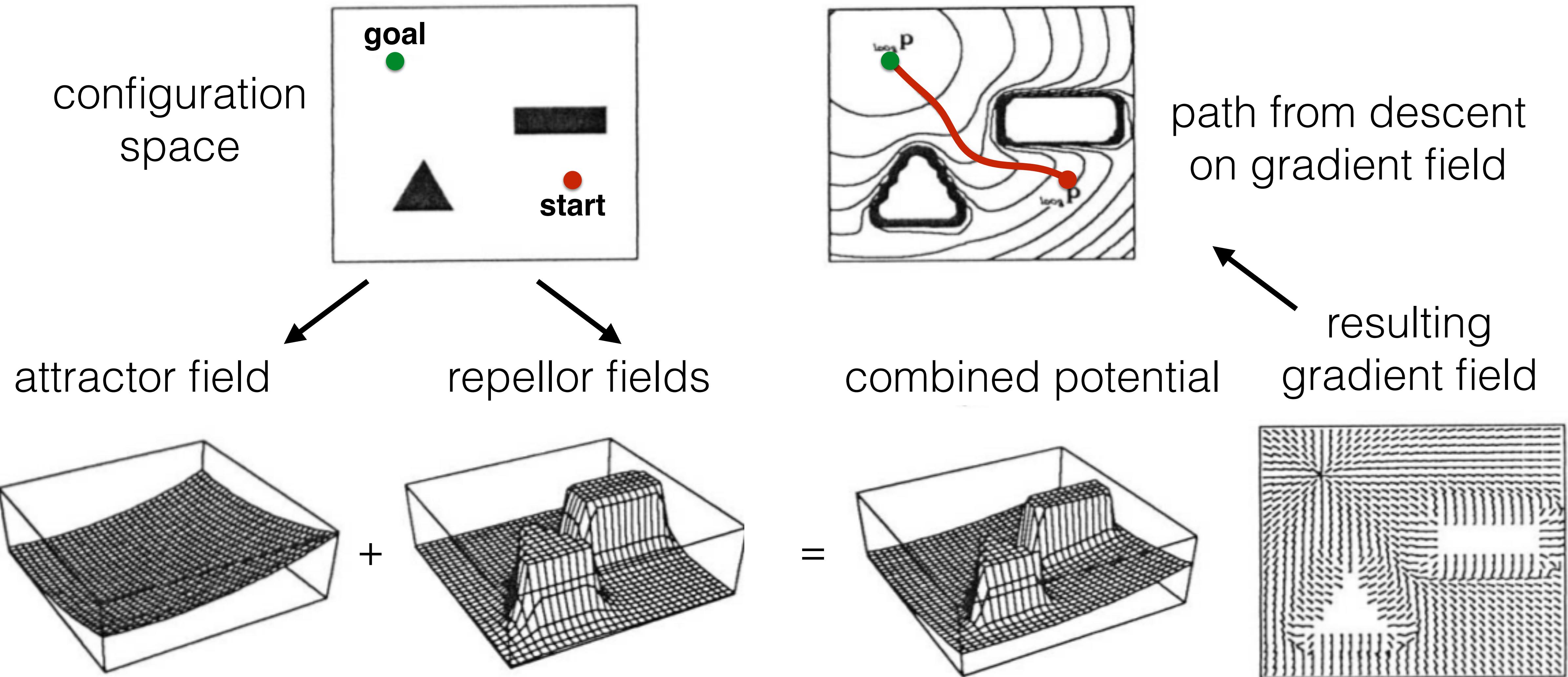
# "Bowl" Repellor



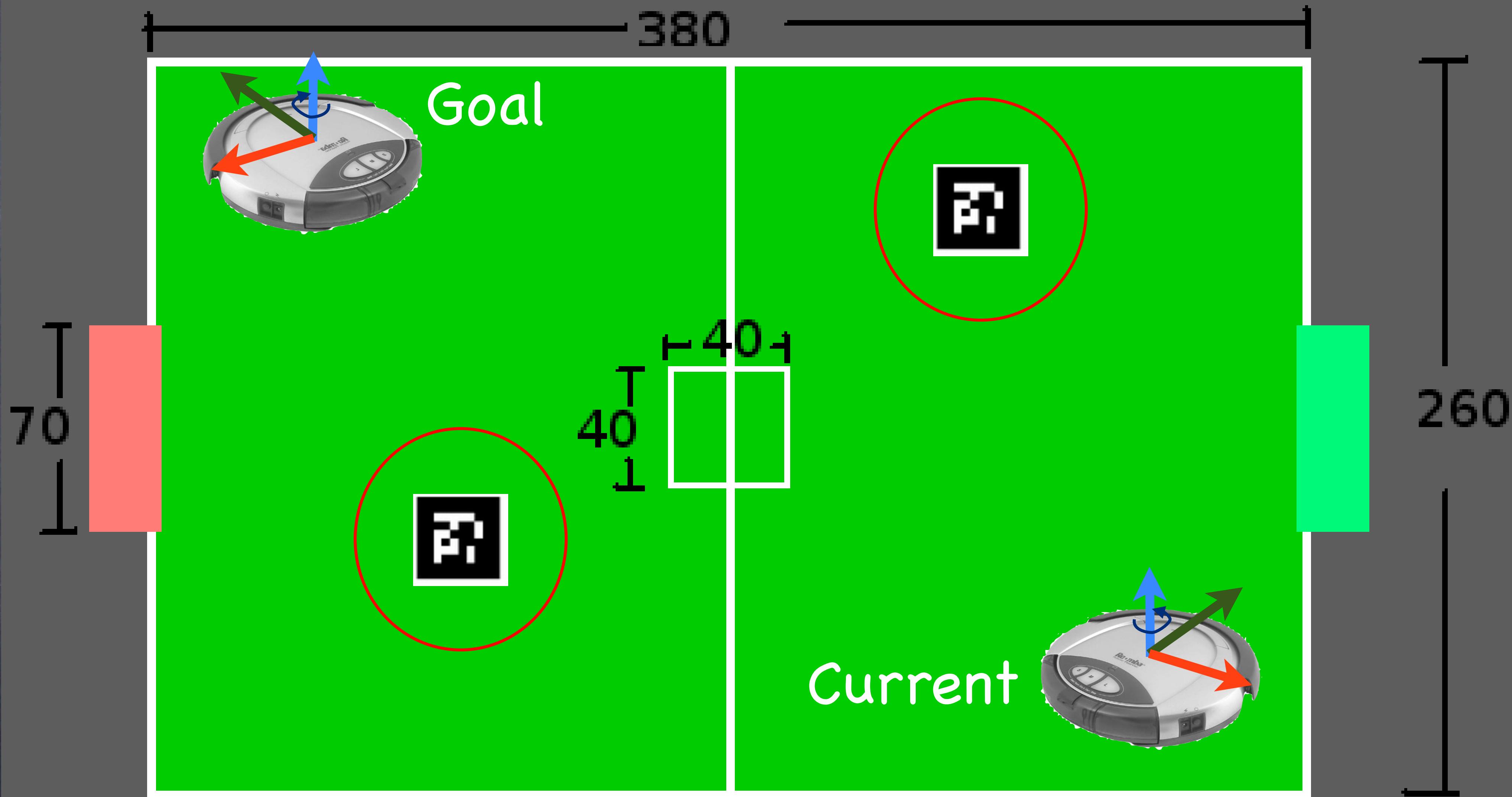
repellor should only have local influence,  
repelling only around boundary improves path



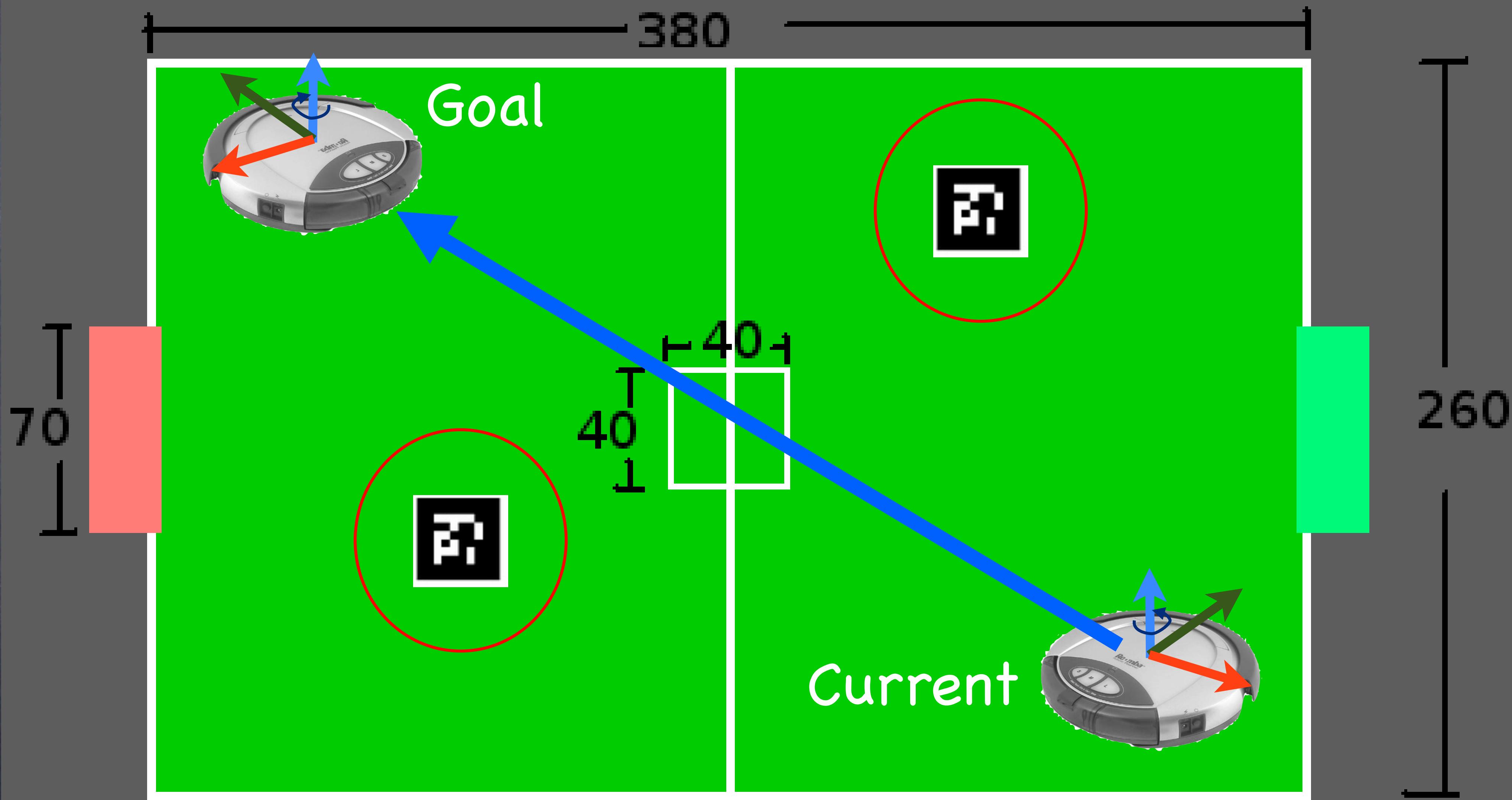
## 2 Obstacle example



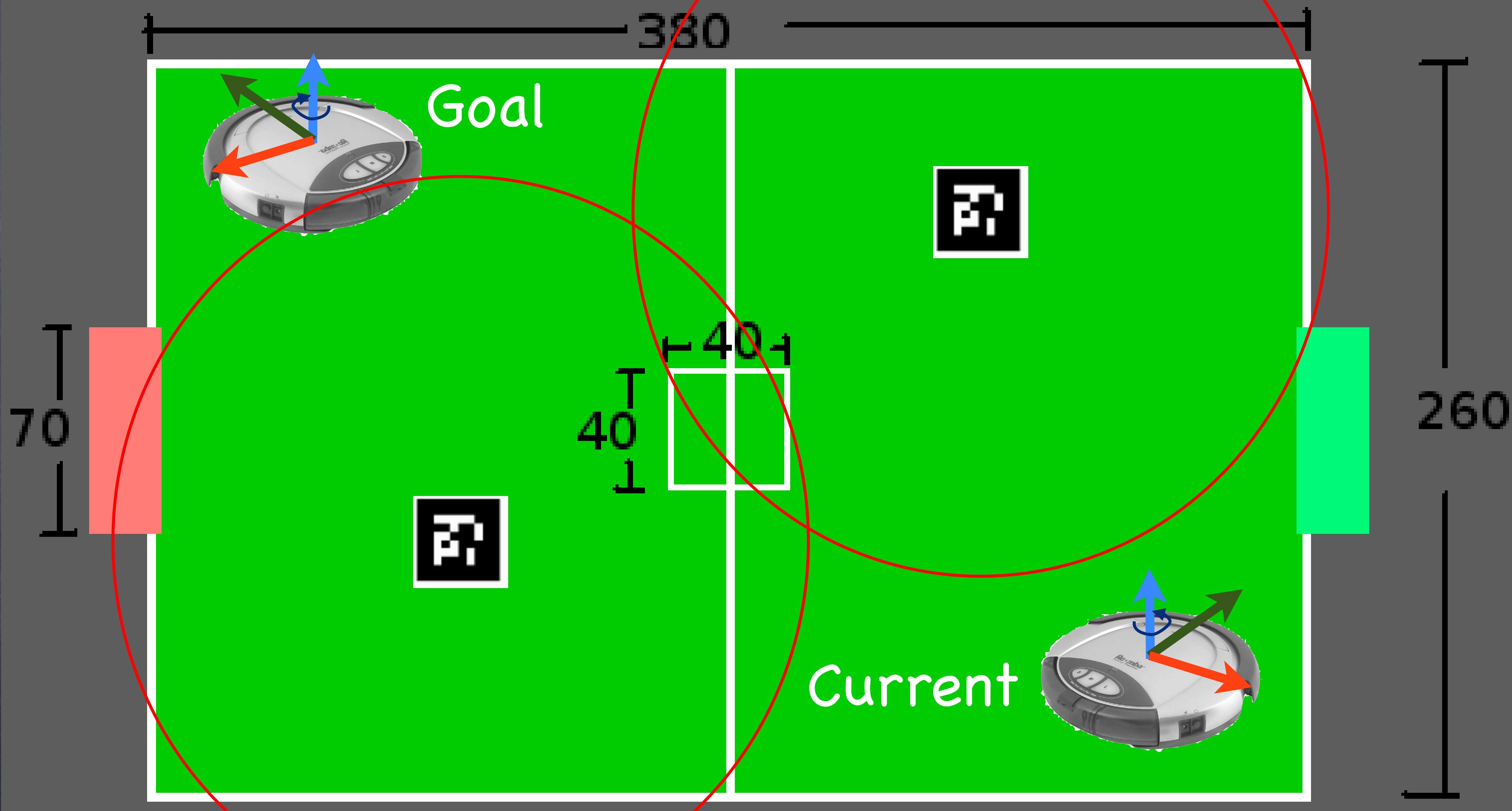
describe performance for this case  
with cone attractor to goal and bowl repellors  
with limited weight



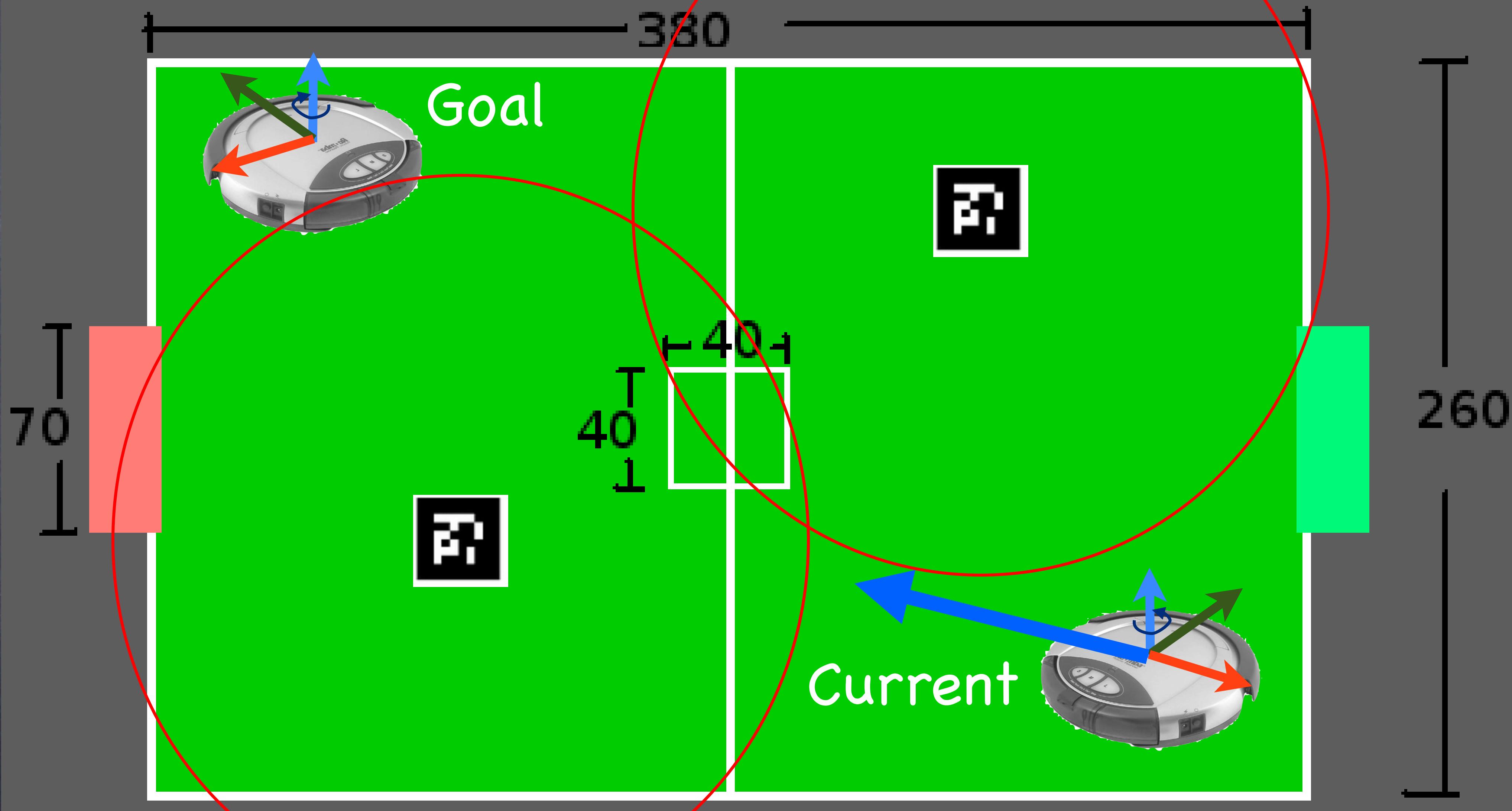
describe performance for this case  
with cone attractor to goal and bowl repellors  
with limited weight



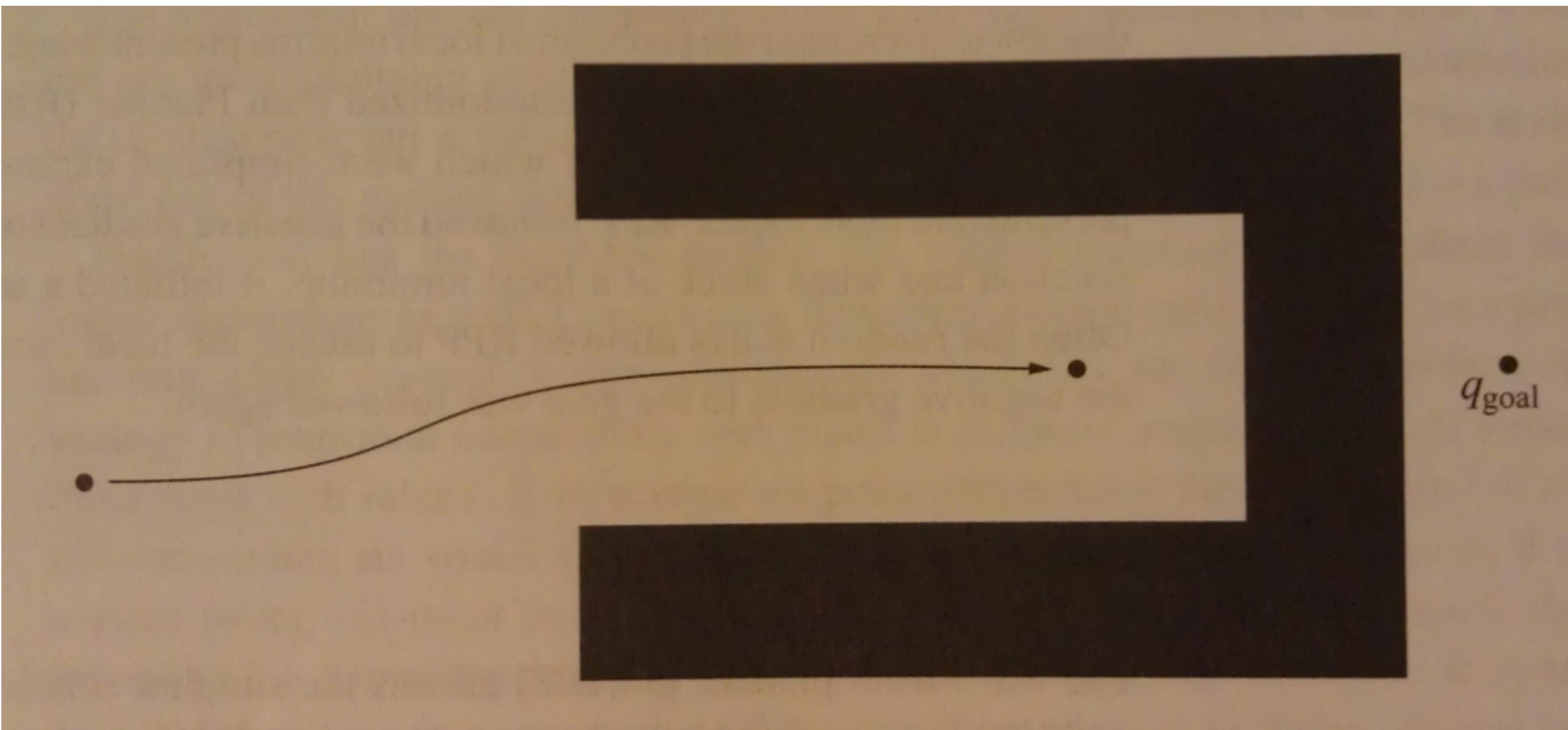
describe performance for this case  
with cone attractor to goal and bowl repellors  
with limited weight



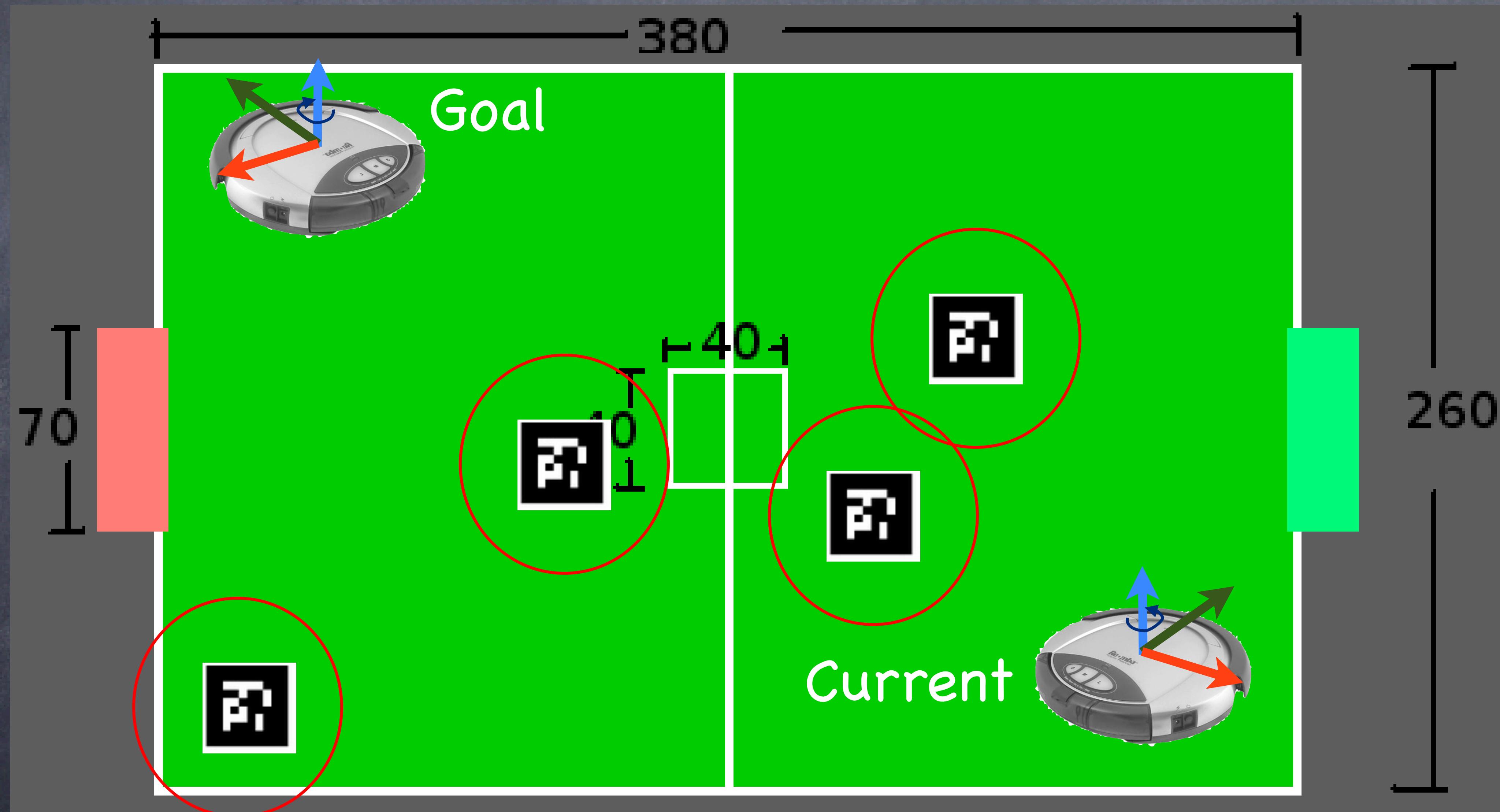
describe performance for this case  
with cone attractor to goal and bowl repellors  
with limited weight



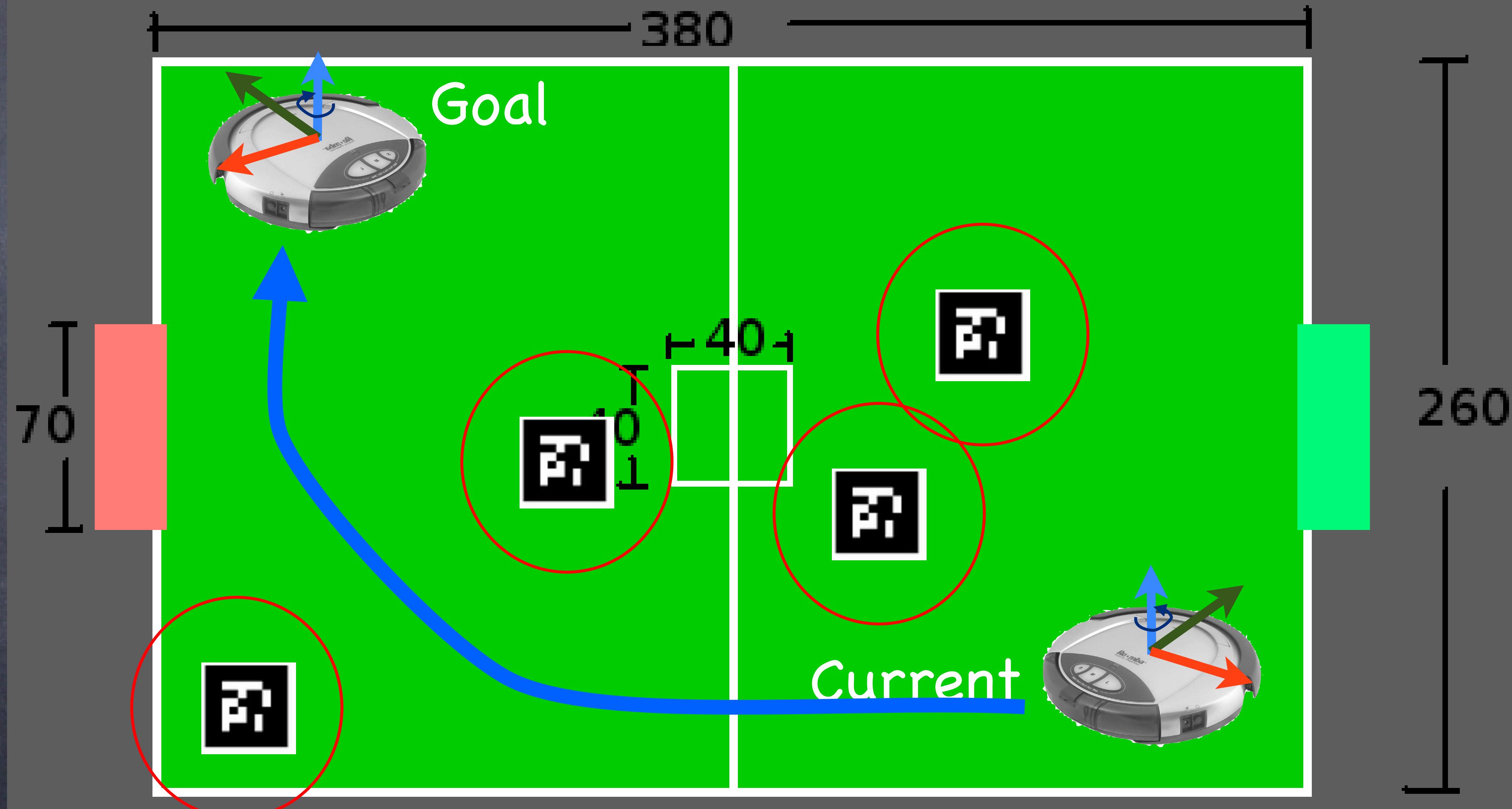
# Local Minima



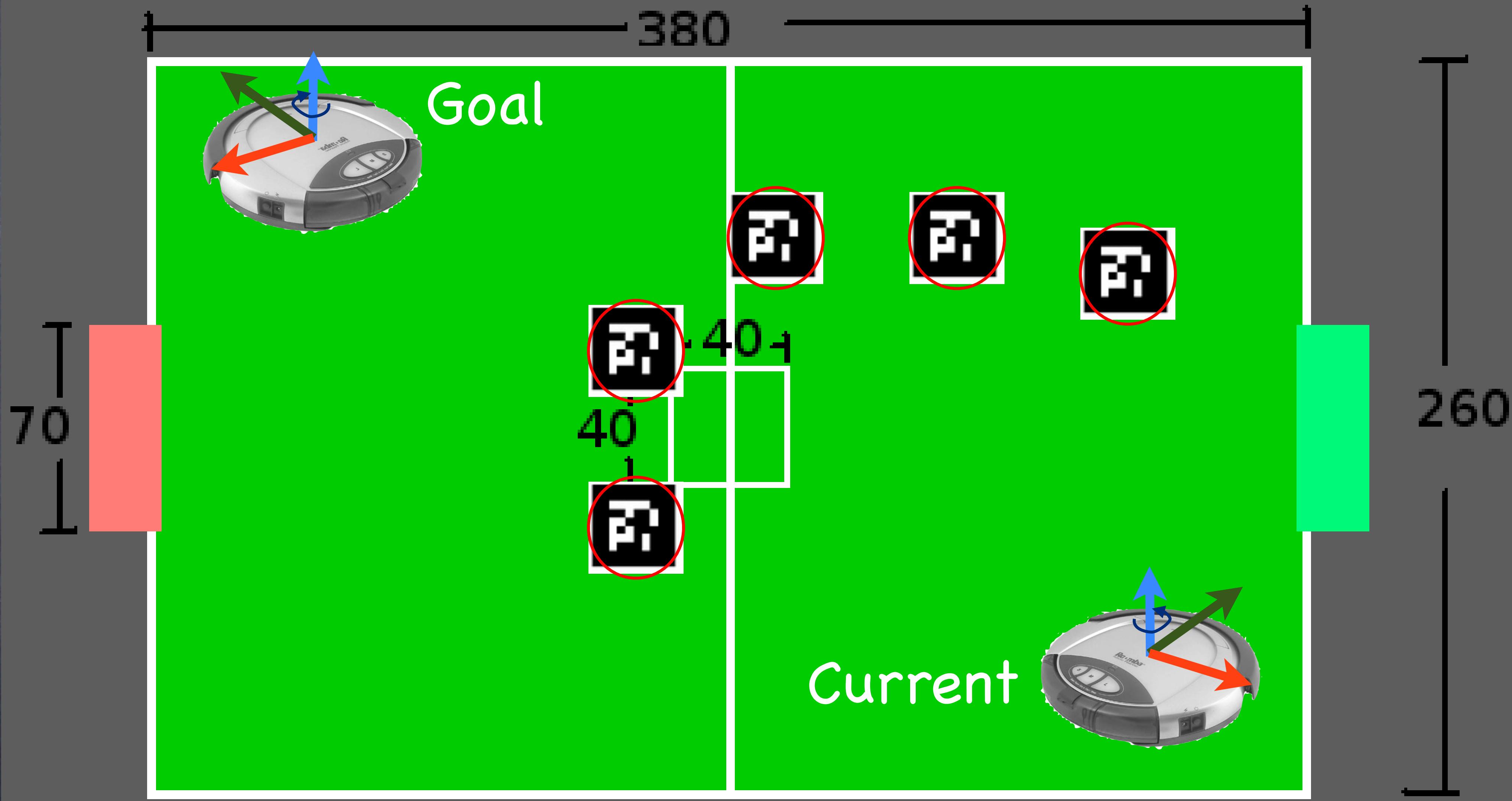
describe performance for this case



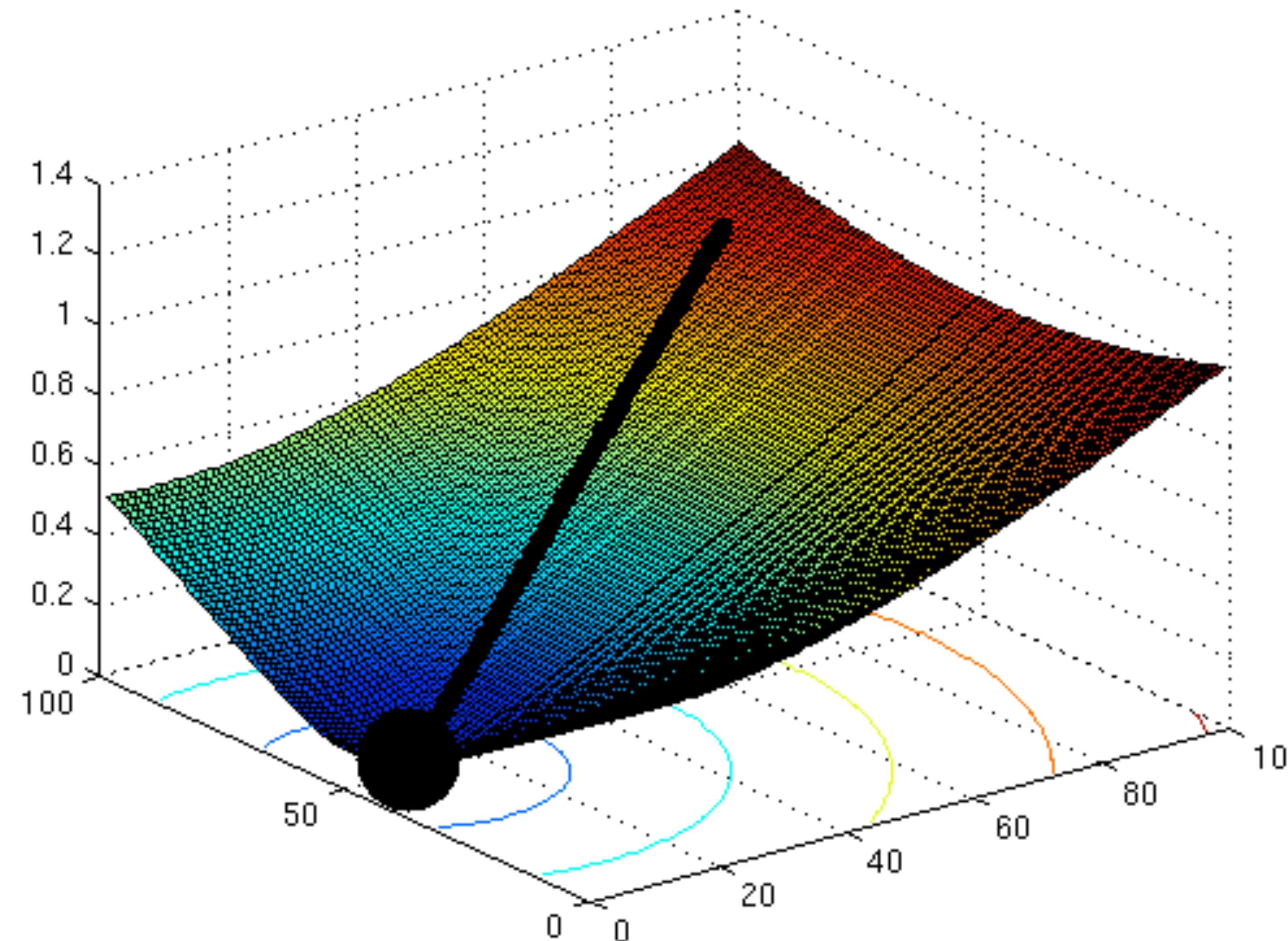
describe performance for this case



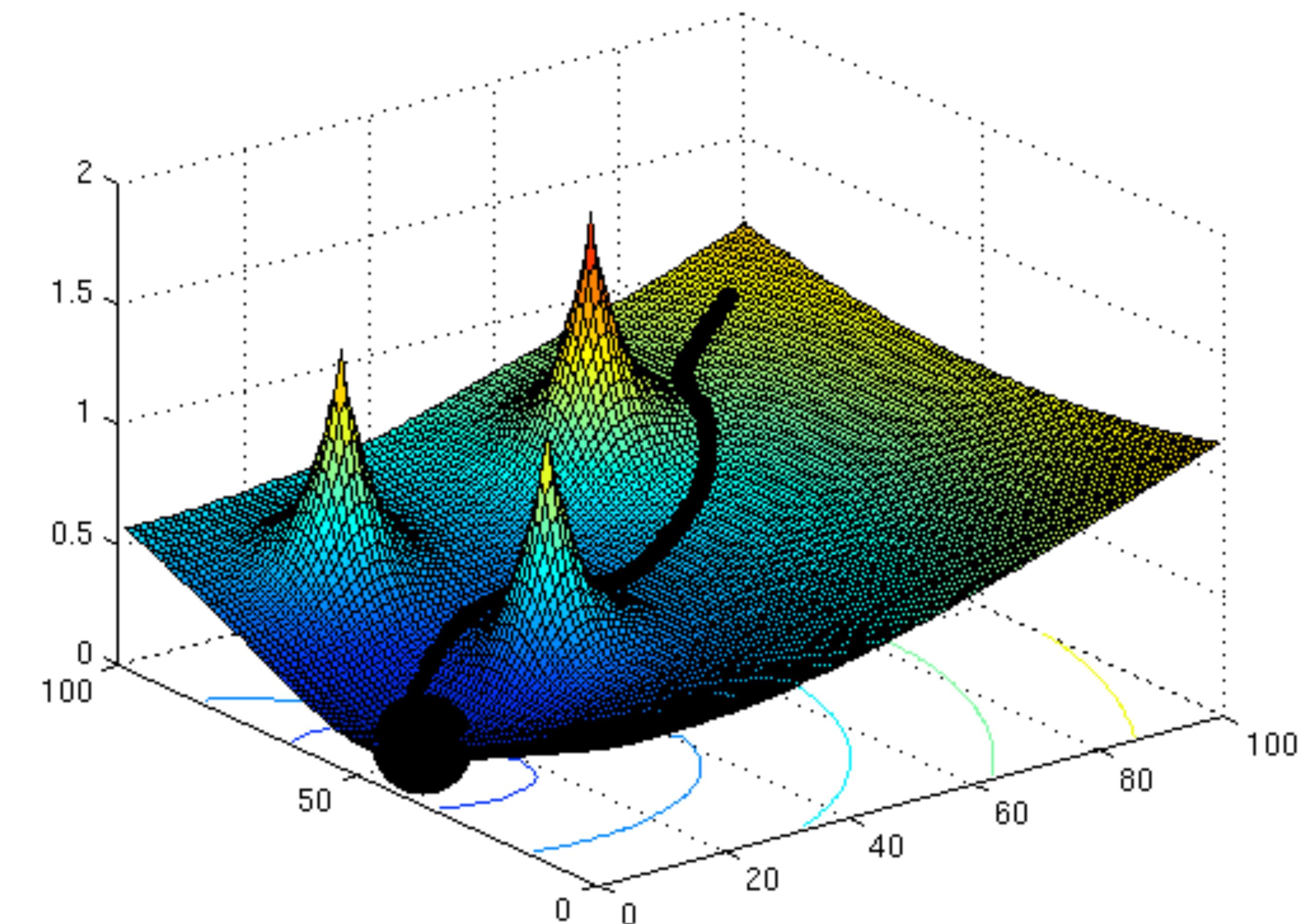
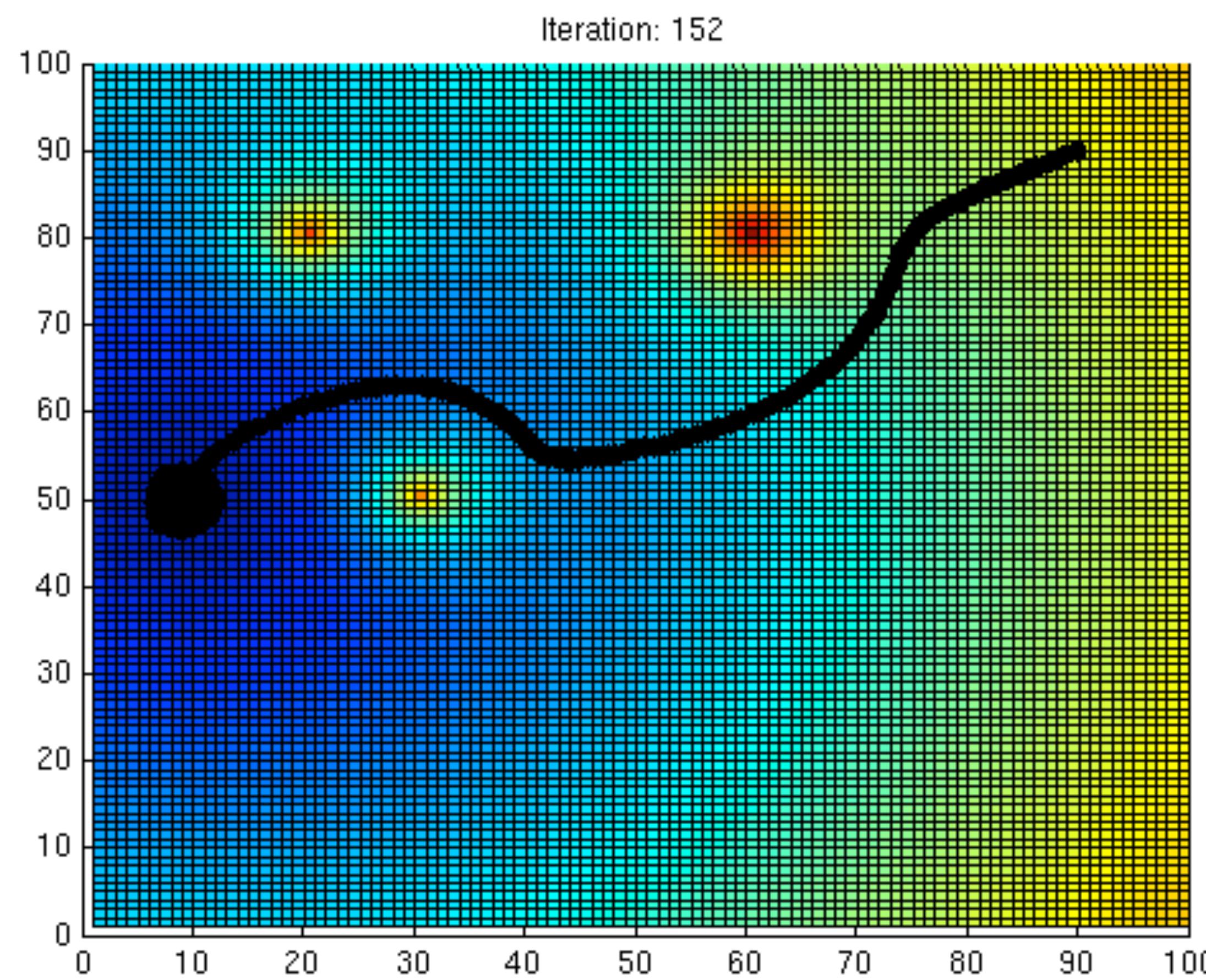
describe performance for this case



# matlab example

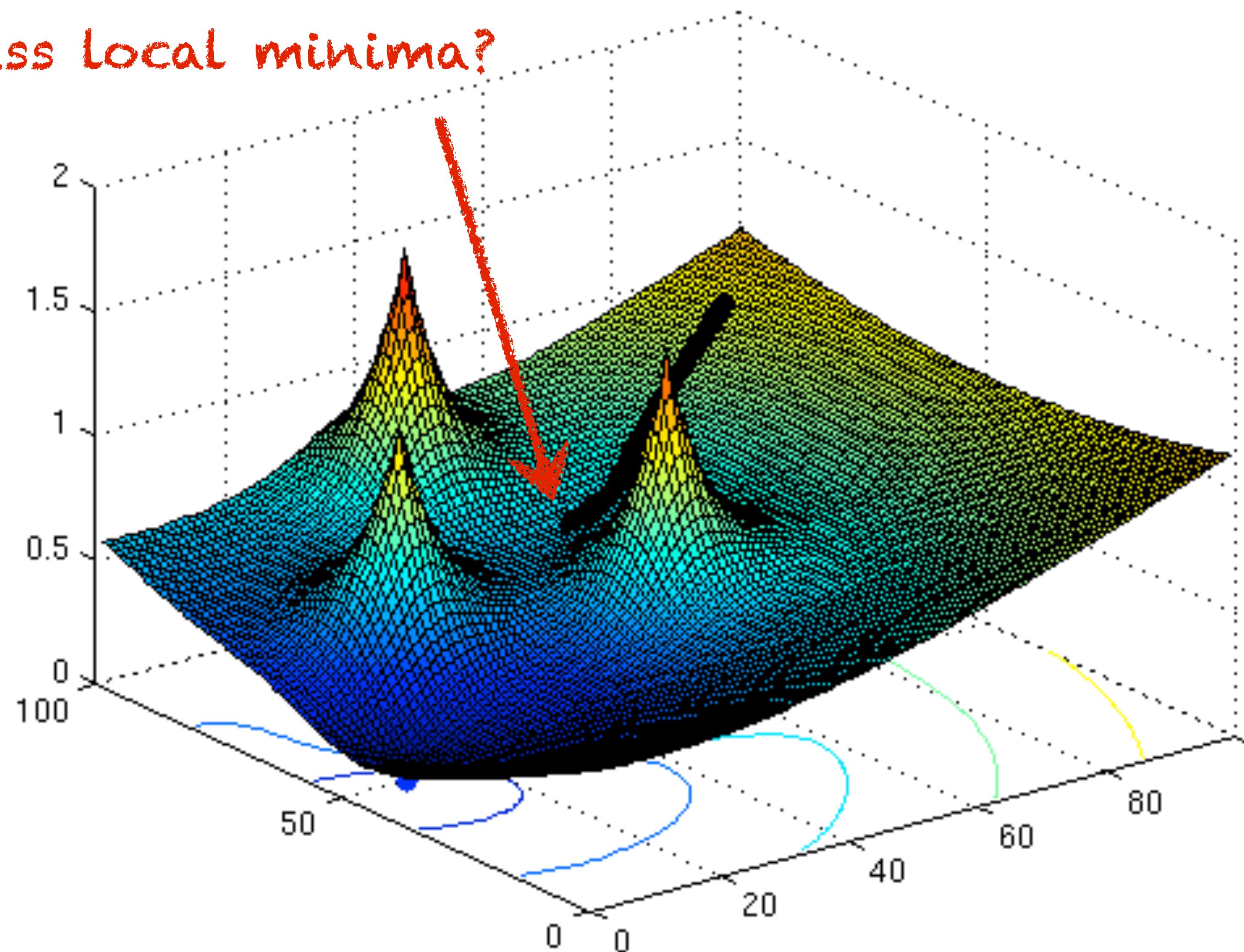


# matlab example



# matlab example

How to address Local minima?



How can we get out of  
local minima?

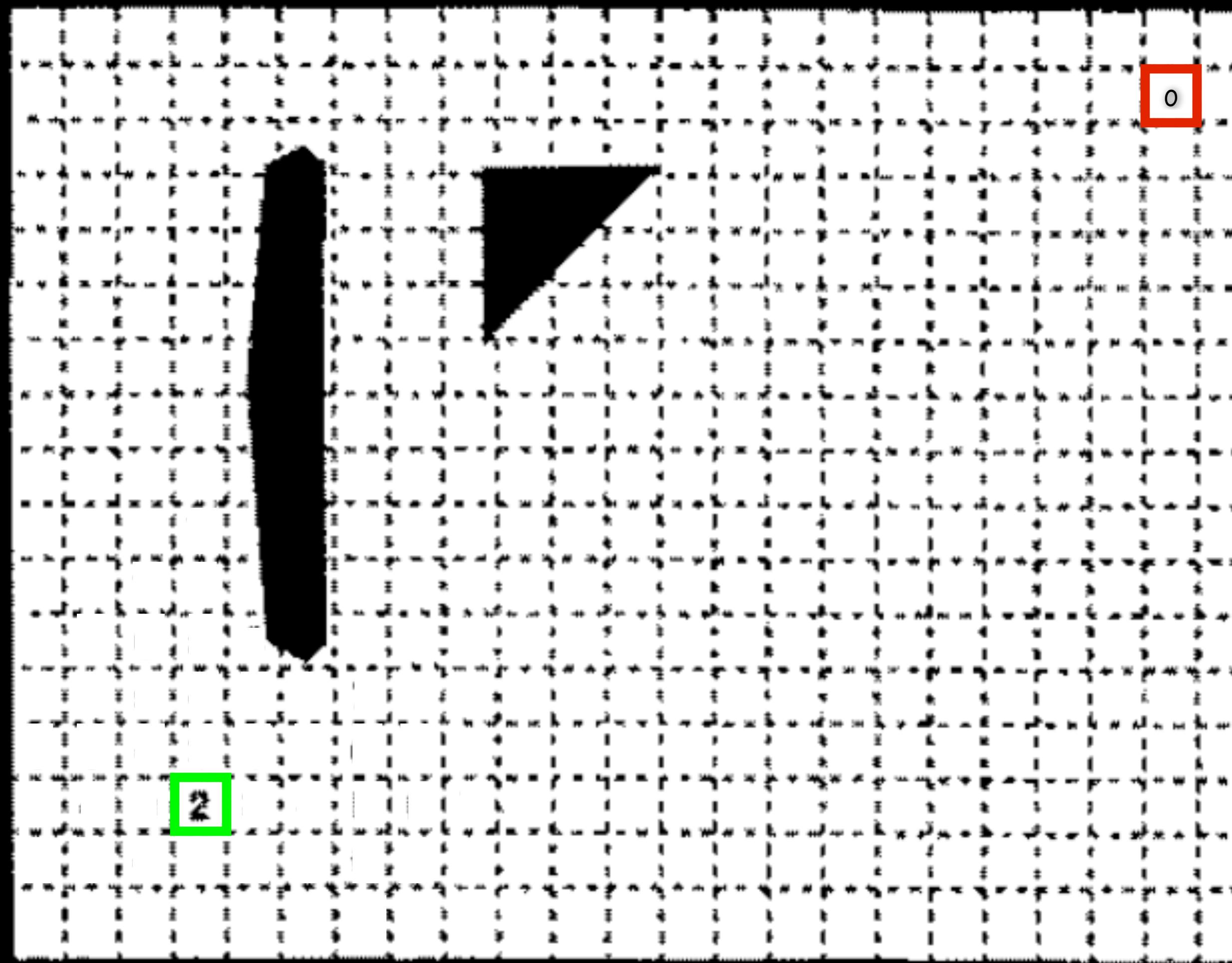
How can we get out of  
local minima?

Go back to planning.

# Wavefront Planning

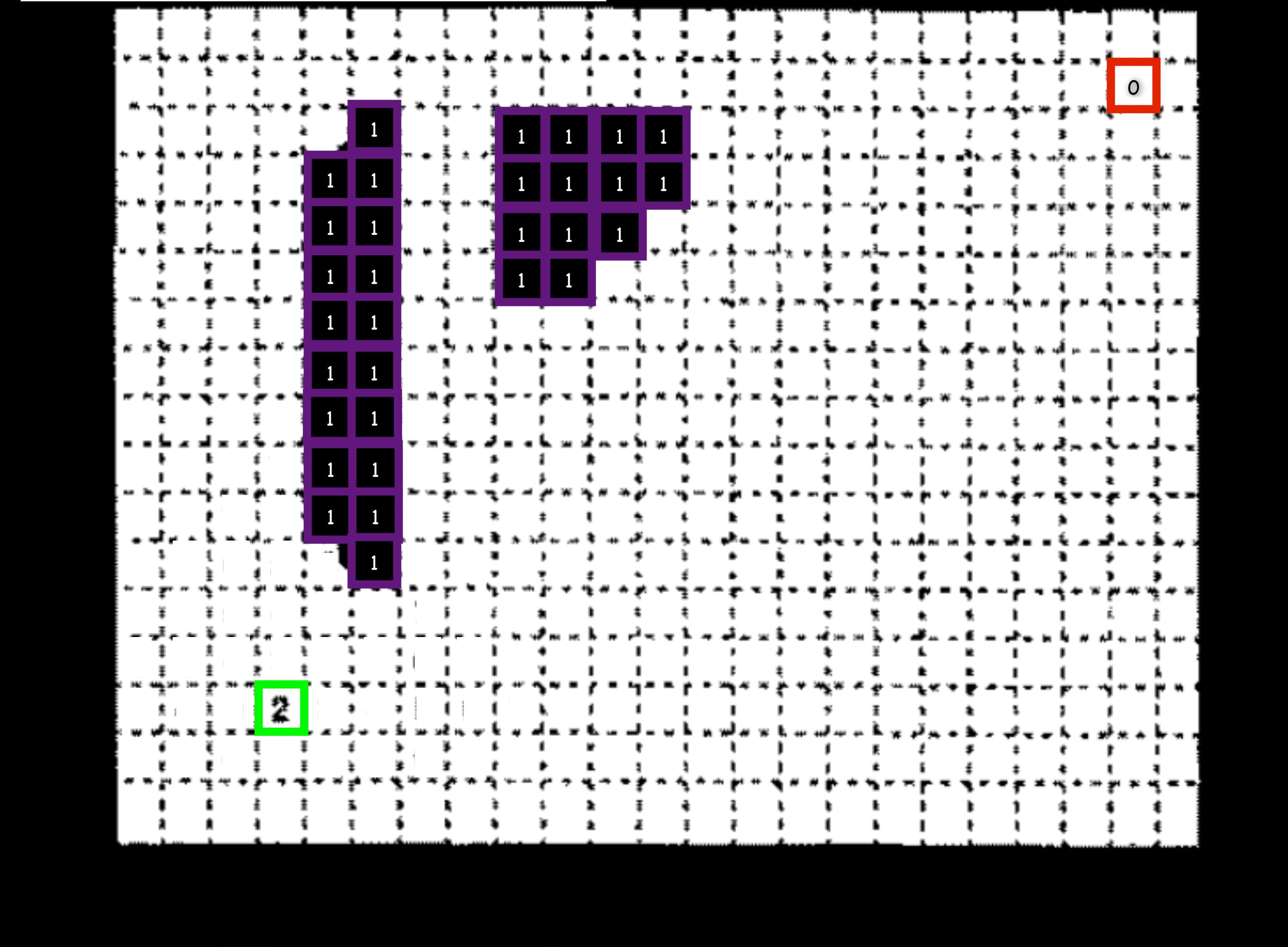
- Discretize potential field into grid
  - Cells store cost to goal with respect to potential field
  - Computed by Brushfire algorithm (essentially BFS)
- Grid search to find navigation path to goal

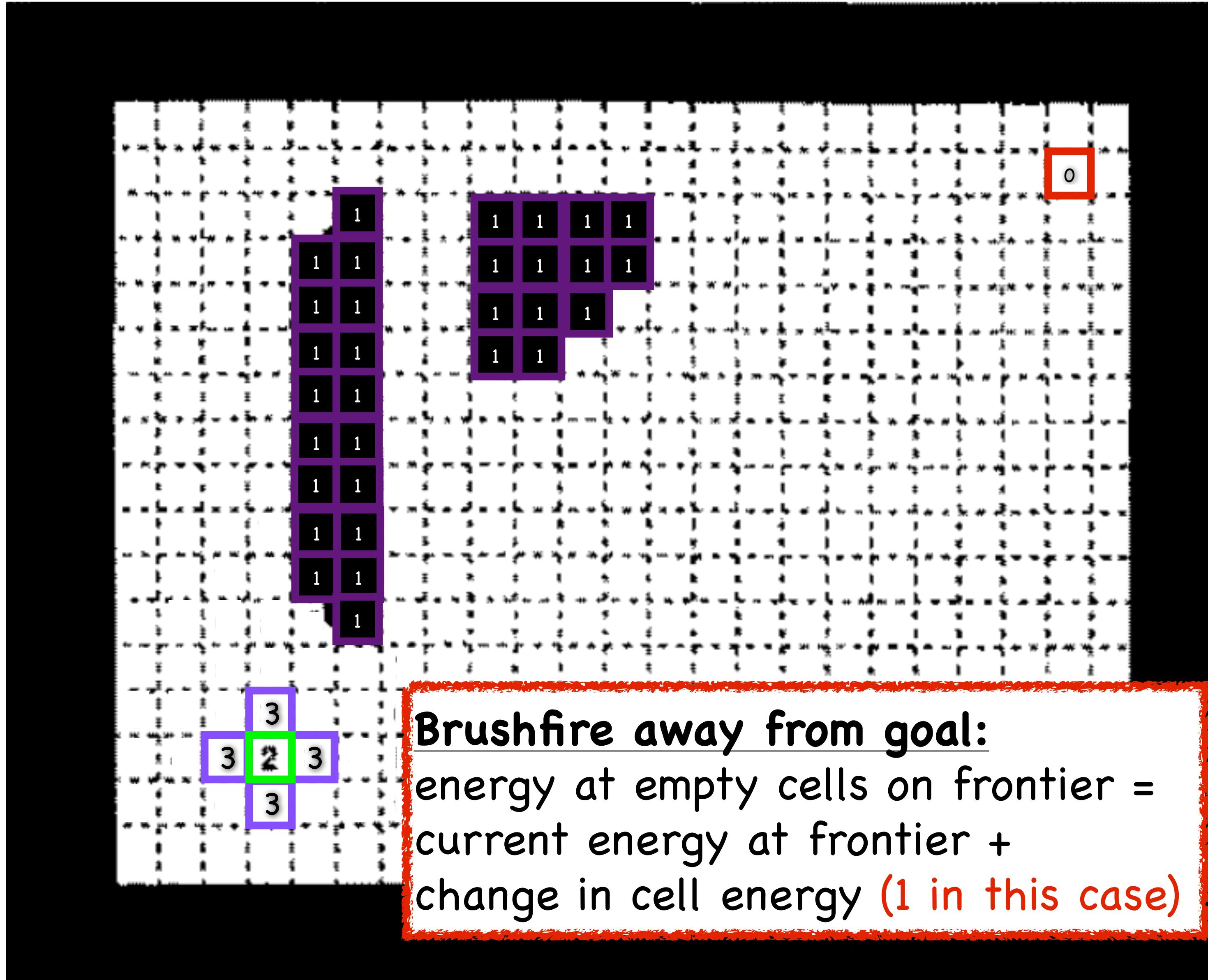
Start: mark with 0

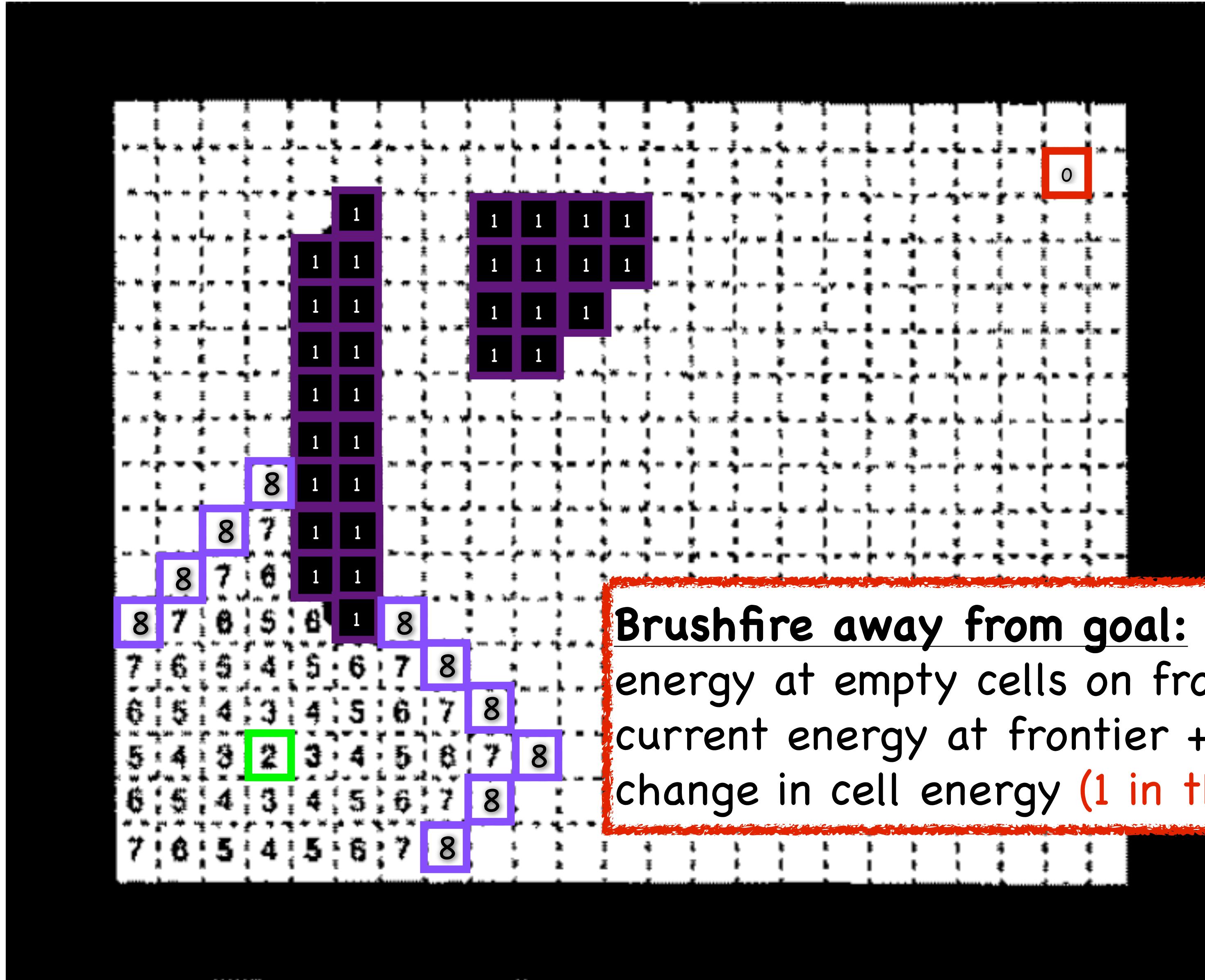


Goal: mark with 2

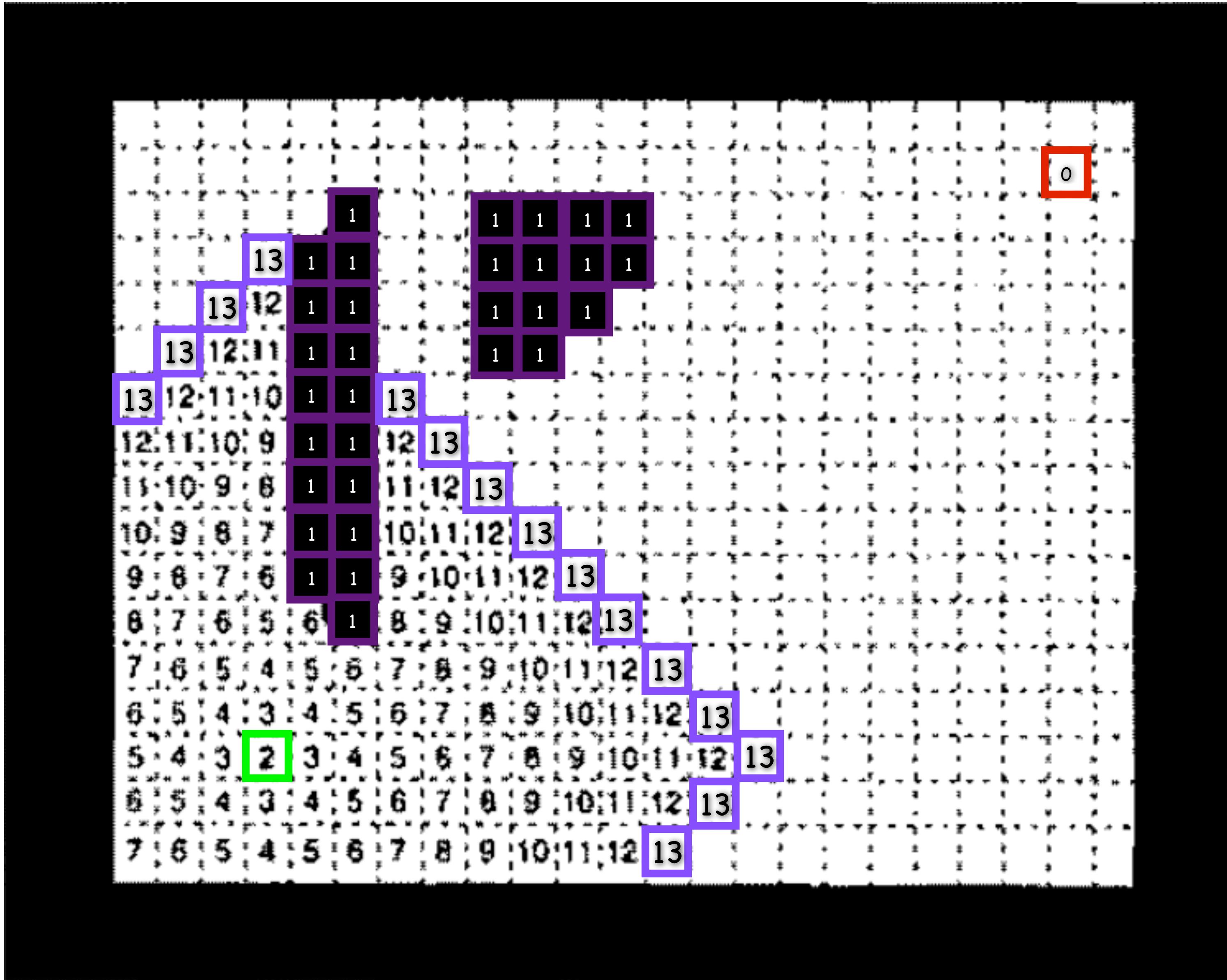
## Obstacles: mark with 1

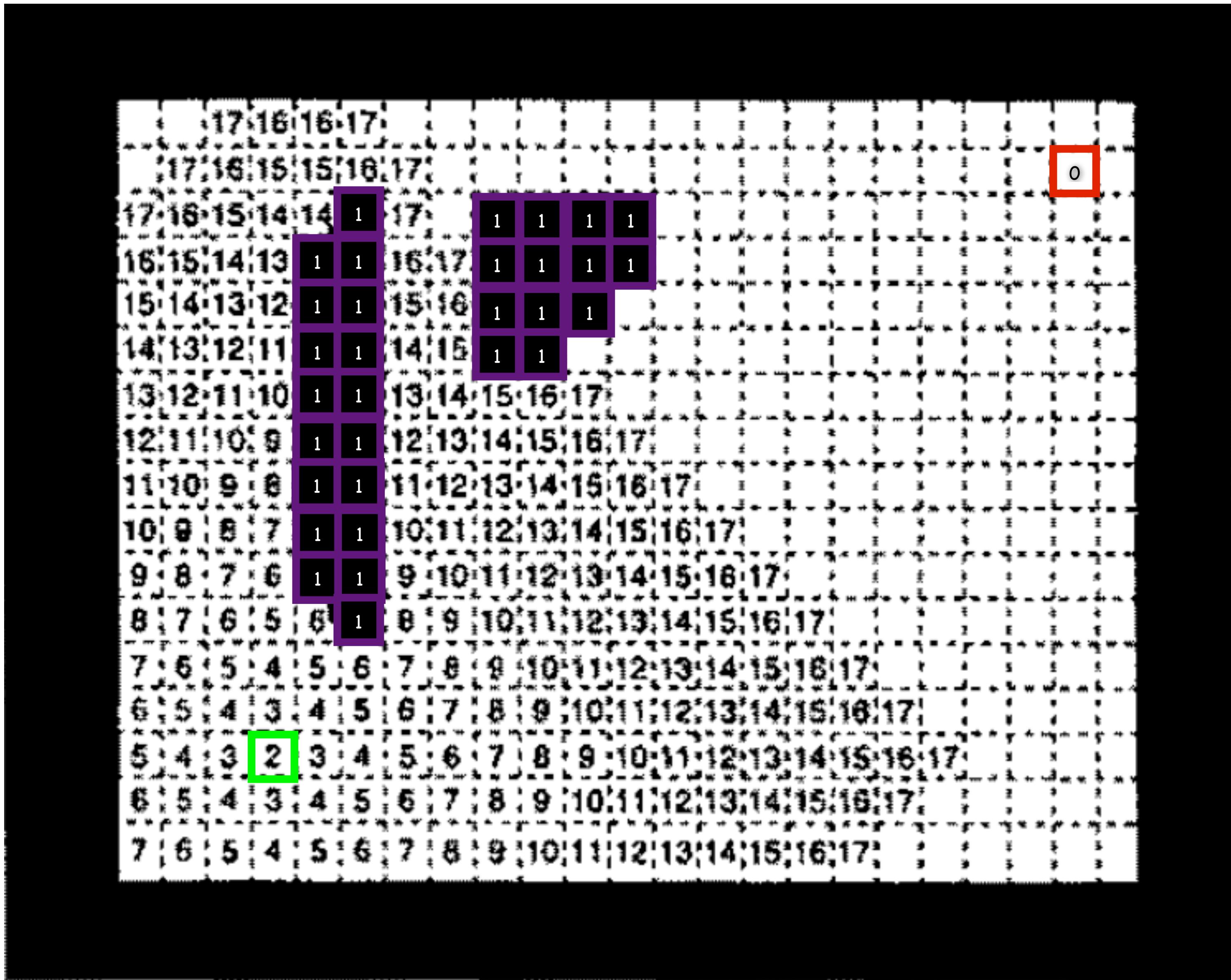


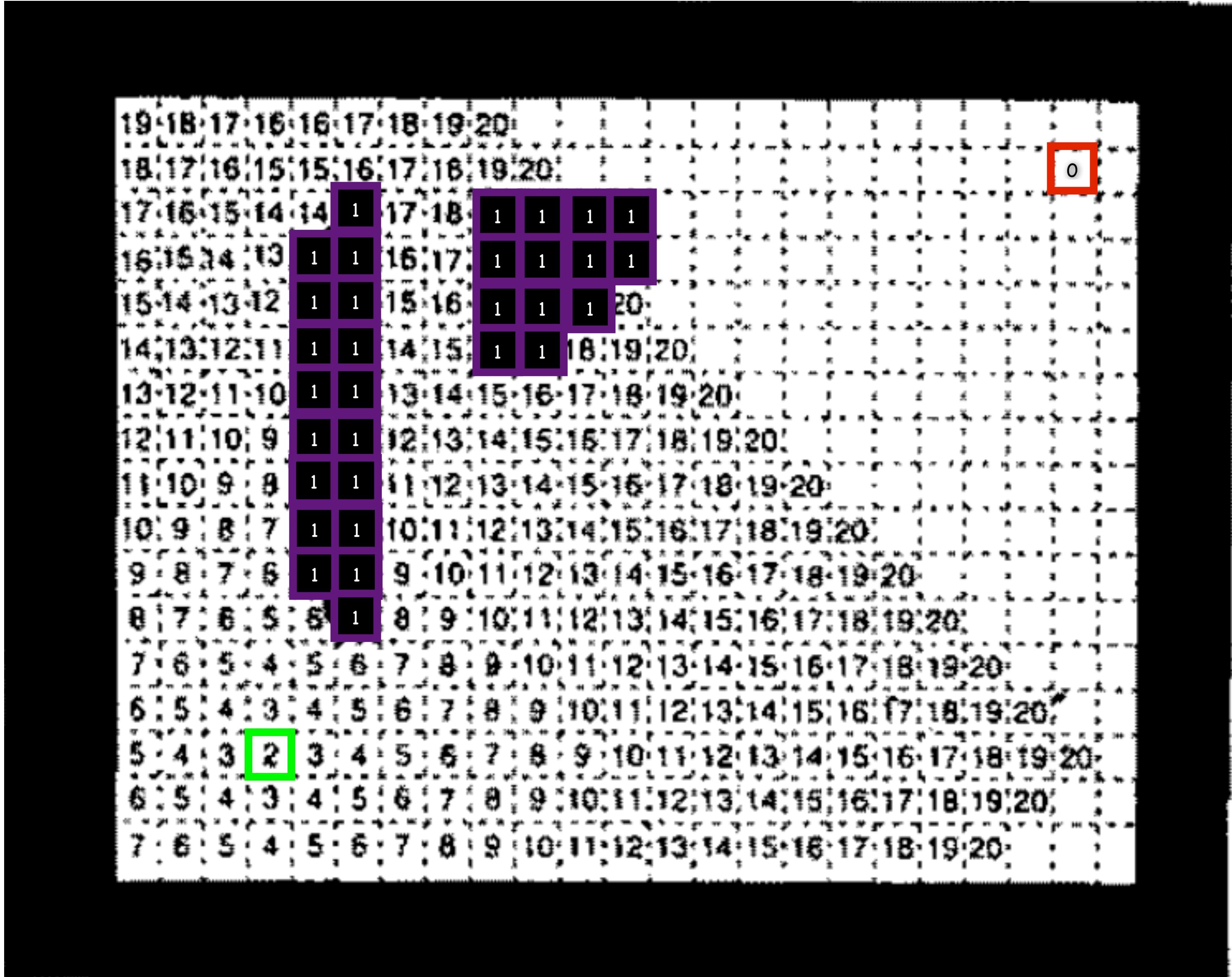




**Brushfire away from goal:**  
energy at empty cells on frontier =  
current energy at frontier +  
change in cell energy (1 in this case)



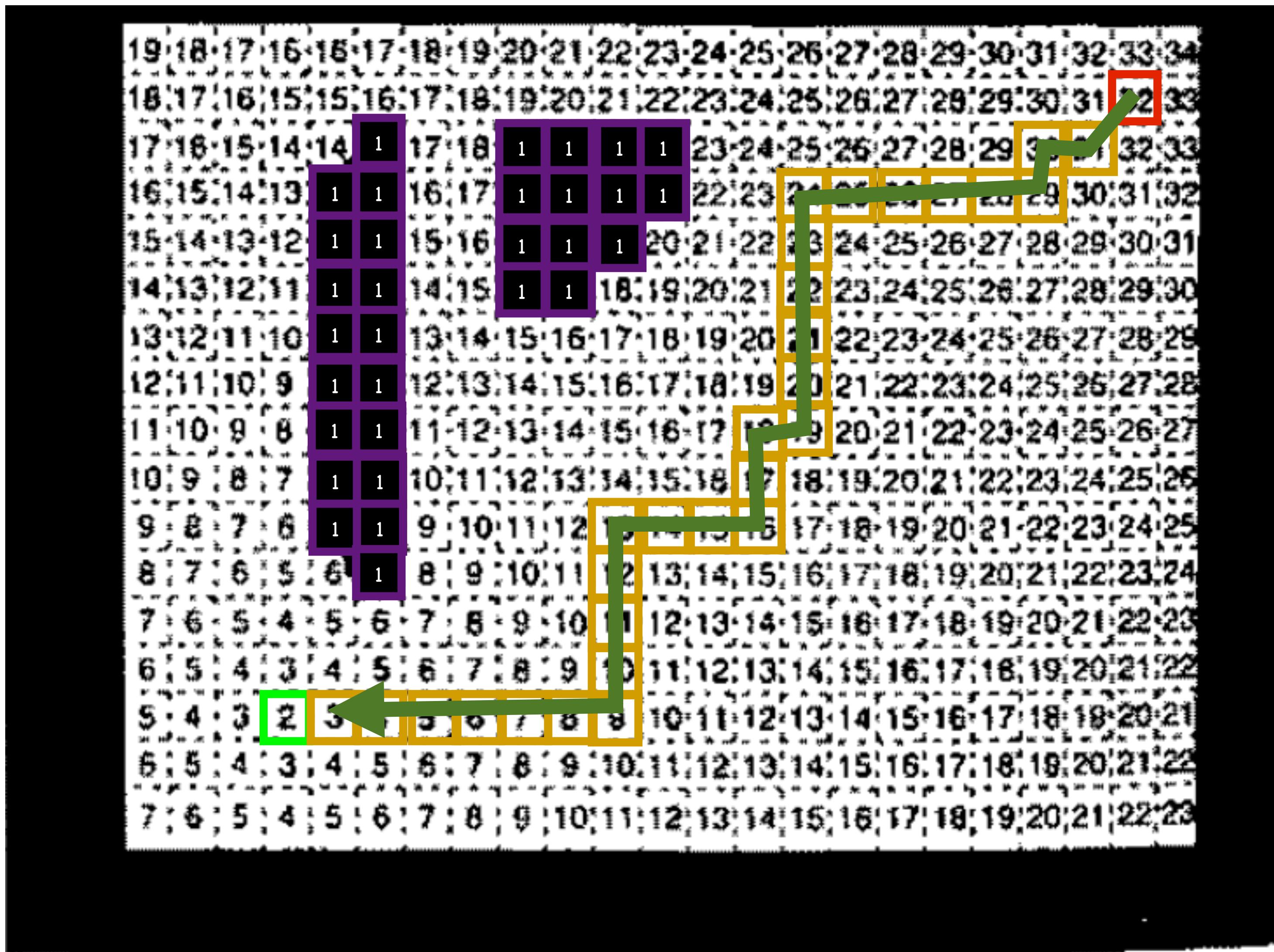




19;18;17;16;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
18;17;16;15;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17;16;15;14;14;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16;15;14;13;13;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15;14;13;12;12;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14;13;12;11;11;14;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
13;12;11;10;10;13;14;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
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9;8;7;6;6;9;10;11;12;13;14;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
8;7;6;5;5;8;9;10;11;12;13;14;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
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5;4;3;2;3;4;5;6;7;8;9;10;11;12;13;14;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6;5;4;3;4;5;6;7;8;9;10;11;12;13;14;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7;6;5;4;5;6;7;8;9;10;11;12;13;14;15;16;17;18;19;20;21;22;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

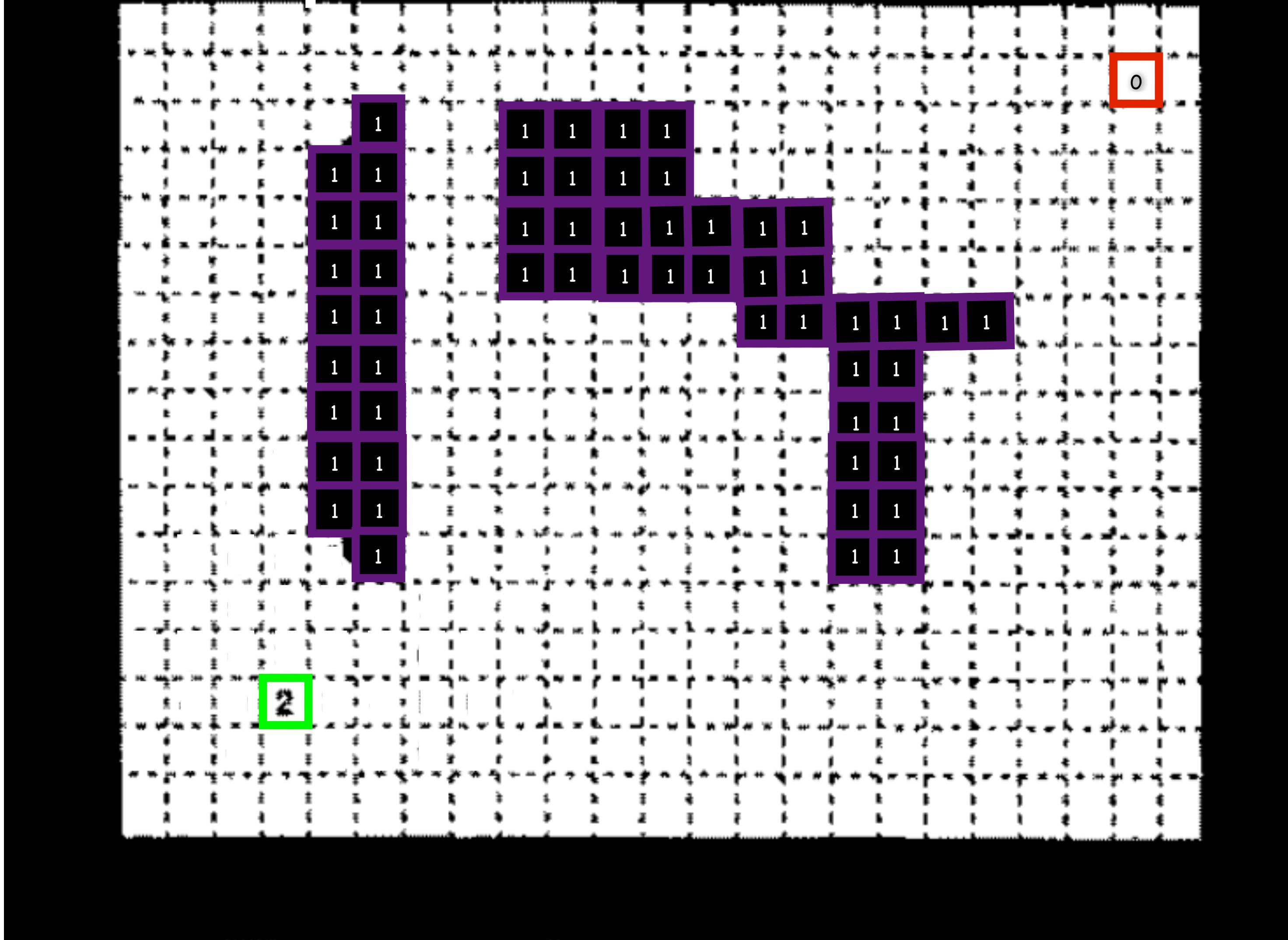
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19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	32
17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	32	33
16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	32	33	34
15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	32	33	34	35
14	13	12	11	10	9	8	7	6	5	4	3	2	1	32	33	34	35	36
13	12	11	10	9	8	7	6	5	4	3	2	1	32	33	34	35	36	37
12	11	10	9	8	7	6	5	4	3	2	1	32	33	34	35	36	37	38
11	10	9	8	7	6	5	4	3	2	1	32	33	34	35	36	37	38	39
10	9	8	7	6	5	4	3	2	1	32	33	34	35	36	37	38	39	40
9	8	7	6	5	4	3	2	1	32	33	34	35	36	37	38	39	40	41
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6	5	4	3	2	1	32	33	34	35	36	37	38	39	40	41	42	43	44
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4	3	2	1	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46
3	2	1	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47
2	1	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
1	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49

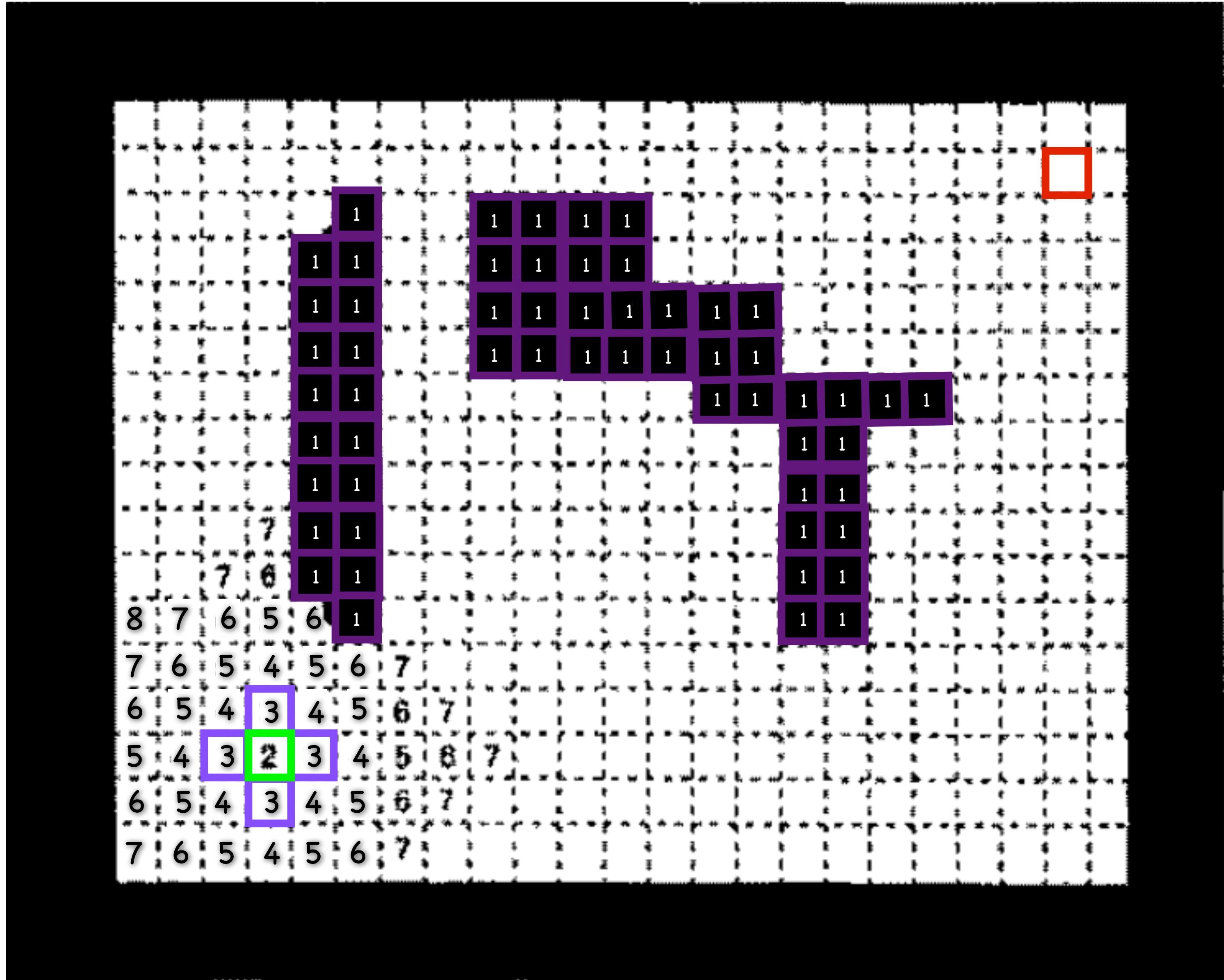
Once start reached,  
follow brushfire potential to goal

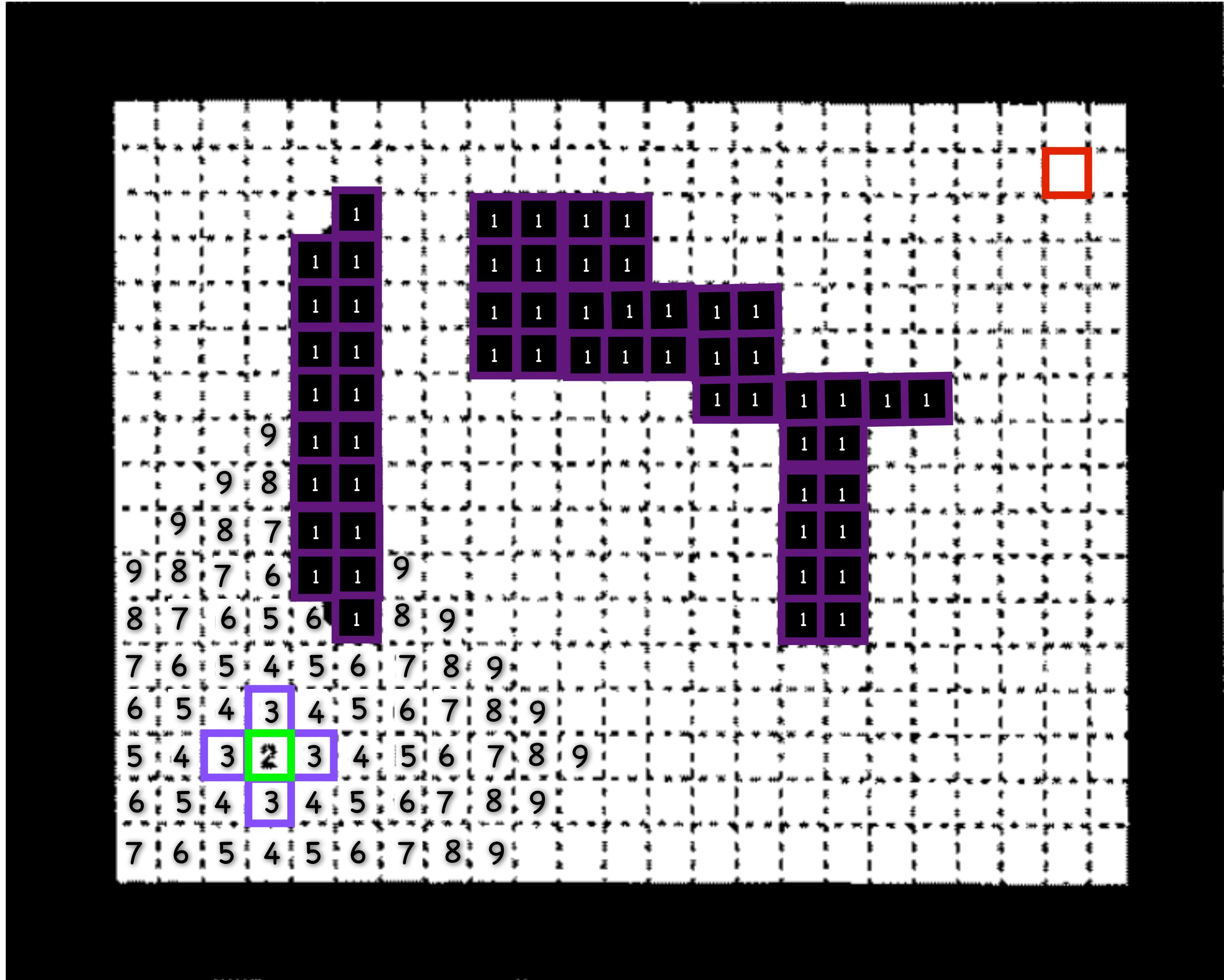


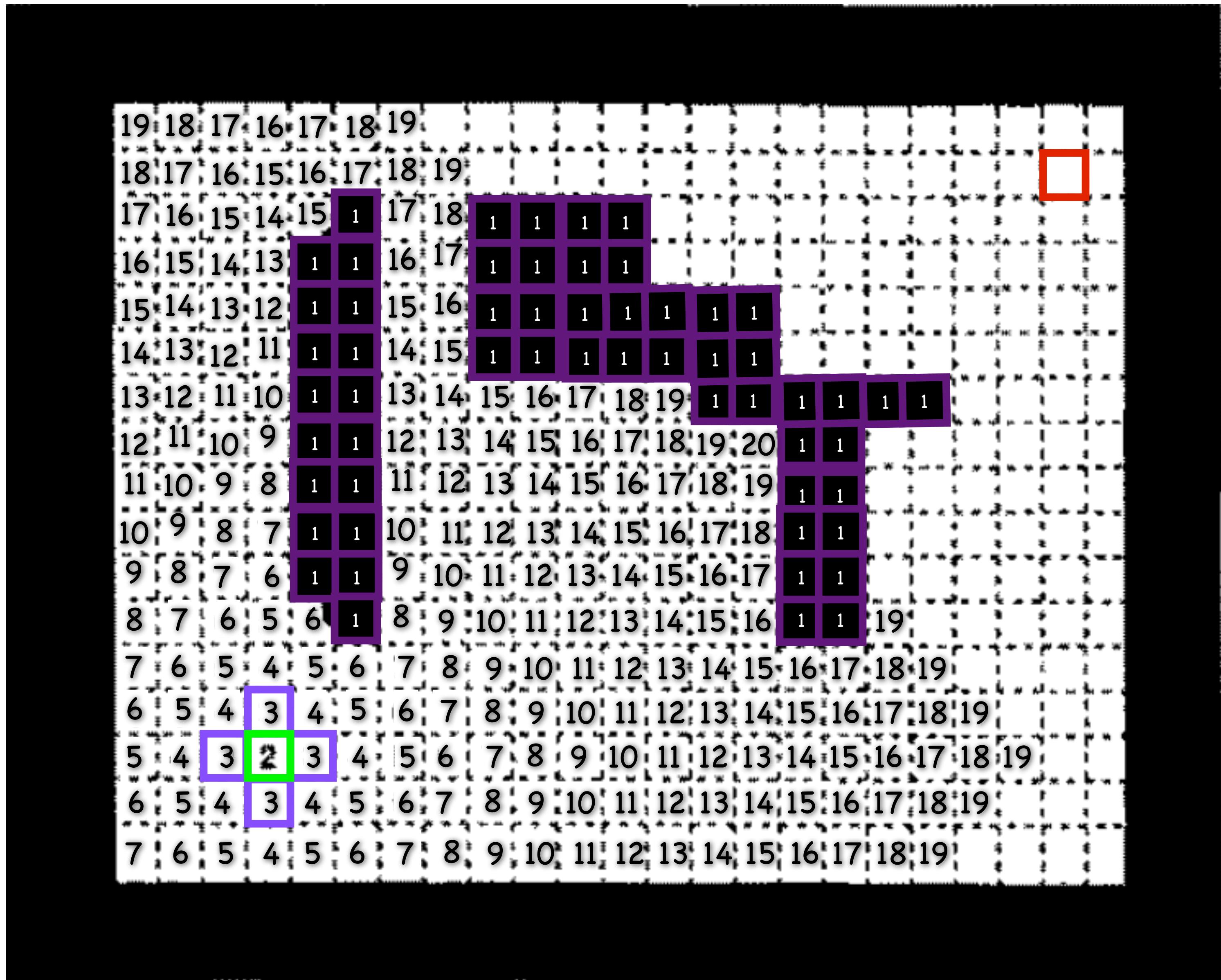
# Example with Local Minima

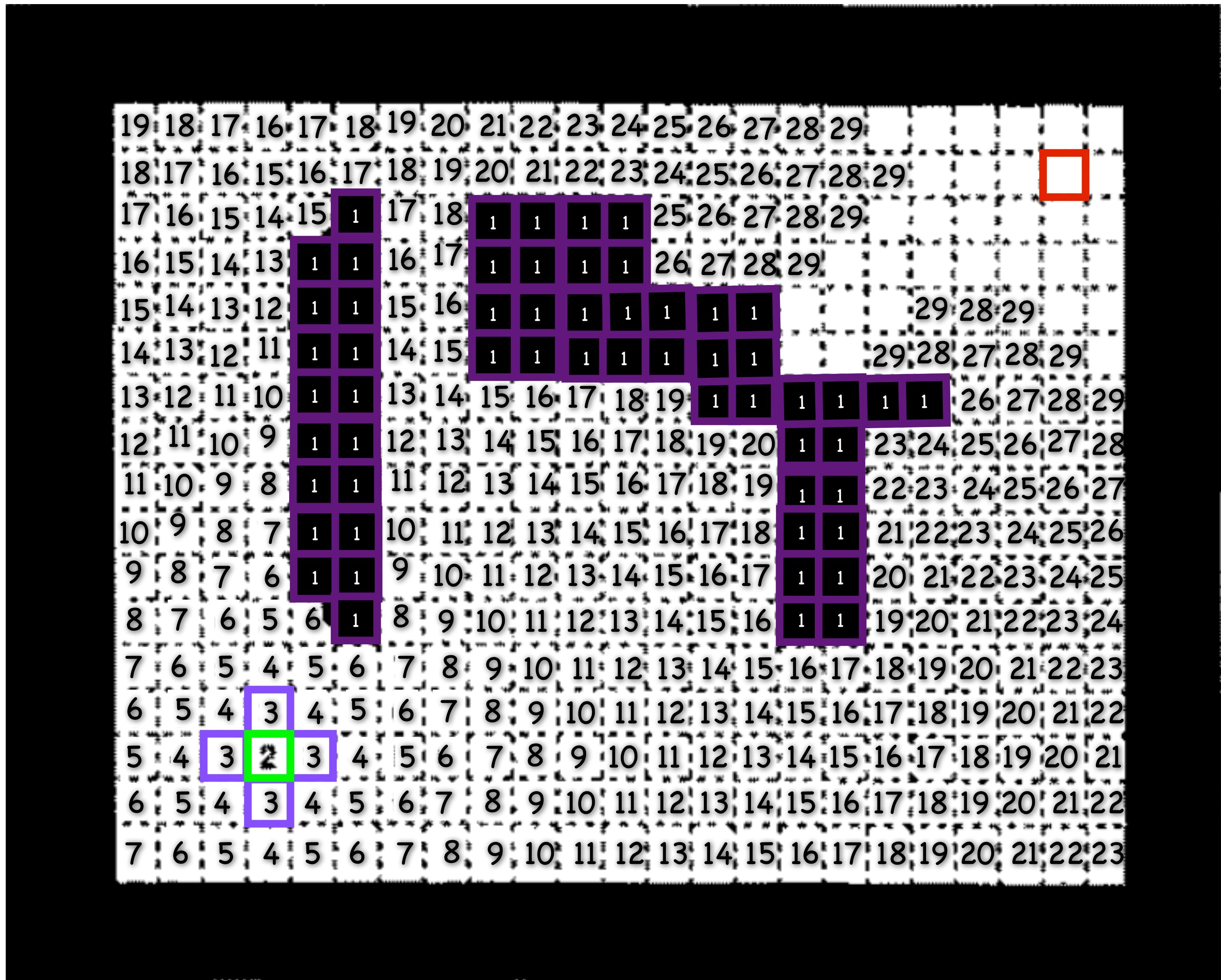
# Example with Local Minima





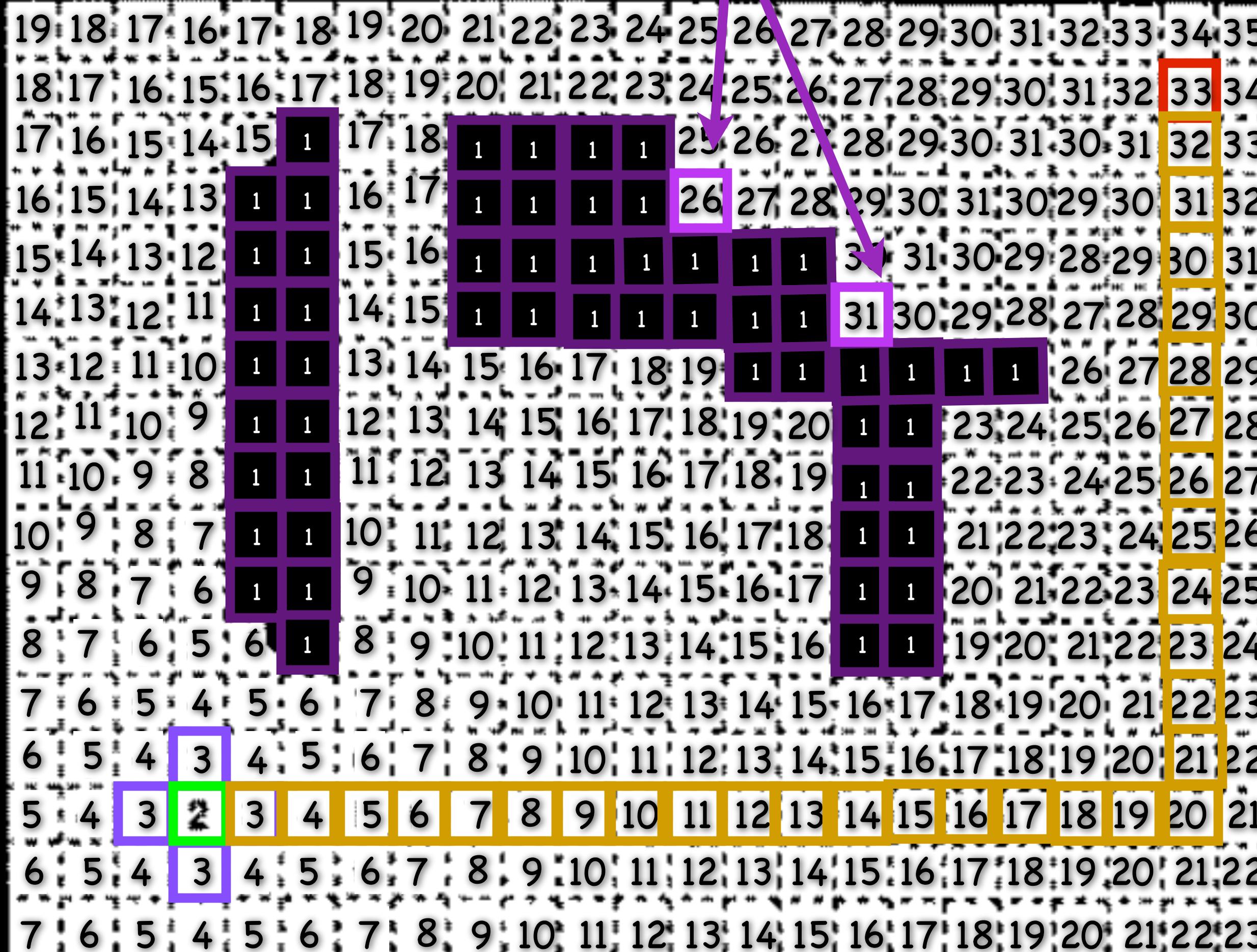






19	18	17	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
18	17	16	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
17	16	15	14	15	1	17	18	1	1	1	1	25	26	27	28	29	30	31	30	31	32	33
16	15	14	13	14	13	16	17	1	1	1	1	26	27	28	29	30	31	30	29	30	31	32
15	14	13	12	14	13	16	15	1	1	1	1	1	1	1	30	31	30	29	28	29	30	31
14	13	12	11	13	12	15	14	1	1	1	1	1	1	1	31	30	29	28	27	28	29	30
13	12	11	10	12	11	14	13	15	16	17	18	19	1	1	1	1	1	1	26	27	28	29
12	11	10	9	11	10	12	13	14	15	16	17	18	19	20	1	1	23	24	25	26	27	28
11	10	9	8	11	10	11	12	13	14	15	16	17	18	19	1	1	22	23	24	25	26	27
10	9	8	7	10	9	11	12	13	14	15	16	17	18	1	1	21	22	23	24	25	26	27
9	8	7	6	9	8	10	11	12	13	14	15	16	17	1	1	20	21	22	23	24	25	26
8	7	6	5	6	8	9	10	11	12	13	14	15	16	1	1	19	20	21	22	23	24	25
7	6	5	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
6	5	4	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
5	4	3	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
6	5	4	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
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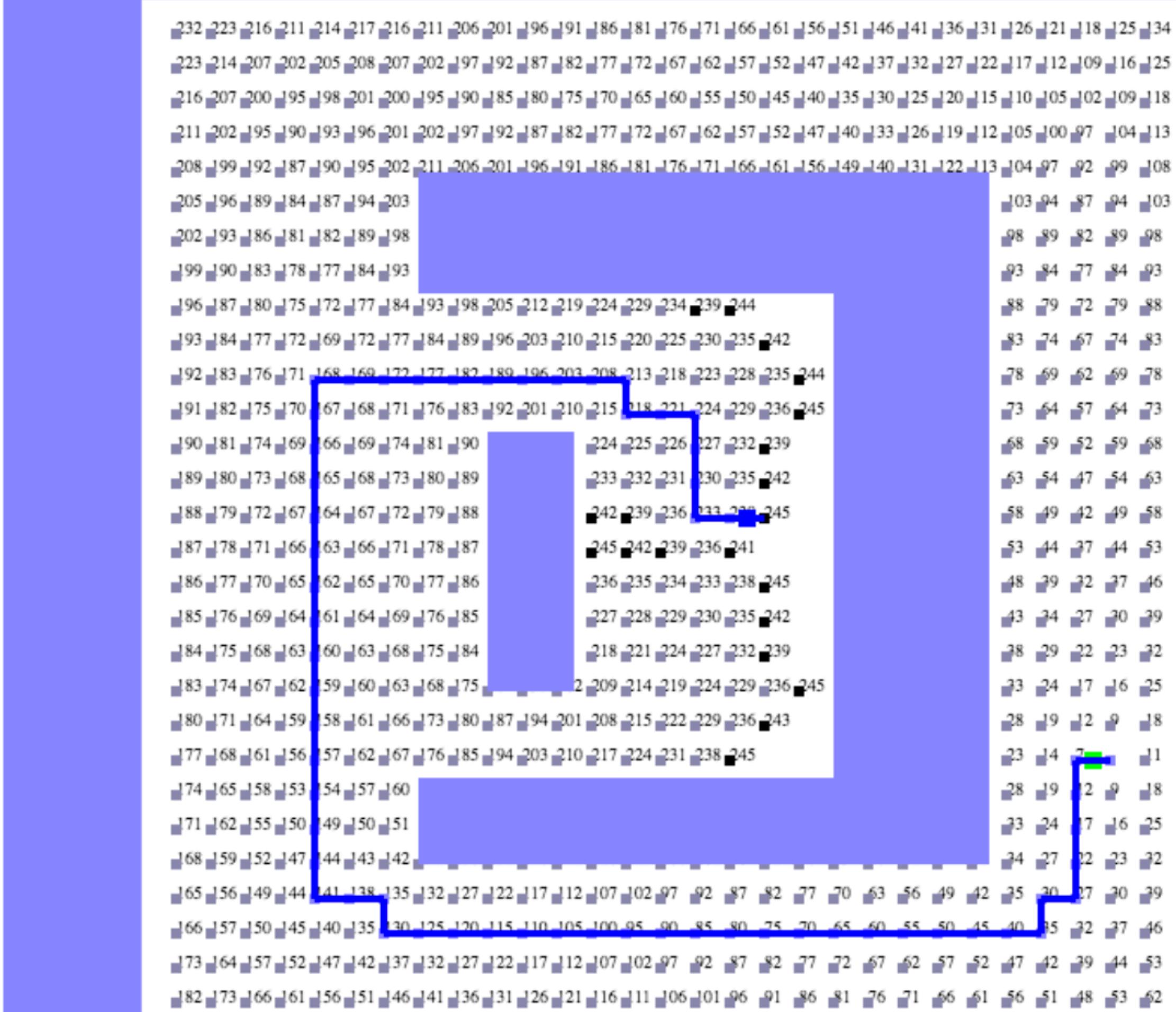
local minima avoided



# Maithili's wavefront planner

My 2D planner

```
start: 2.5,2 | goal: 4.5,3.4
iteration: 1468 | visited: 0 | queue size: 296
path length: 61.00
mouse (6.05,-1.04)
```



Can we extend potential fields  
for arm navigation?

# Potential Fields for Robot Arm

- Define endeffector goal as the attractive potential with cone potential
- Define repulsive potentials wrt. collision objects
  - Select points on robot links with “bowl” potential from nearest object
- Use manipulator Jacobian to transform potential at each point into velocities at robot joints
- Weighted sum of transformed velocities to generate control

# Navigation Recap

# Navigation Recap

## Bug X

- Complete
- Non-optimal
- Planar

## Subsumption and FSMs

- Fast but not adaptive
- Emphasis on good design

## Potential Fields

- Complete in special cases
- Non-optimal
- General C-spaces
- Scales w/dimensionality

## Grid Search/Wavefront

- Complete
- General C-spaces
- Limited dimensionality

## Random walk

- Will find path eventually

## Sampling roadmaps/RRT

- Probabilistically complete
- General
- Tractable (with good sampling)
- Scales w/dimensionality
- Not necessarily optimal

Next time ...

Collision Detection

