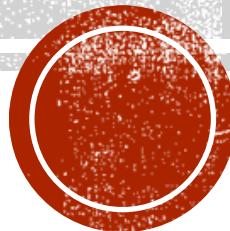


# MARS ROVER

Project Supervisions:

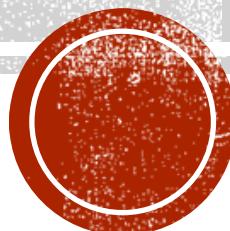
Prof. Gamal M. El-Bayoumi   Prof. Ayman H. Kassem



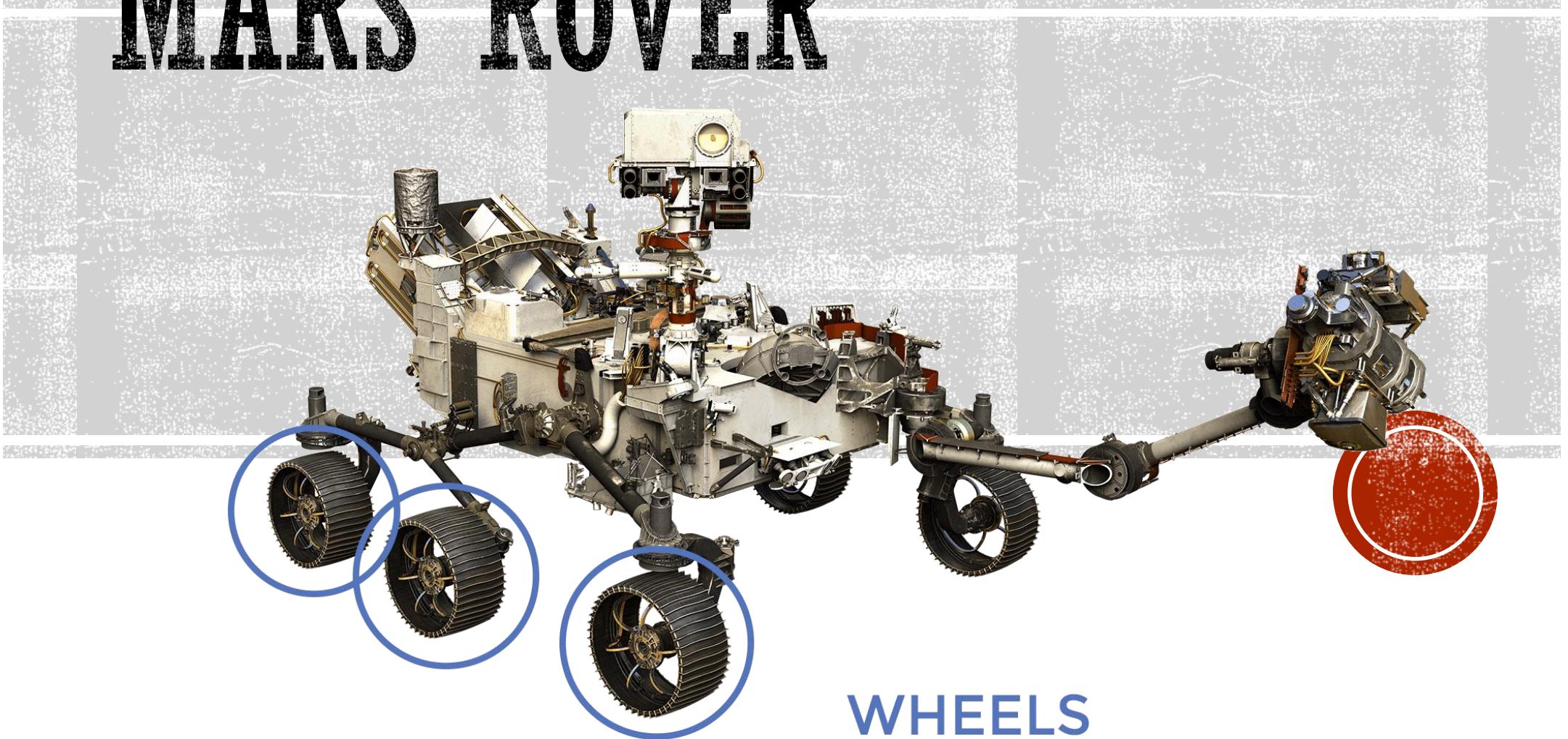
# TEAM MEMBERS

- Karim Ahmed Kamal El-din
- Mohamed Ismail Ibrahim
- Anas Abd-Elmenam Farrag

# **INTRODUCTION**



# MARS ROVER



WHEELS

- A **Mars rover** is a motor vehicle that travels across the surface of the planet Mars upon arrival.
- They examine more territory, they can be directed to interesting features, they can place themselves in sunny positions to weather winter months, and they can advance the knowledge of how to perform very remote robotic vehicle control.
- They have a lot of sensors for identifying what's Around the Mars
- They have a robotic Arm can dig the ground or hold the Rockets

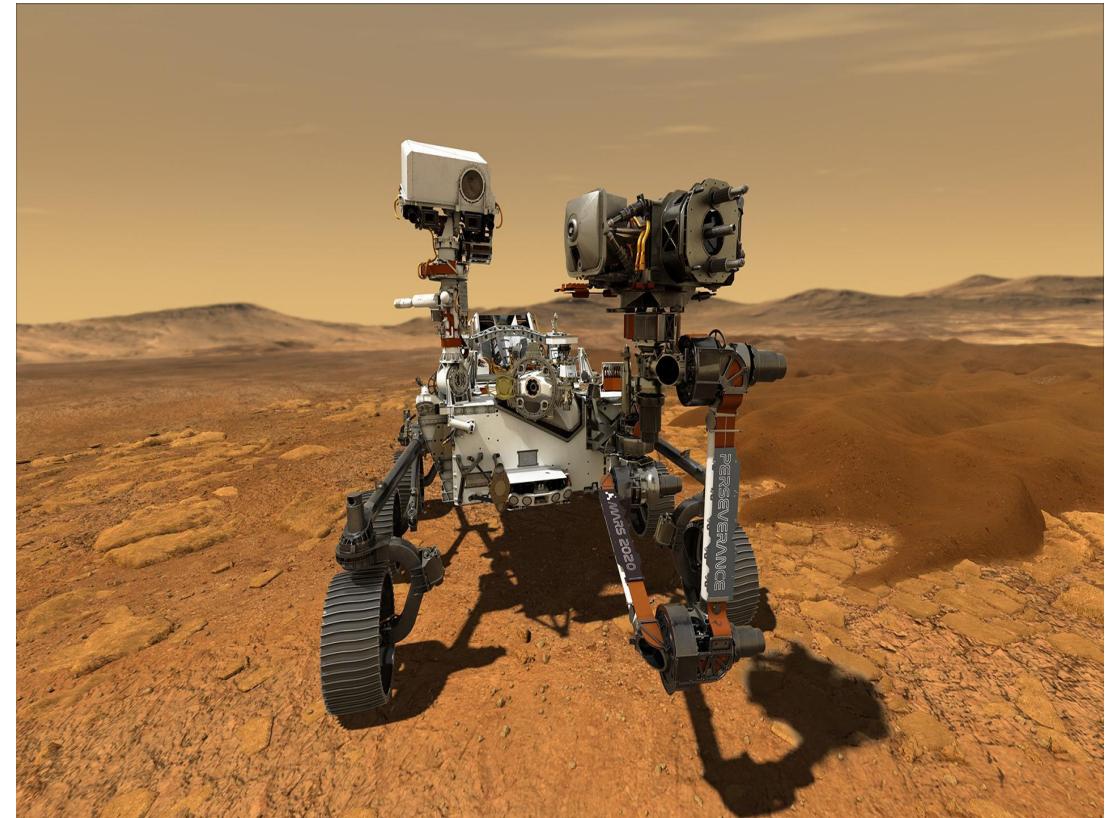
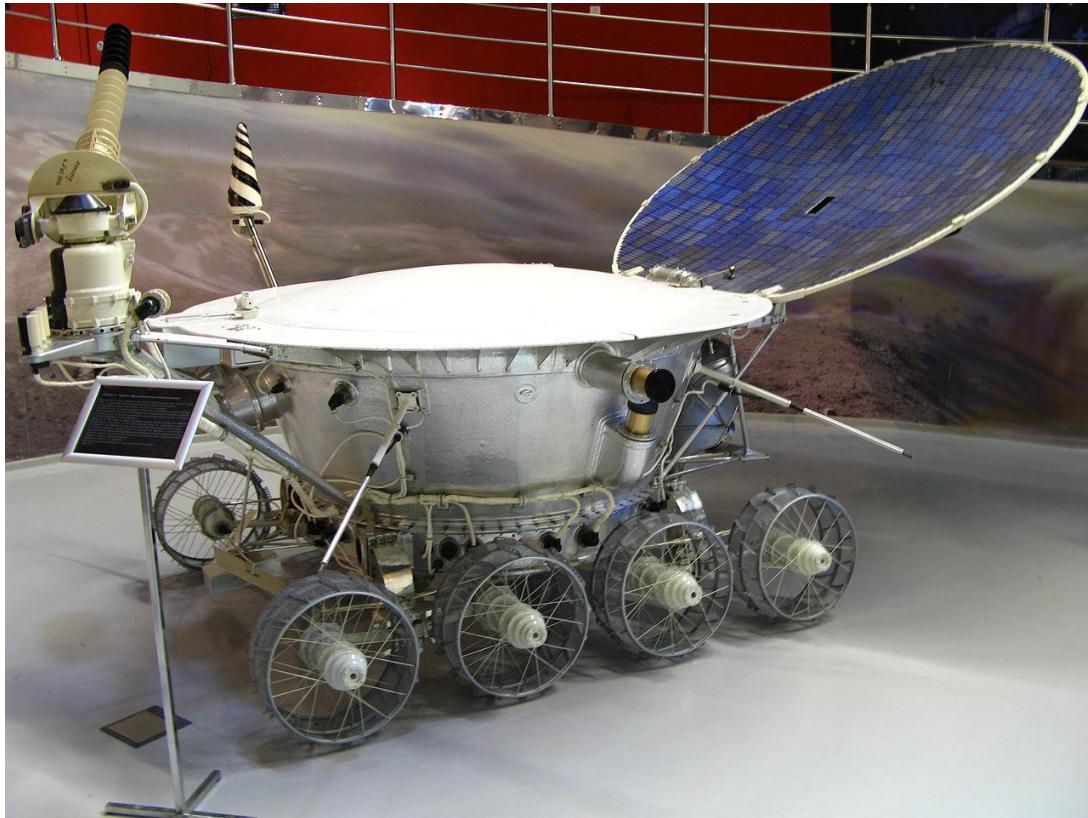


# **WHY ROVERS ?!**

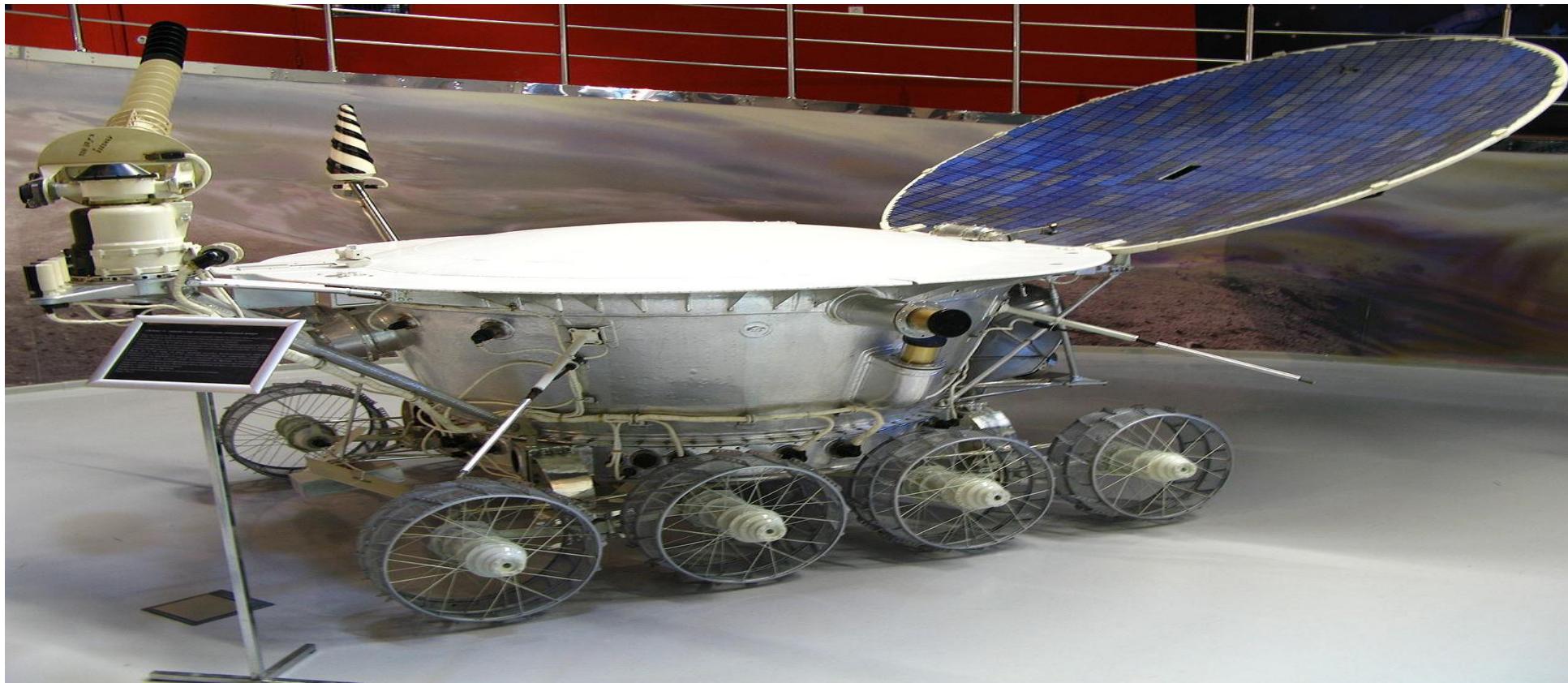
- Discovering the space without the risk of humans life
- Determine whether life ever arose on mars
- Characterize the climate of Mars
- Saving time
- Reduce the Cost



# DEVELOPMENT OF THE ROVER



# LUNOKHOD 1(1970)

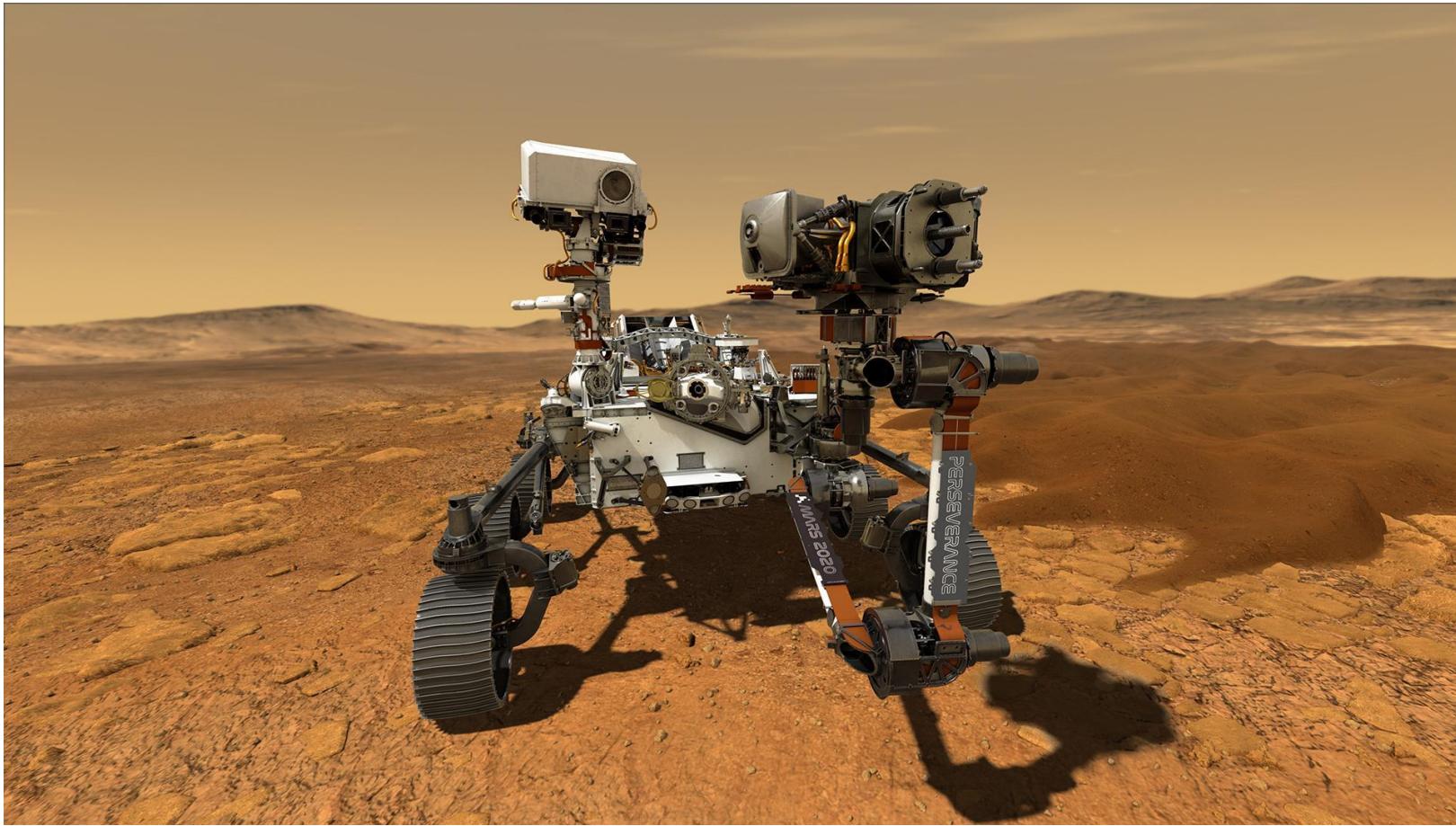


# LUNOKHOD 1

- 8 Wheels
- Cone Shaped Antenna
- Four Television Cameras
- Test Lunar Soil
- During 5 Days , The rover drove 197 m , and returned 14 close-up images
- After 10 months , They lost the Communication with Rover



# PERSEVERANCE



# PERSEVERANCE(MARS2020)

- Launched on July 30, 2020
- Expected to land on mars on February 18, 2021
- Mission duration at least one mars year(687 earth day)
- 1025 kg
- 7 scientific instruments
- Explore a geologically different landing site



# MECHANICAL SYSTEMS

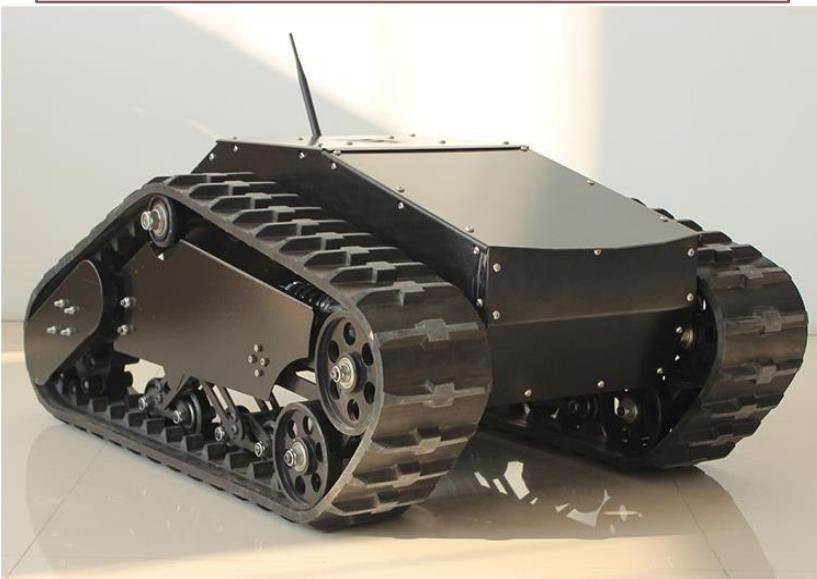
- Locomotion
- Suspension
- Steering



# LOCOMOTION

- locomotion system which determines the stability and capacity while traversing on rough terrain

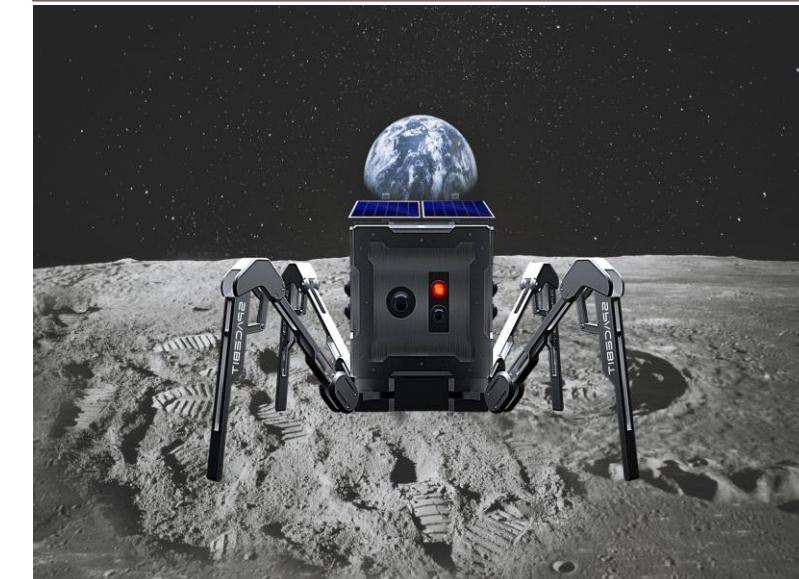
Tracked Rover



Wheeled Rover



Legged- Rover



# LOCOMOTION

**Previous Wheels (12 cm)**



**Our design wheels(radius = 25 cm)**



# SUSPENSION SYSTEM

- which connects the wheels to the main body or platform

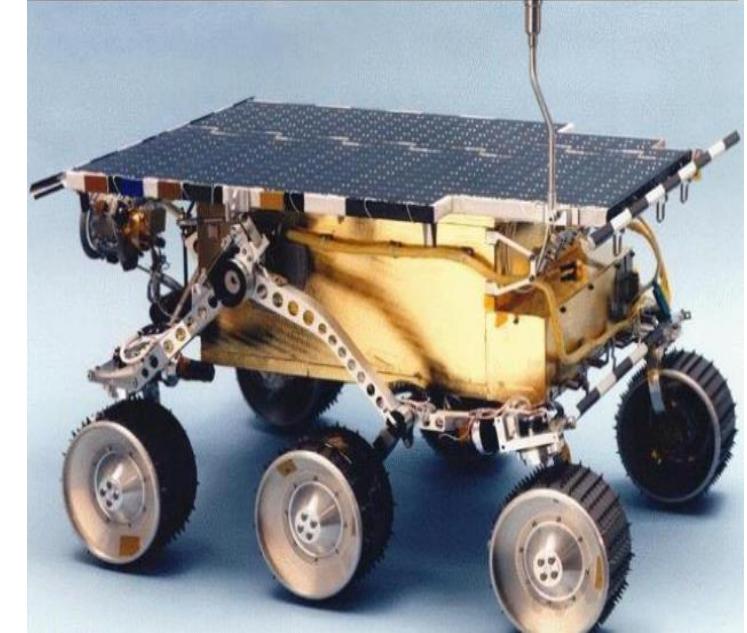
**Independent Spring Suspension**



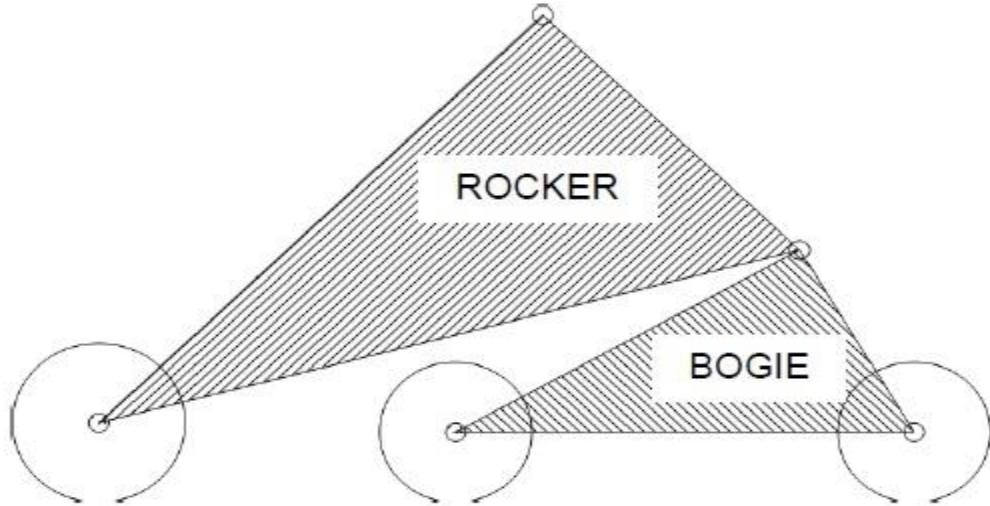
**Articulated Body Suspension**



**Rocker-Bogie Suspension**



# ROCKER-BOGIE SUSPENSION



**Rocker**: Connects the front wheel to the differential and the bogie in the rear.

**Bogie**: Connects the middle and rear wheels to the rocker.

**Differential**: Connects to the left and right rockers and, to the rover body

The rocker bogie suspension is capable of a high degree of mobility. It has a ground clearance larger than a wheel diameter, unlike articulated body vehicles. The single rigid body is more stable for sensor mounting and thermal control



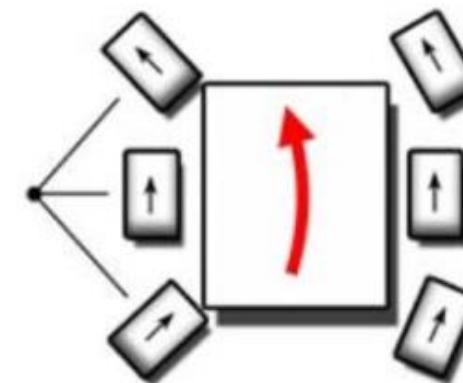
# ALSO SUPPORTS THE DIFFERENT TYPES OF STEERINGS



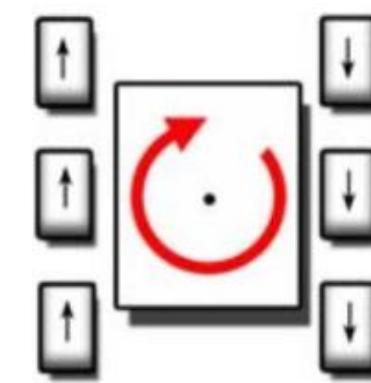
(a) *Crabbing*



(b) *Zero radius*



(c) *Ackerman*

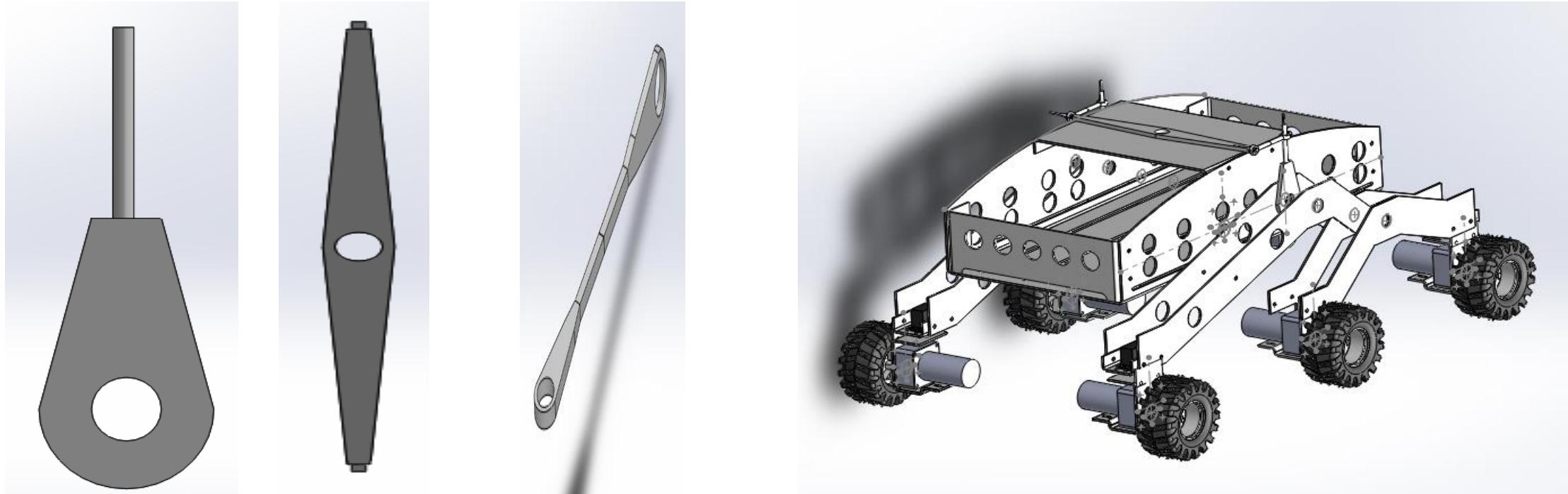


(d) *Differential/Skid*



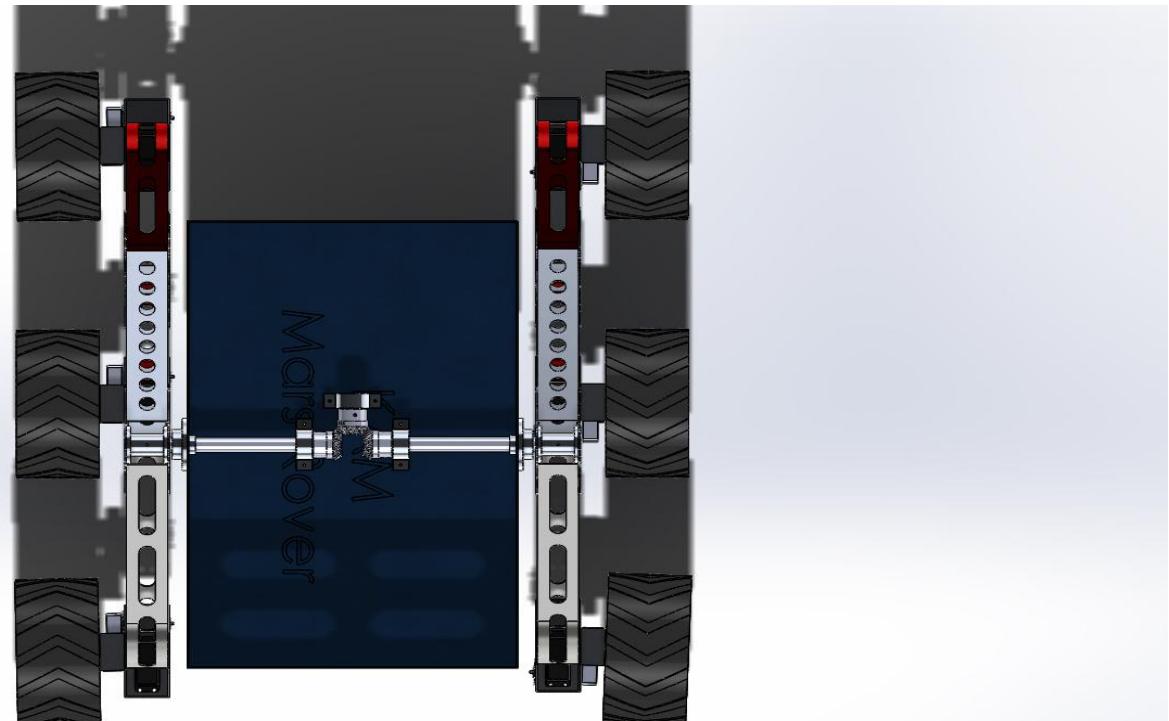
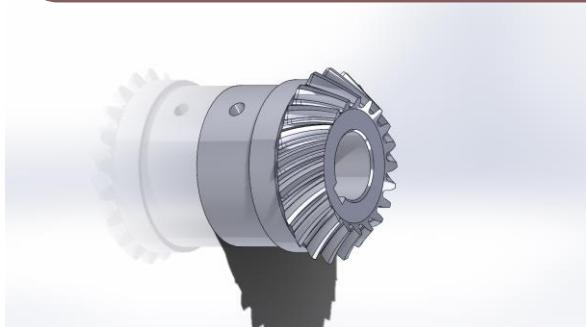
# PREVIOUS DIFFERENTIAL PART(PIVOT)

- 1- can't put the solar panels and the sensors
- 2- less stable in overcoming the terrain
- 3- has a problem in simulations (gazebo)

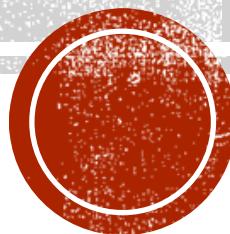


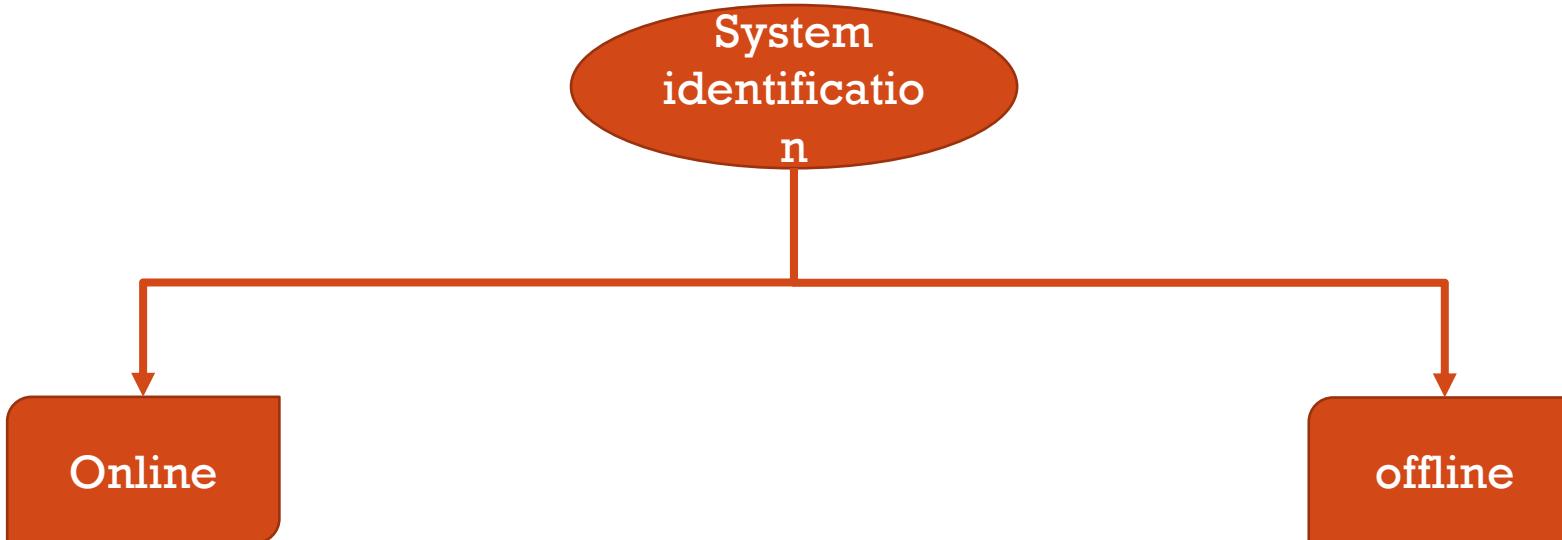
# OUR DIFFERENTIAL DESIGN(DIFFERENTIAL GEAR)

The differential is composed of three identical beveled gears situated 90-degrees from each other at the center of the rover



# **SYSTEM IDENTIFICATION**





- **Online system identification** means that while rover operation system identification tool collects required data and expect the transfer function
- **Offline system identification** means that we took required data then used the system identification on another time



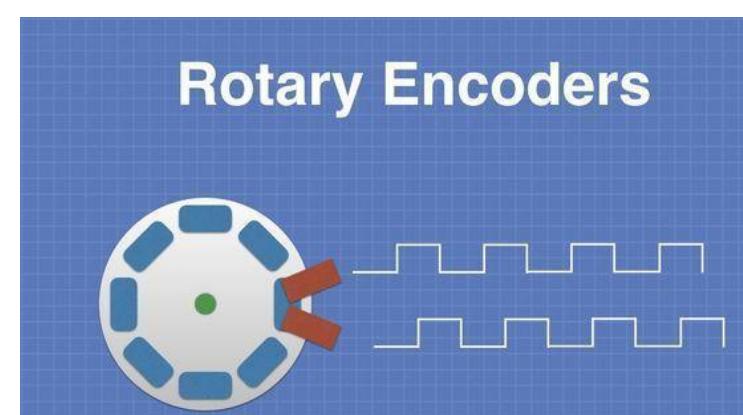
# MOTOR SPECS

12 V DC geared motor: 5000 rpm reduced to 83 rpm  
with reduction ratio 60.24

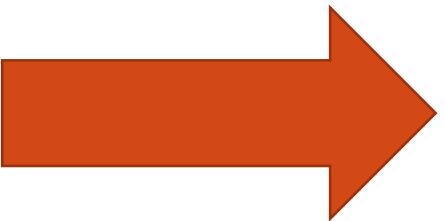


# Encoder specs

Rotary encoder have 7 disk spots equipped with magnetic hall sensor( for each cycle has 7 high digital signals)



PWM



RPM



$$PWM = 255 * |\sin(\omega t)|$$

$$PWM = 255 * |\sin(2\pi f * \text{no.of iterations} * T_{sampling})|$$

$$RPM = \frac{\text{encoder count}}{\text{time in min}} * \frac{1}{\text{encoder disk spots} * \text{gear ratio}}$$

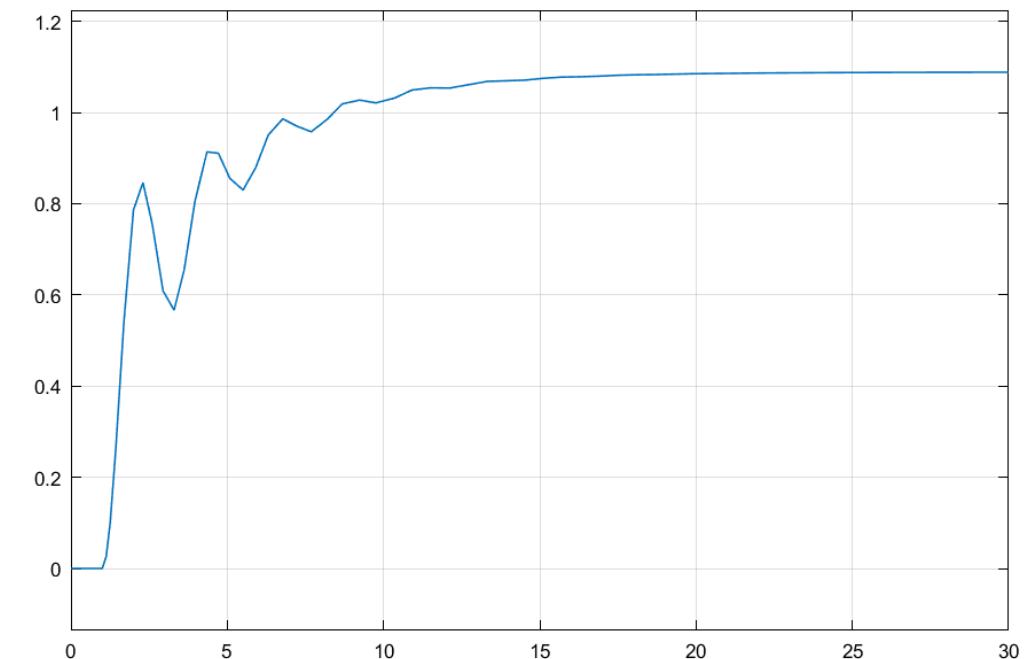




Using this tool to all six motors getting the following results

$$T_1 = \frac{RPM}{PWM} = \frac{3.32 s^2 + 2.431}{S^3 + 1.117 s^2 + 8.276 s + 2.233}$$

Response



# CONTROLLER DESIGN

“PID TUNER”

we perform Simulink model to simulate the transfer function in closed loop form with unity feed-back and PID controller

We perform 2 controllers showing the results in following figure PI and PID

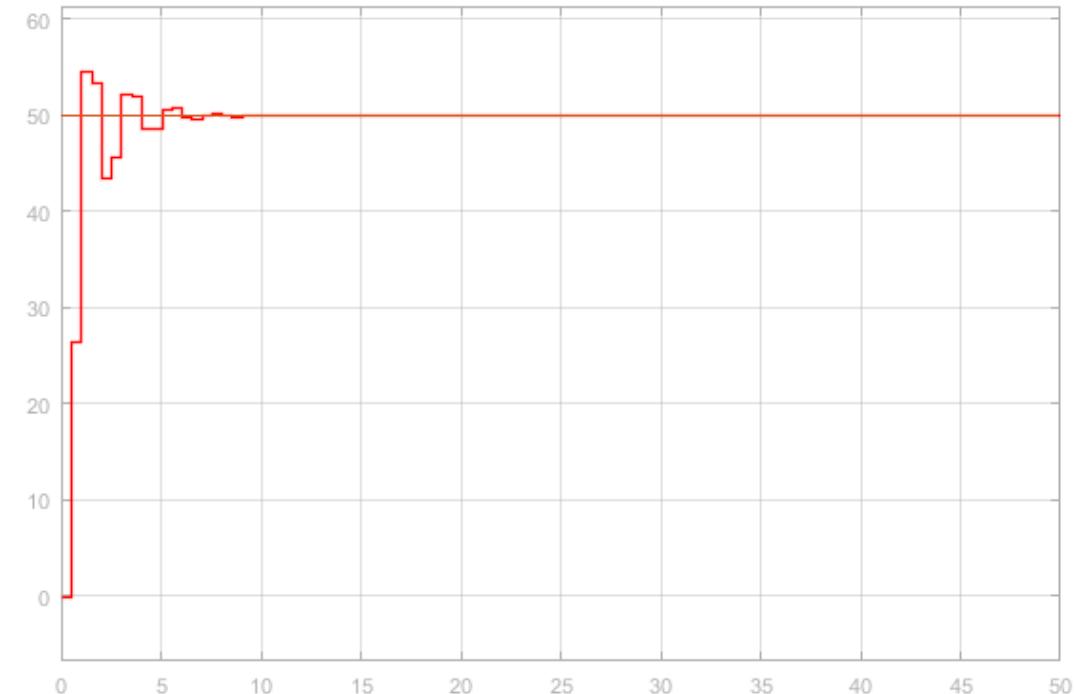
## PI results



<b>K<sub>p</sub></b>	1.3
K <sub>i</sub>	2.438
K <sub>d</sub>	0



<b>Rise time</b>	0.5
Settling time	5
Overshoot	9%



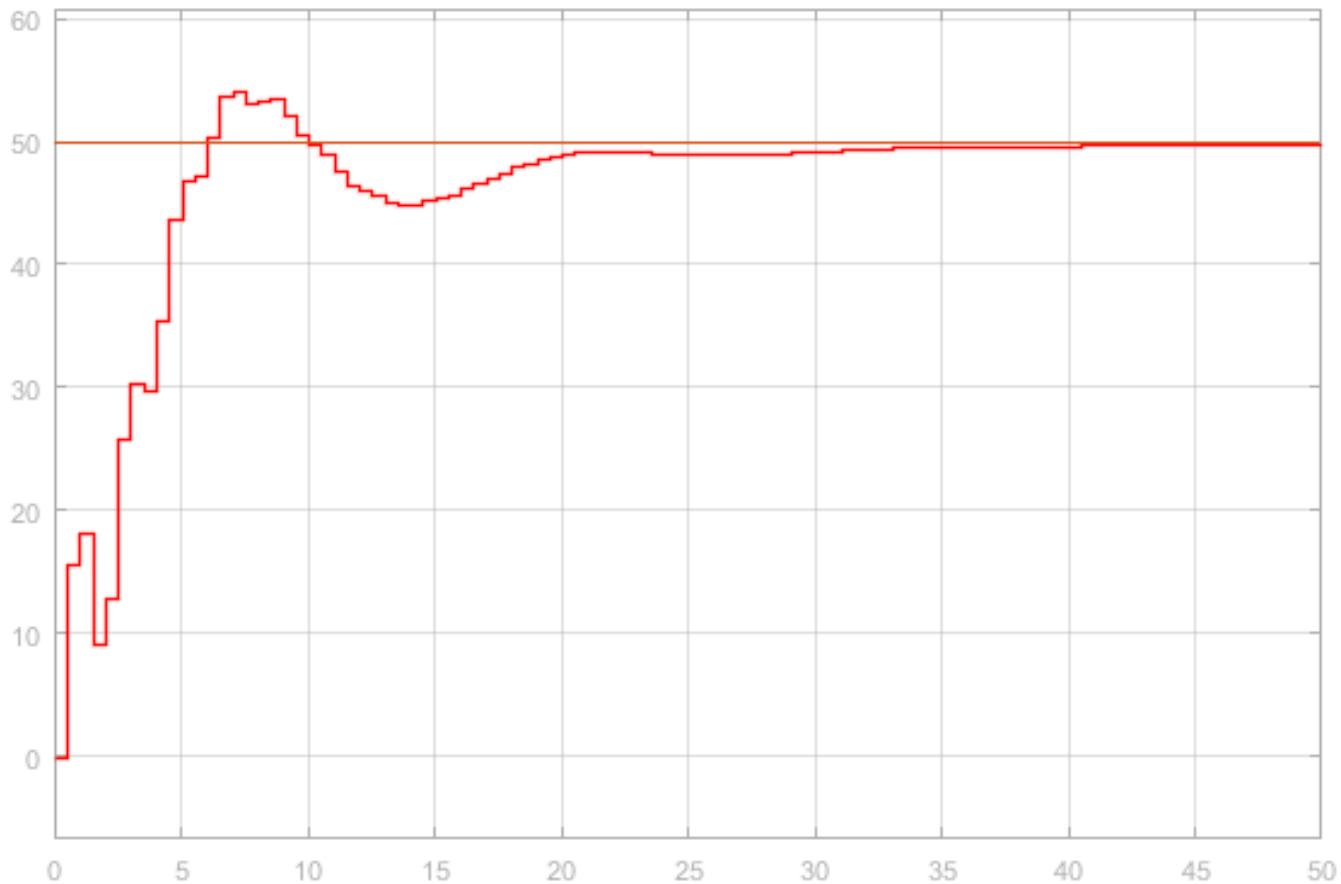
# PID Results

controller →

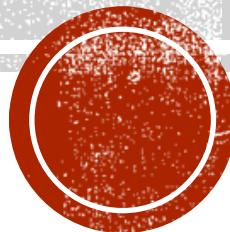
<b>Kp</b>	<b>1.89</b>
Ki	0.255
Kd	4.483

response →

<b>Rise time</b>	<b>4.5</b>
Settling time	19.5
Overshoot	7%

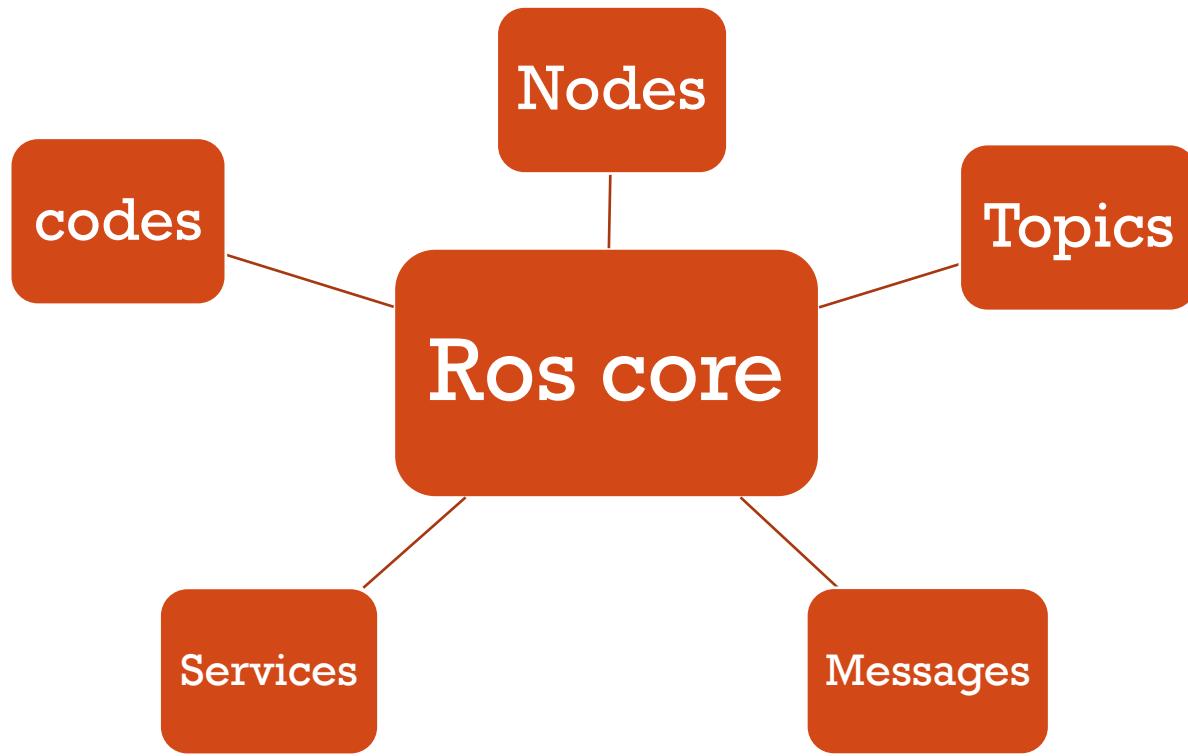


# **ROBOTIC OPERATING SYSTEM (ROS)**



# WHAT IS ROS?

- The Robot Operating System (ROS) is a flexible framework for writing robot software. It is a collection of tools, libraries, and conventions that aim to simplify the task of creating complex and robust robot behavior across a wide variety of robotic platforms



# NODES

- Nodes are processes that perform computation. ROS is designed to be very modular. So, a robot control system usually comprises many nodes. For example, one node controls a laser range-finder
- A ROS node is written with the use of a ROS client library, such as roscpp or rospy.

# Messages

- Nodes communicate with each other by passing messages. A message is simply a data structure, comprising typed fields. Standard primitive types (integer, floating point, Boolean, etc.) are supported, as are arrays of primitive types. Messages can include arbitrarily nested structures and arrays (much like C structs)
- Example : twist msg (Vector3 linear, vector3 angular)  
(x,y,z ; p,q,r)

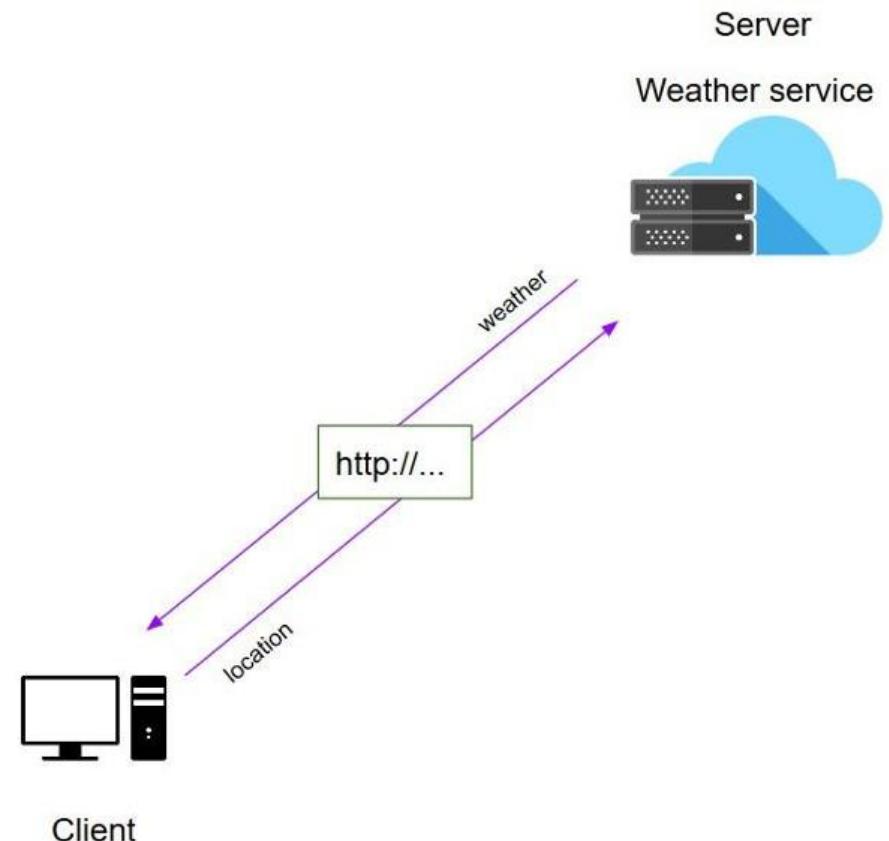


# TOPICS

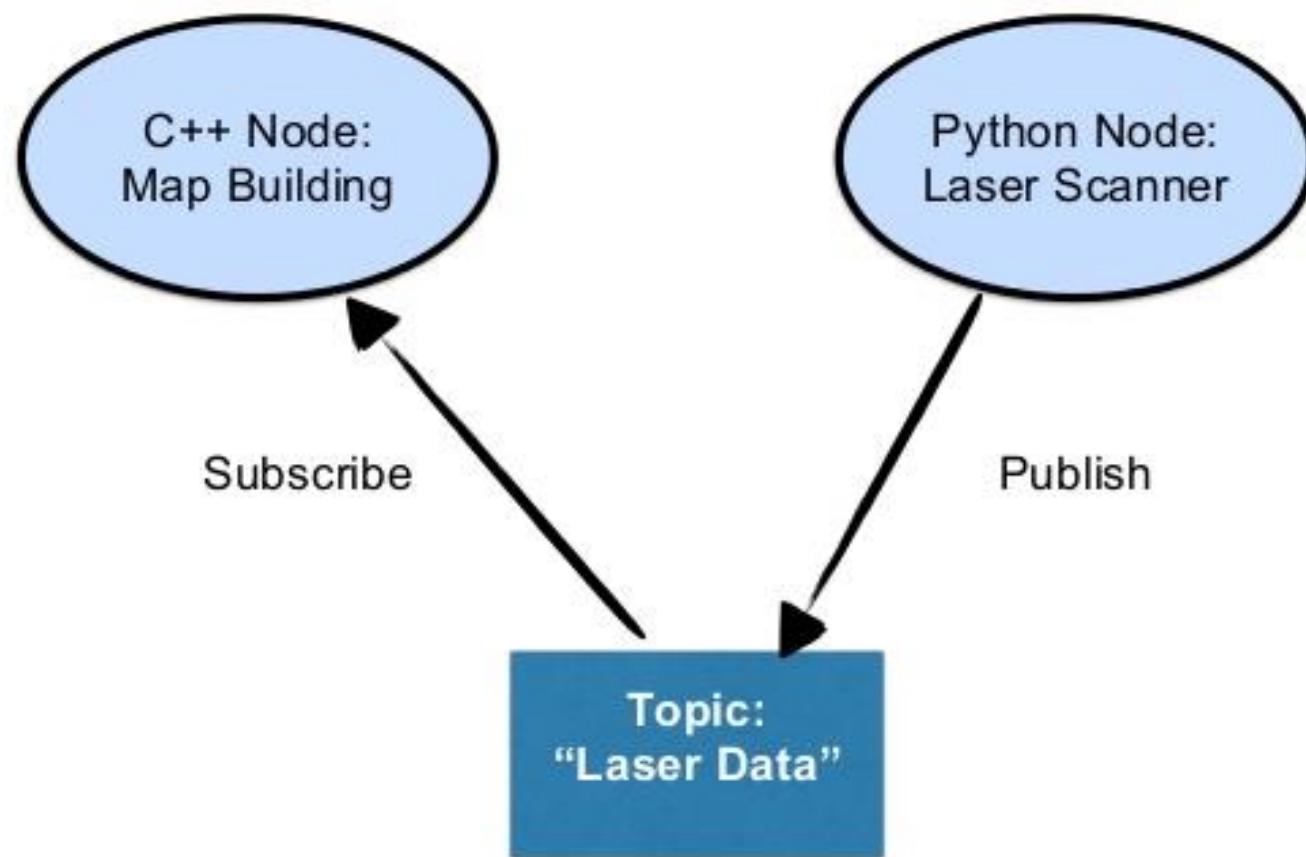
- Messages are routed via a transport system with publish / subscribe semantics

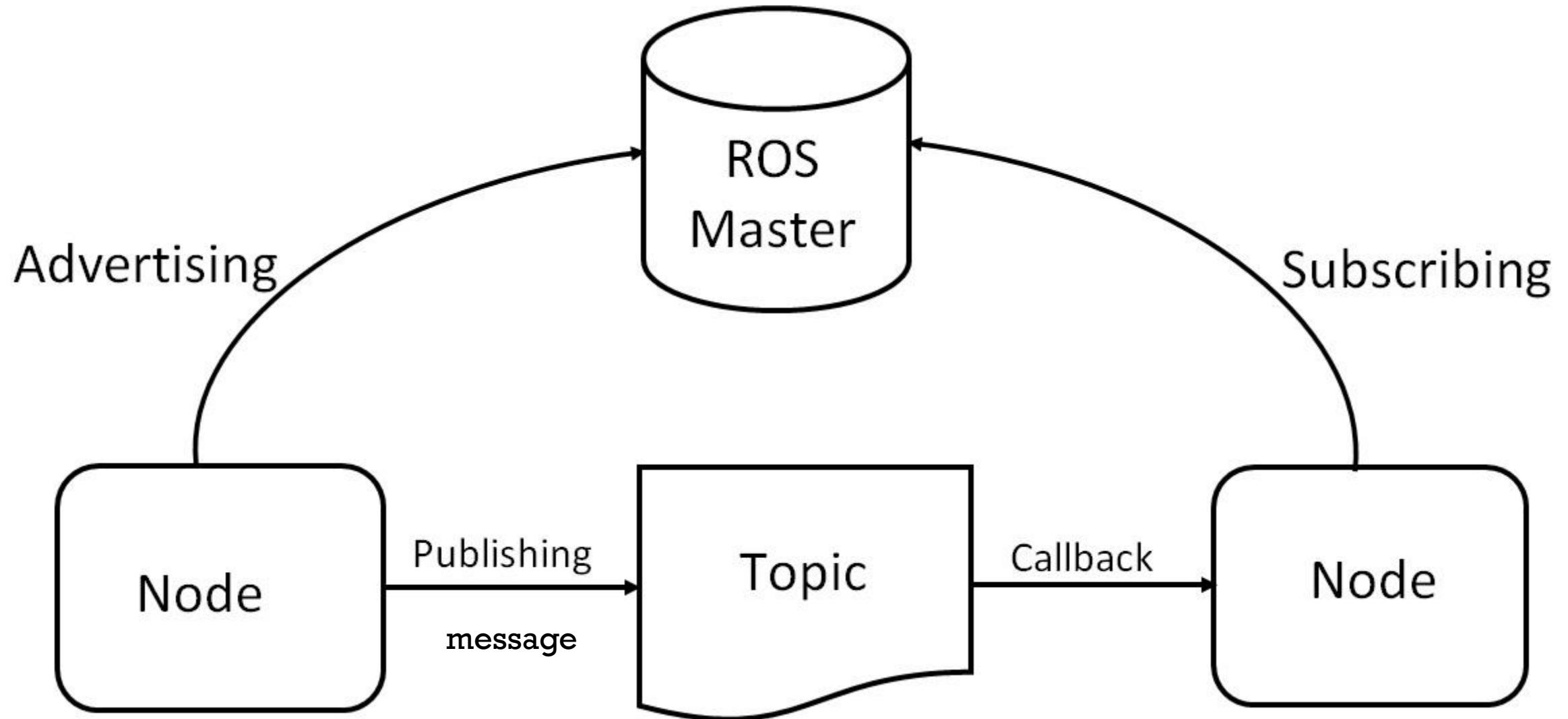
## Services

- Is a client/server system
- A providing node offers a service under a name and a client uses the service by sending the request message and awaiting the reply



# Multiple Languages



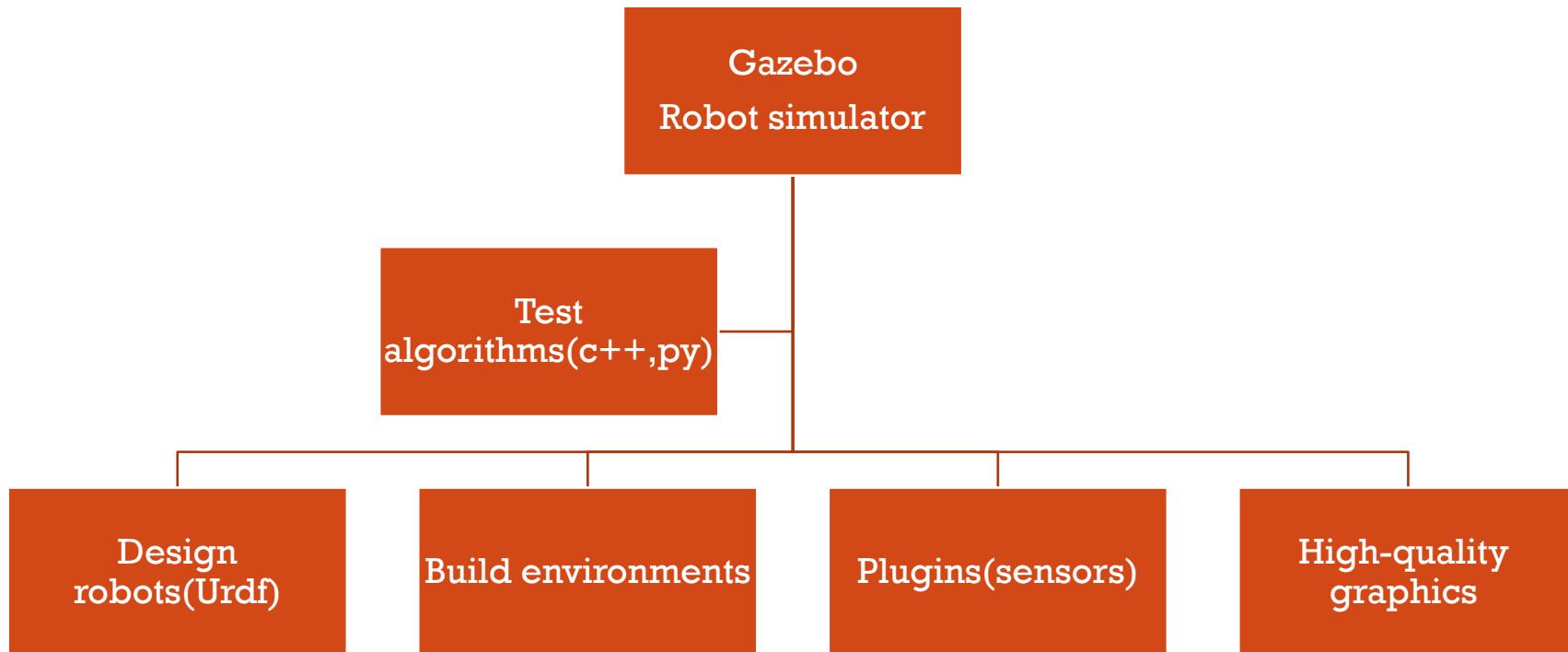


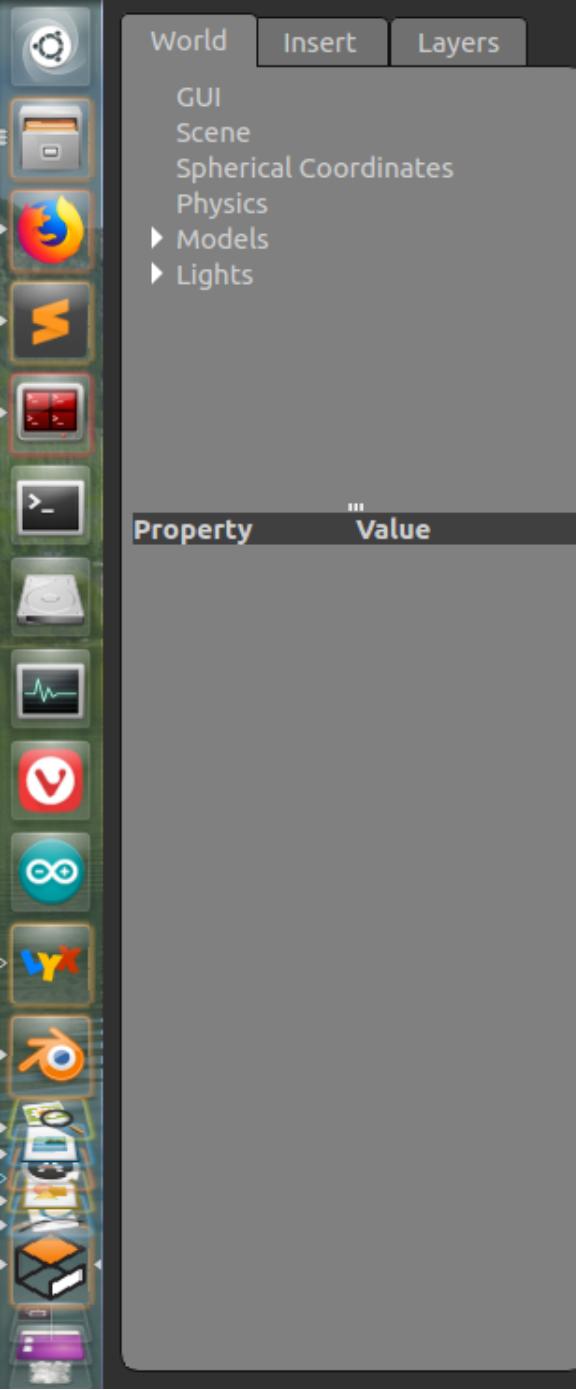
# ROS Tools

Gazebo

Rviz







Real Time Factor: 0.99

Sim Time: 00 00:00:24.103

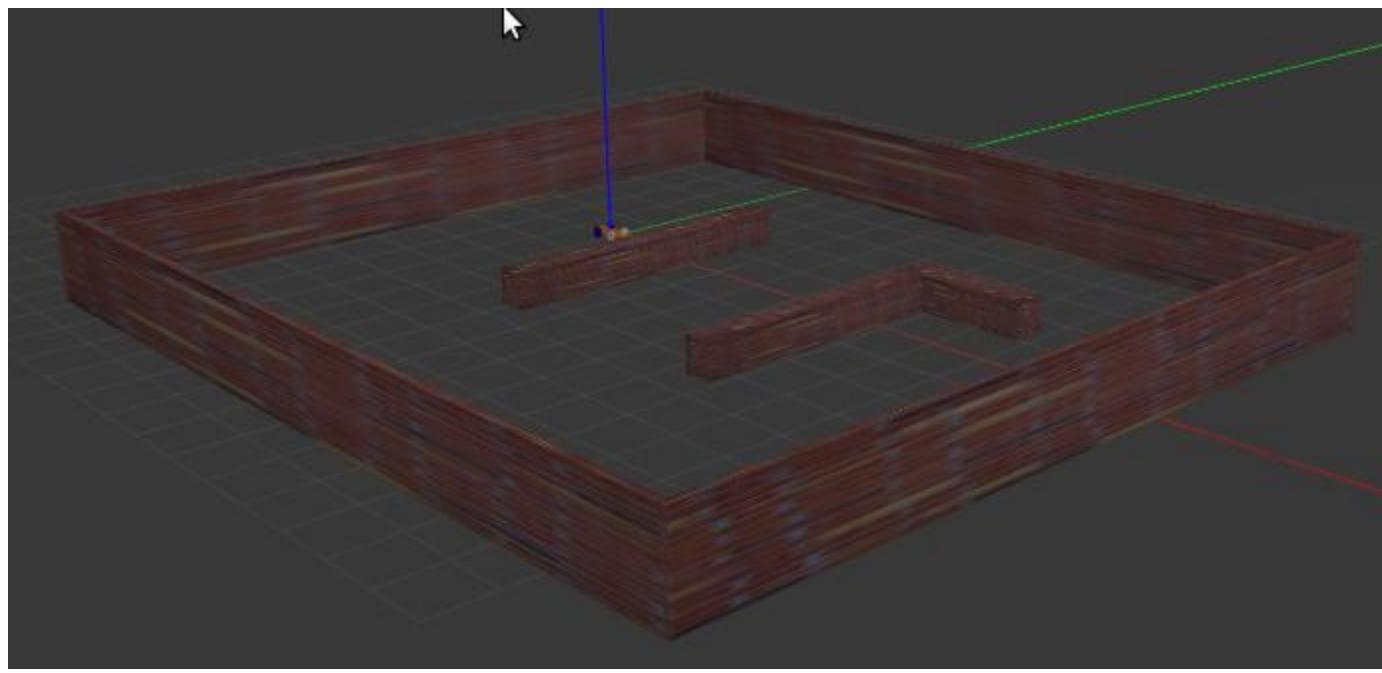
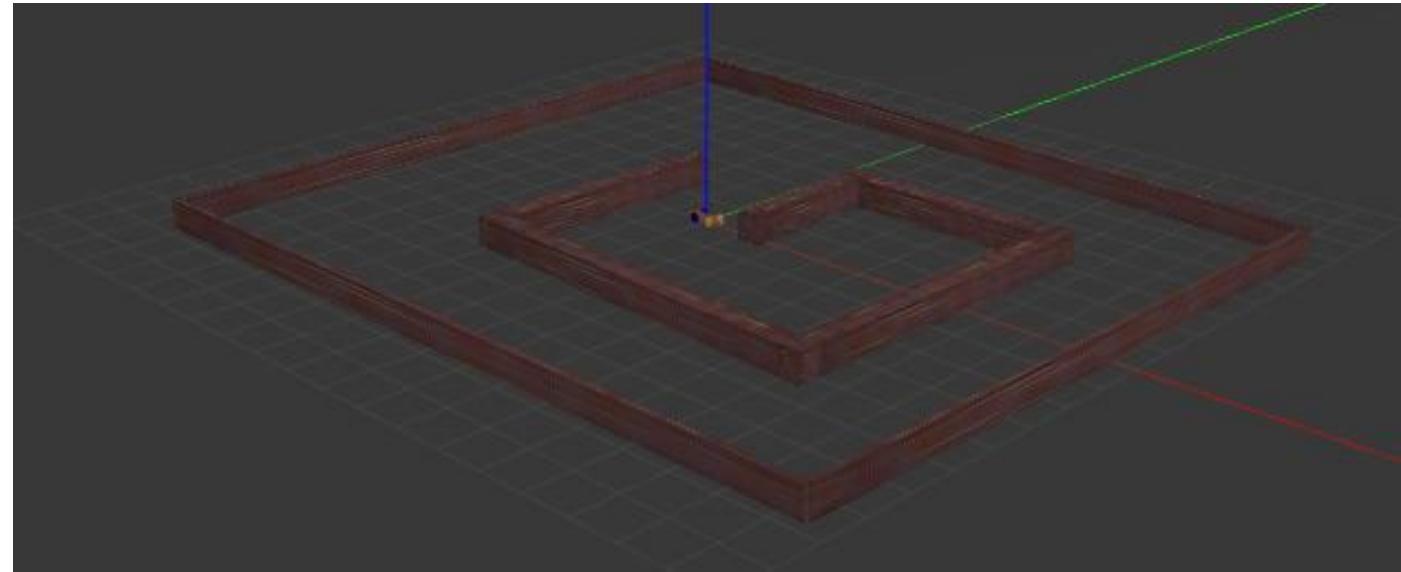
Real Time: 00 00:00:24.270

Iterations: 24103

FPS: 61.8441

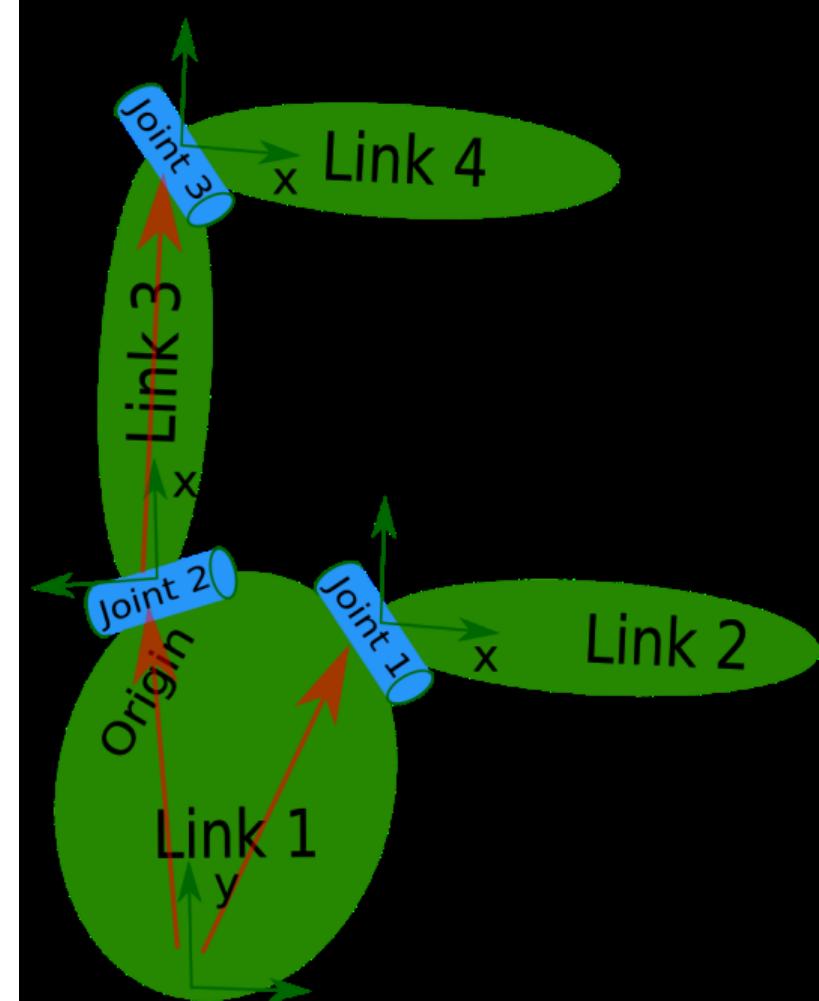
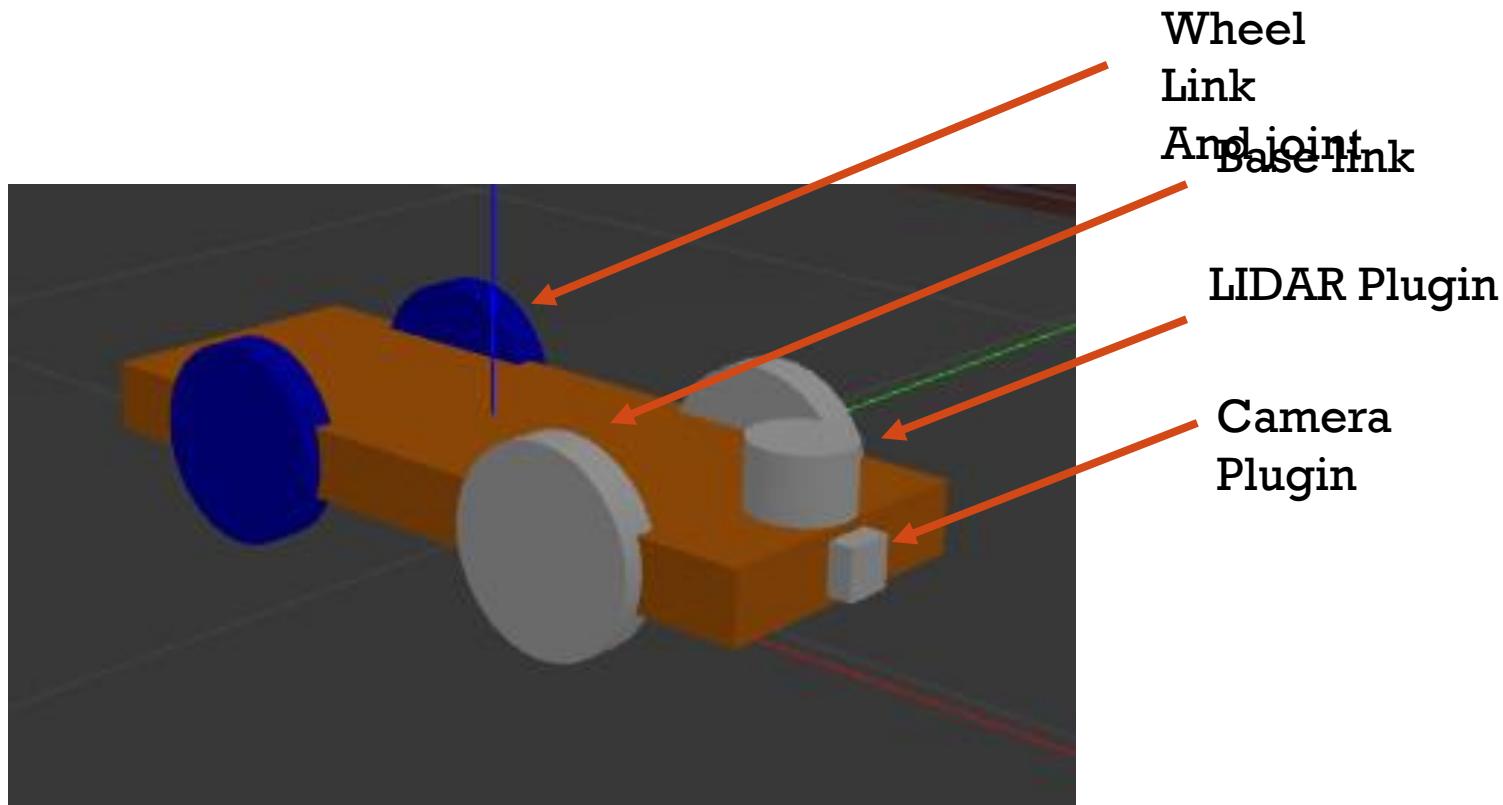
Reset

## Different environments(worlds)



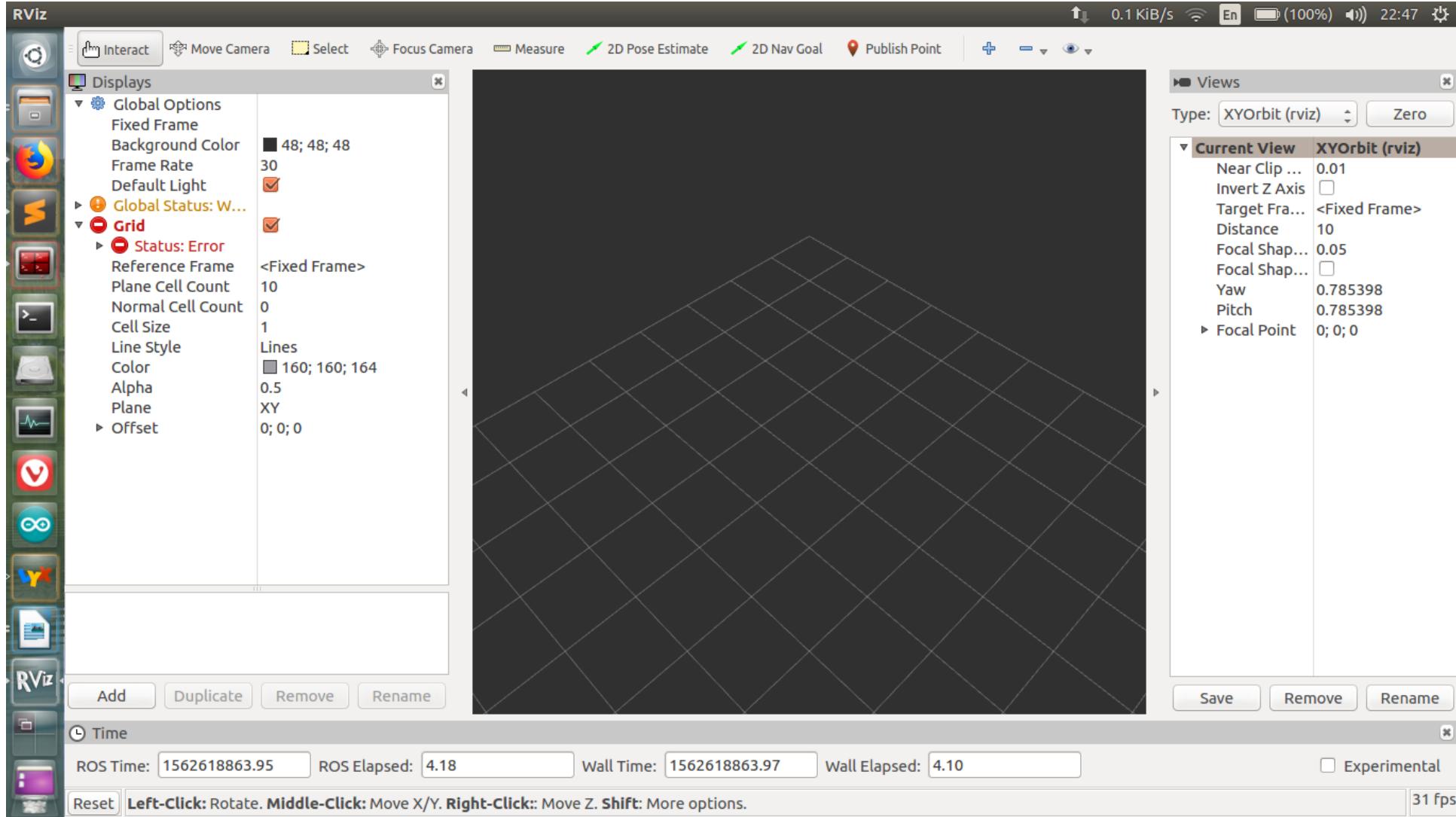
## URDF:

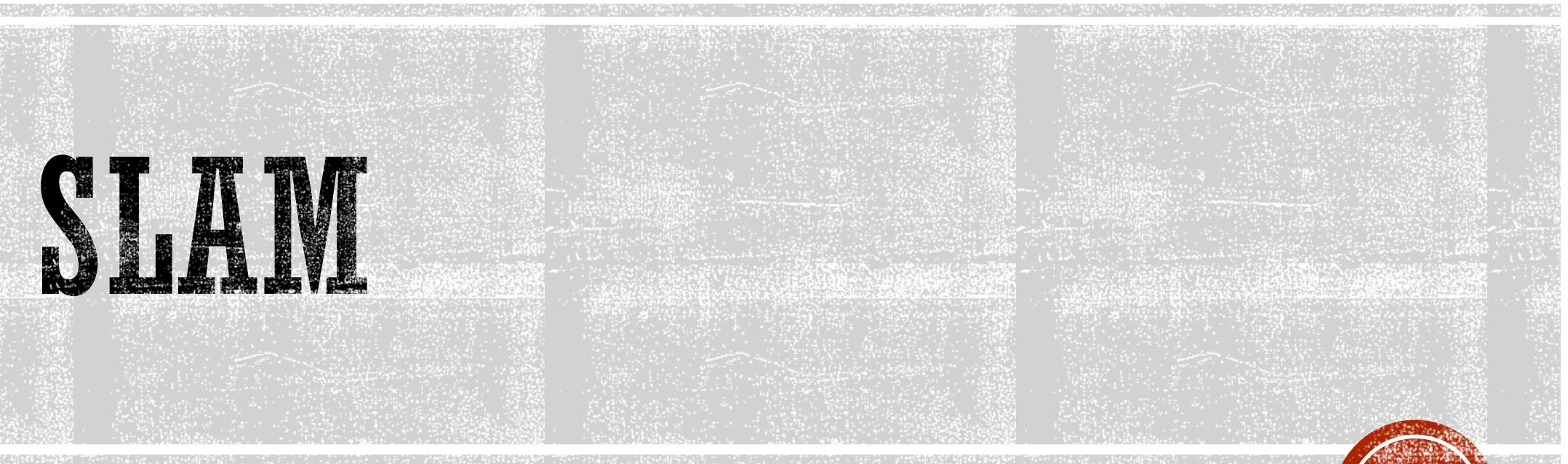
The Unified Robot Description Format (URDF) is an XML specification to describe a robot. URDF is used in ROS to write robot description for use in simulation and visualization software.



# RVIZ

- is a ROS graphical interface that allows you to visualize a lot of information, using plugins for many kinds of available topics.





Simultaneous Localization And Mapping

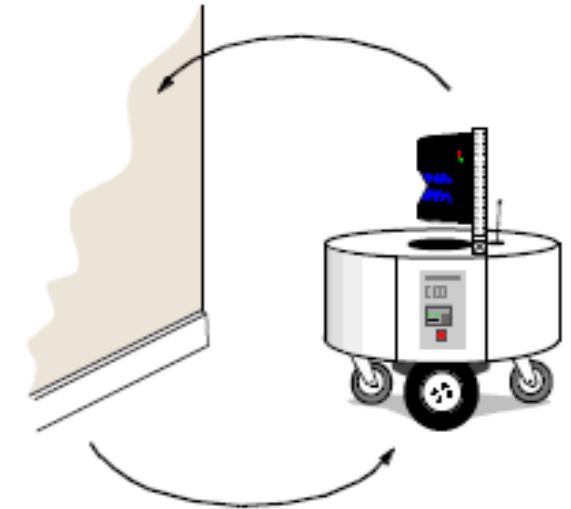
39

# 1. WHAT IS SLAM?

- simultaneous localization and mapping (SLAM) is the computational problem of constructing or updating a map of an unknown environment while simultaneously keeping track of an agent's location within it.

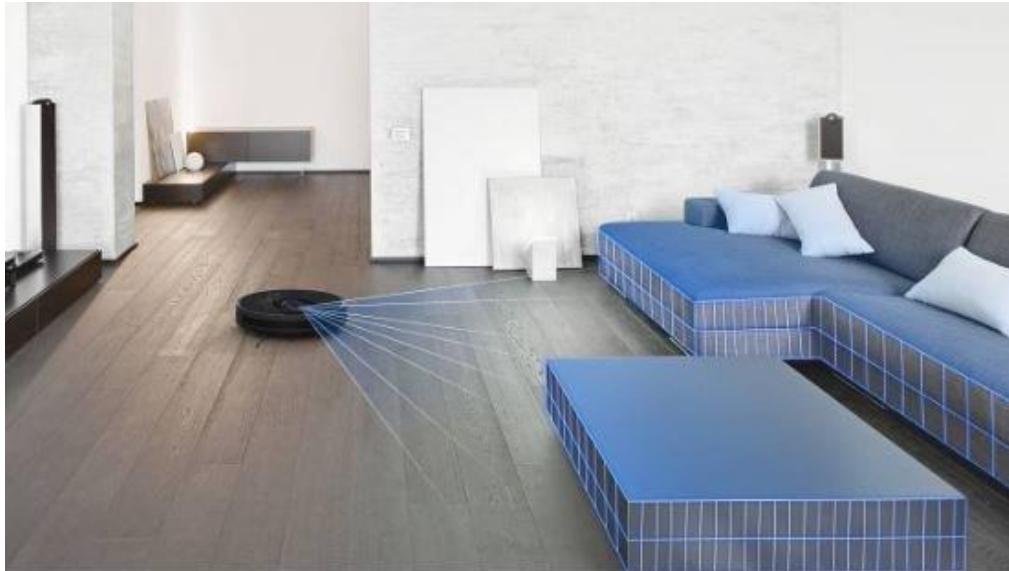
# WE CAN SAY THAT SLAM IS A CHICKEN-OR-EGG PROBLEM AS:

- A map is needed for localization and
- A pose estimate is needed for mapping.

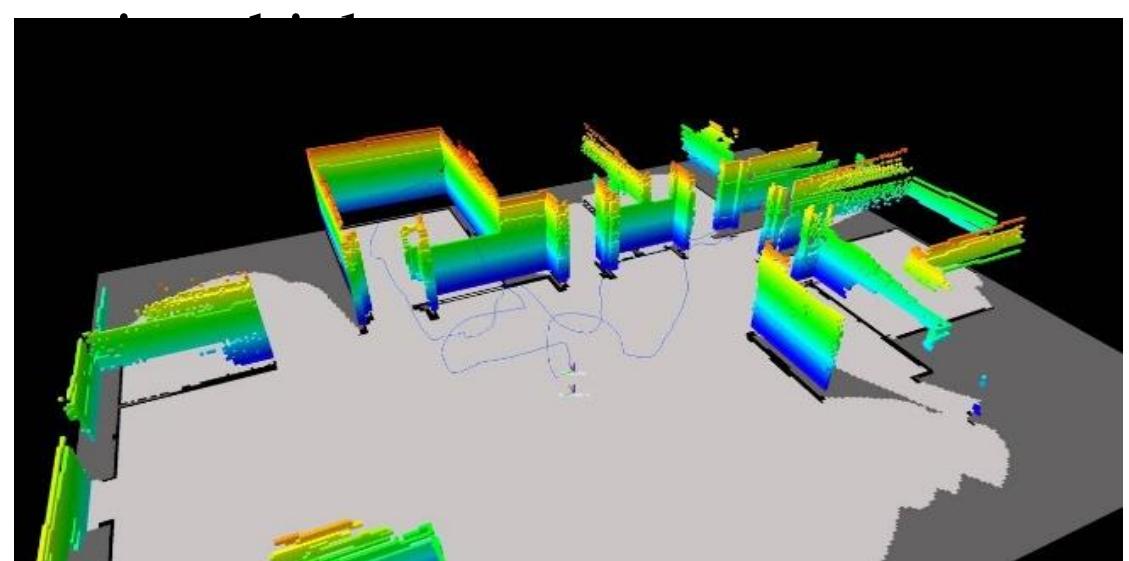


# SLAM APPLICATIONS

- vacuum cleaner

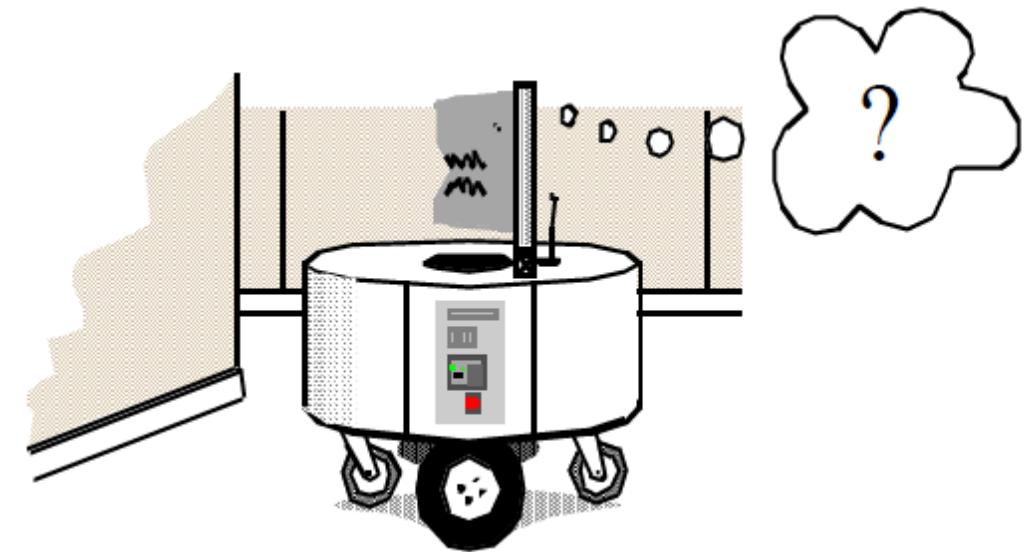


- surveillance with unmanned



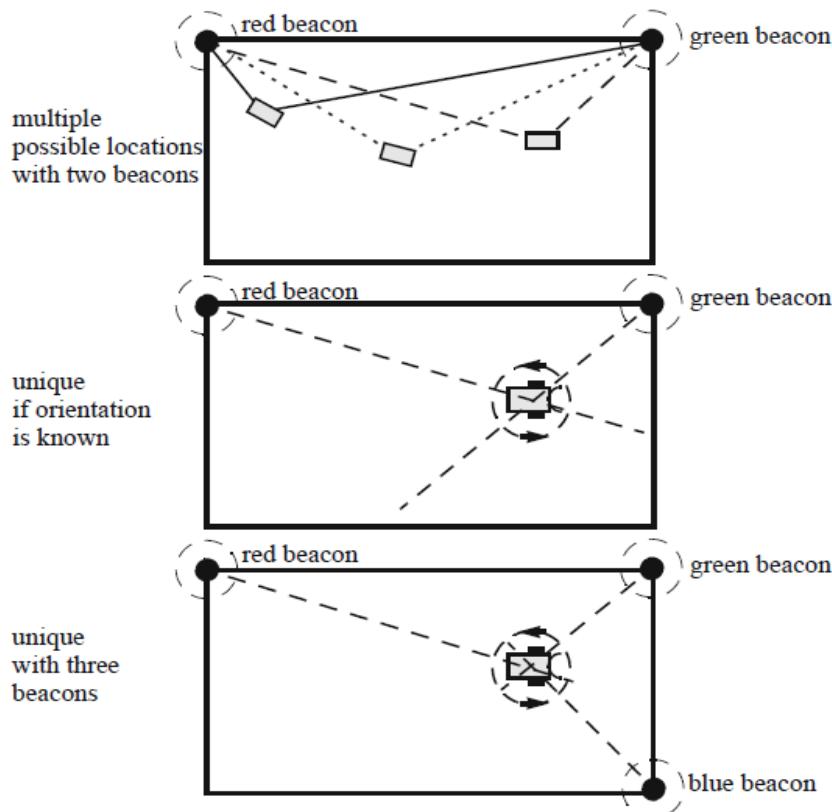
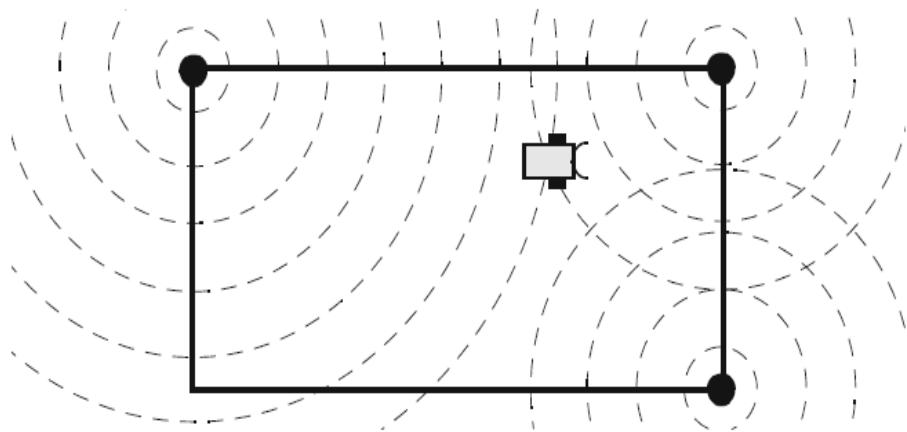
## 2. LOCALIZATION

- One of the central problems for driving robots is localization. For many application scenarios, we need to know a robot's position and orientation at all times.

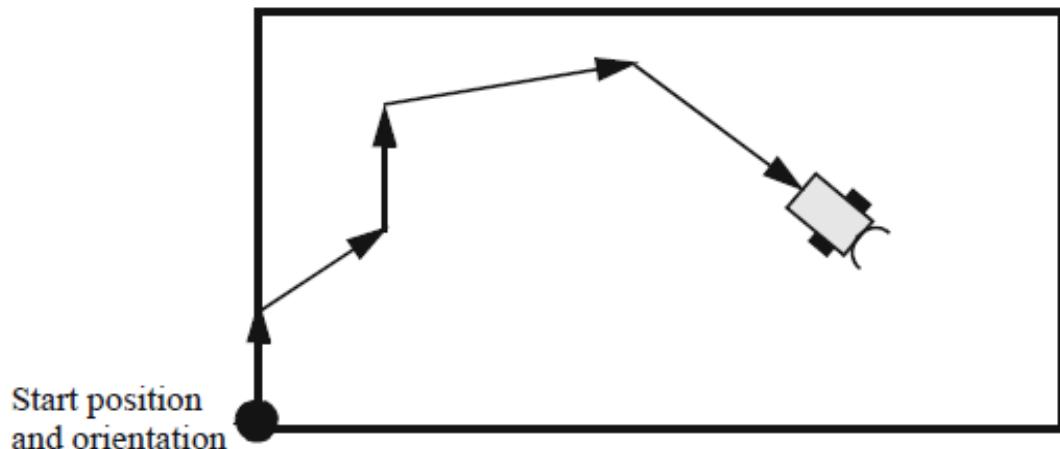


# LOCALIZATION USING EXTERNAL SENSORS

- Using synchronized beacons that are sending out sonar signals at the same regular time intervals, but at different frequencies.
- light emitting homing beacons instead of sonar beacons

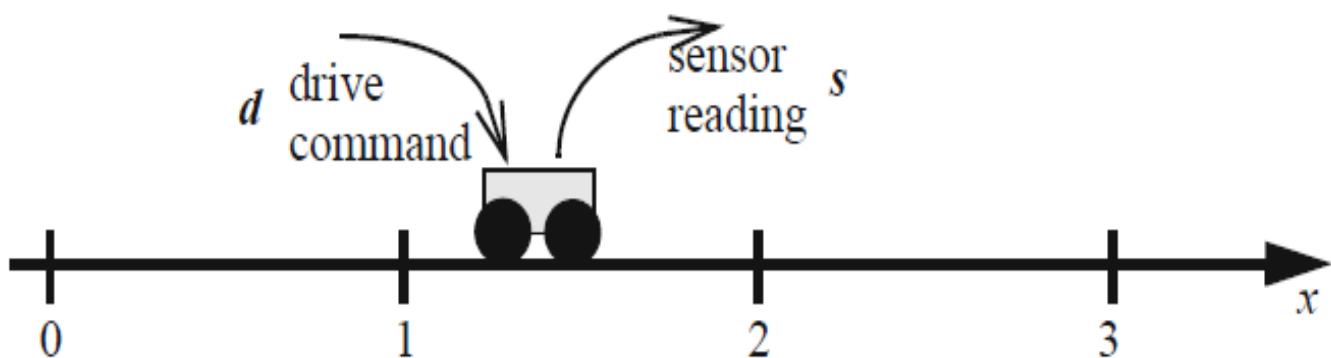


- Dead reckoning
  - It is required to know the robot's starting position and orientation. For all subsequent driving actions (for example straight sections or rotations on the spot or curves), the robot's current position is updated as per the feedback provided from the wheel encoders.



# 3. PROBABILISTIC LOCALIZATION

- All robot motions and sensor measurements are affected by a certain degree of noise. The aim of probabilistic localization is to provide the best possible estimate of the robot's current configuration.



# EXAMPLE:

- Assume a robot is driving in a straight line along the  $x$  axis, starting at the true position  $x=0$ . The robot executes driving commands with distance  $d$ , where  $d$  is an integer, and it receives sensor data from GPS
- The robot's driving accuracy
  - $p(\Delta x = d - 1) = 0.2; p(\Delta x = d) = 0.6; p(\Delta x = d + 1) = 0.2$
- the robot's position sensor accuracy
  - $p(x = s - 1) = 0.1; p(x = s) = 0.8; p(x = s + 1) = 0.1$

- Assuming the robot has executed a driving command with  $d=2$  and after completion of this command, its local sensor reports its position as  $s=2$ . The probabilities for its actual position  $x$  are as follows, with  $n$  as normalization factor:

- $$\begin{aligned} p(x=1) &= n \cdot p(s=2 | x=1) \cdot p(x=1 | d=2, x'=0) \cdot p(x'=0) \\ &= n \cdot 0.1 \cdot 0.2 \cdot 1 = 0.02n \end{aligned}$$
- $$\begin{aligned} p(x=2) &= n \cdot p(s=2 | x=2) \cdot p(x=2 | d=2, x'=0) \cdot p(x'=0) \\ &= n \cdot 0.8 \cdot 0.6 \cdot 1 = 0.48n \end{aligned}$$
- $$\begin{aligned} p(x=3) &= n \cdot p(s=2 | x=3) \cdot p(x=3 | d=2, x'=0) \cdot p(x'=0) \\ &= n \cdot 0.1 \cdot 0.2 \cdot 1 = 0.02n \end{aligned}$$

- $0.02n + 0.48n + 0.02n = 1$

$$n = 1.92$$

- Now, we can calculate the probabilities for the three positions, which reflect the robot's belief:

- $p(x=1) = 0.04;$
- $p(x=2) = 0.92;$
- $p(x=3) = 0.04$

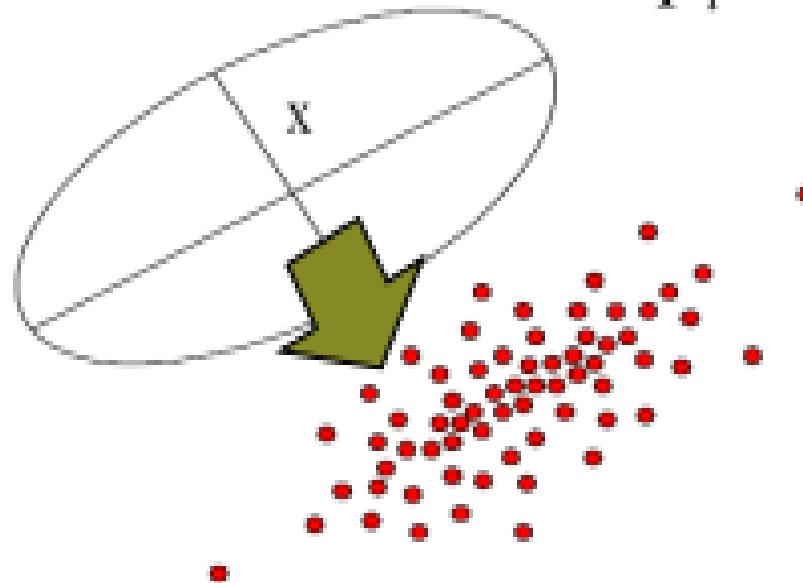
# THE PROBLEM WITH THIS APPROACH

- The biggest problem with this approach is that the configuration space must be discrete. That is, the robot's position can only be represented discretely.
  - To overcome this problem we use SLAM using particle filter.

# OVERVIEW OF PARTICLE FILTER

- allow the use of non-discrete configuration spaces. The key idea in particle filters is to represent the robot's belief as a set of N particles, collectively known as M. Each particle consists of a robot configuration

$$p_i = \{y_{t_i}, w_i\}$$



- Represents pdf as a set of samples (particles)
- Each particle contains one set of values for the state variables
- Good for non-Gaussian, multi-modal pdfs
- Find an approximate solution using a complex model (arbitrary pdf (probability density function)) rather than an exact solution using a simplified model (Gaussians)



# THE ALGORITHM

- To start: Sample from initial pdf,  $p(x_0)$ 
  - For localization, no idea where robot is → throw particles everywhere!
- For each time step, loop with three phases:
  - 1) Prediction
  - 2) Update
  - 3) Resample

# CALCULATION OF BELIEF FOR ROBOT

L0

Pdf of  
current state

Perception  
model

Pdf from last  
time step

$$p(x_t | d_{o \dots t}) = \eta p(z_t | x_t) \int p(x_t | u_{t-1}, x_{t-1}) p(x_{t-1} | d_{o \dots t-1}) dx_{t-1}$$

Normalization  
constant

Resample:

$p(x)$  - the  
posterior  
probability, our  
belief about the  
state variables

Update:

$w(x)$  - the  
importance  
weights

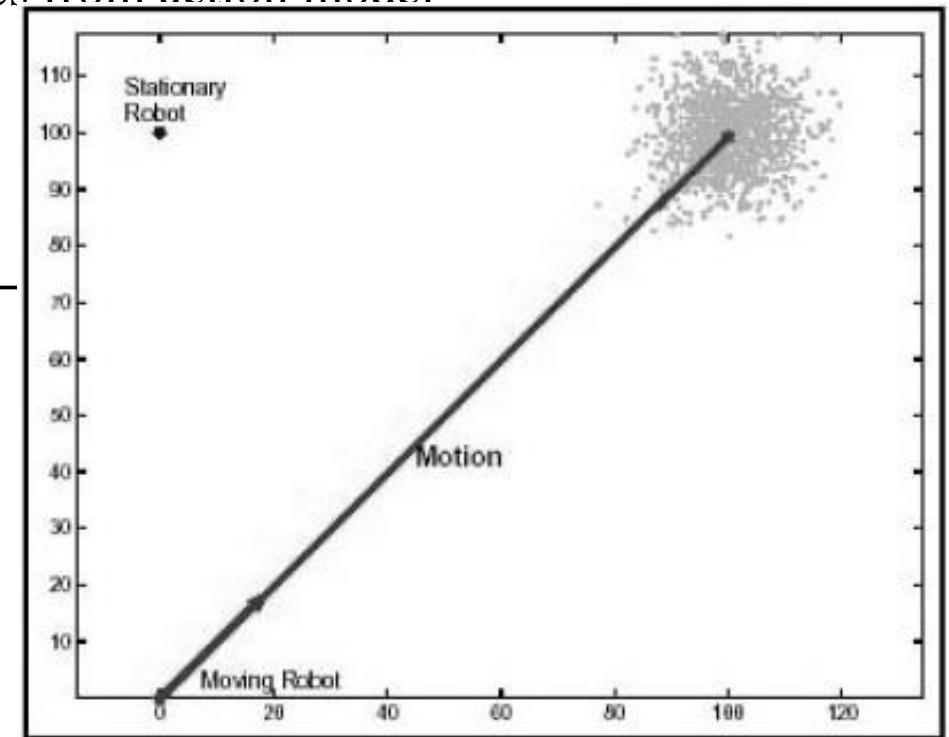
Prediction:

$q(x)$  - the prior probability

# A) PREDICTION

- For each particle, sample and add random, noisy values from action model
- Resulting proposal distribution ( $q(x)$ )  
approximates

$$\int p(x_t | x_{t-1}, u_{t-1}) p(x_{t-1} | d_{p..t-1}) dx_{t-1}$$



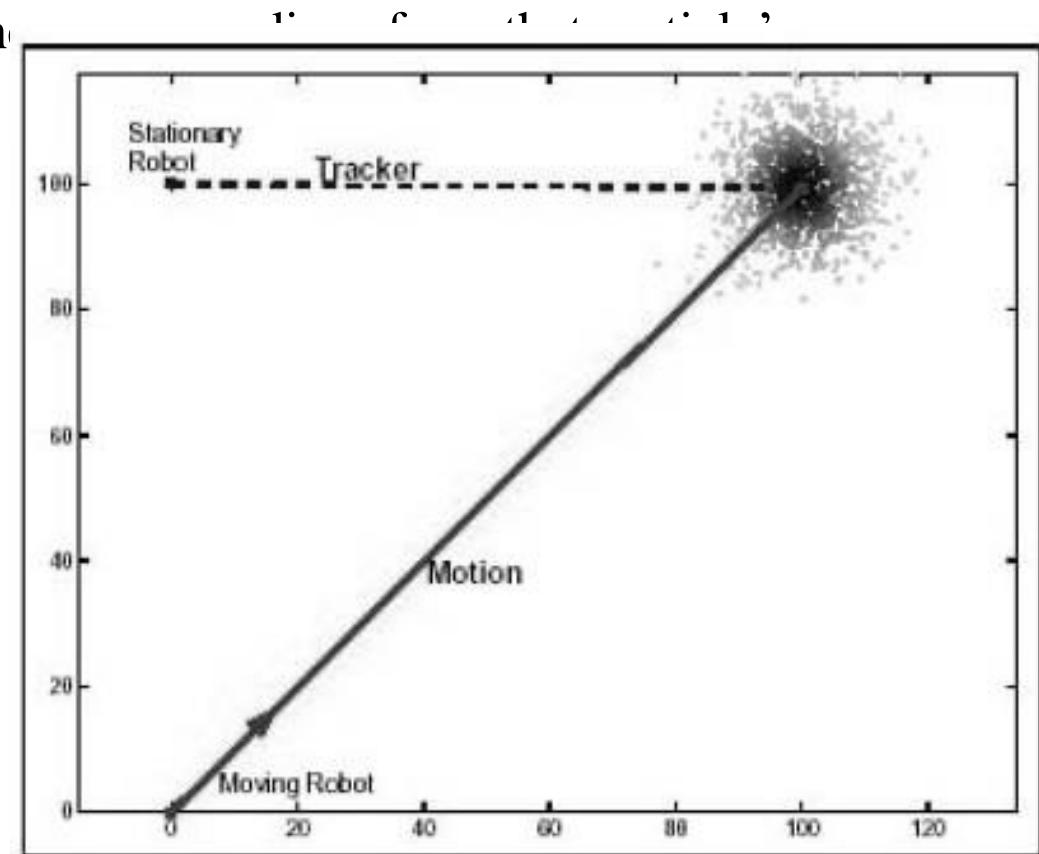
## B) UPDATE

- each particle's weight is the likelihood of getting the hypothesis
- The weight associated with

each particle is

$$w(x) = p(x)/q(x) = p(z_t | x_t),$$

normalized so that all the weights sum to 1



# C) RESAMPLE

- New set of particles are chosen such that each particle survives in proportion to its weight



Resulting distribution is  $p(x)$ :

$$p(x_t | d_{o \dots t}) = \underbrace{\eta}_{p(x)} \underbrace{p(z_t | x_t)}_{w(x)} \underbrace{\int p(x_t | u_{t-1}, x_{t-1}) p(x_{t-1} | d_{o \dots t-1}) dx_{t-1}}_{q(x)}$$

$p(x)$  - the  
posterior  
probability

$w(x)$  - the  
importance  
weights

$q(x)$  - the prior probability

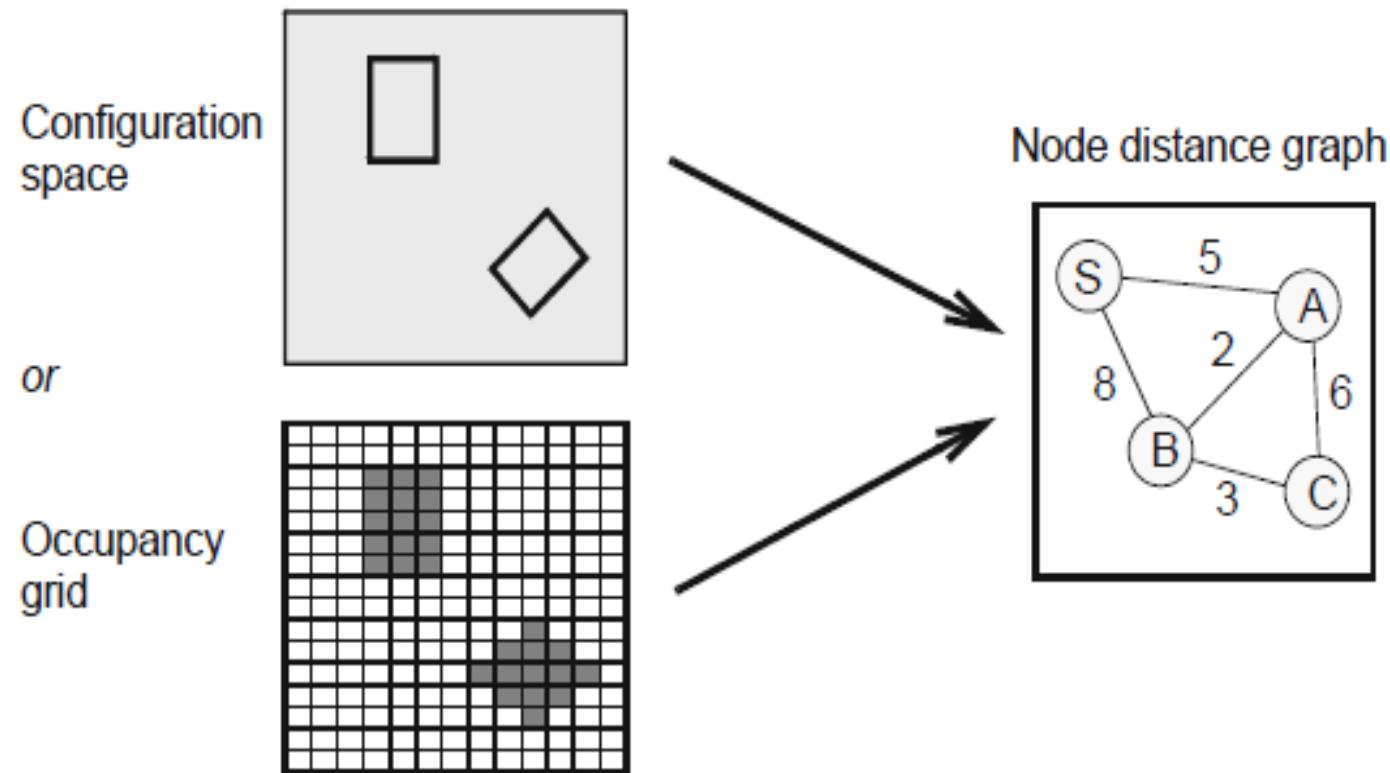
# 4. ENVIRONMENT REPRESENTATION

- a) 2D occupancy grid using Laser sensor (LIDAR)
- b) 3D mapping using RGB-D sensor (Xbox360 Kinect)



# A) 2D OCCUPANCY GRID USING LASER SENSOR (LIDAR)

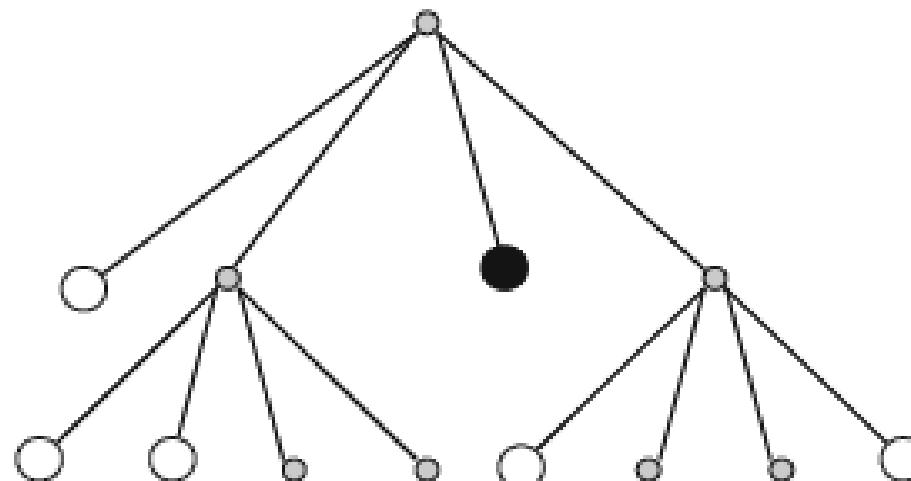
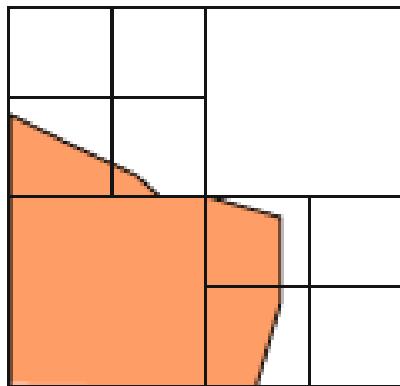
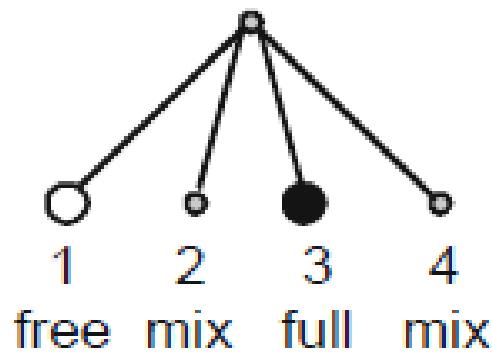
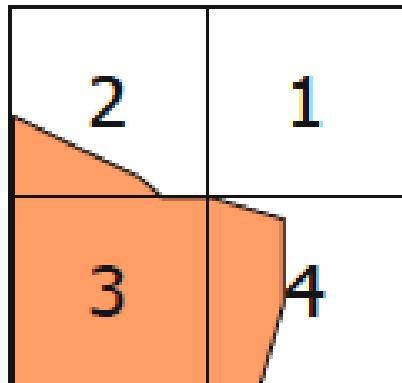
- the environment is specified at a certain resolution with individual pixels either representing free space (white pixels) or an obstacle (black pixels).



# THIS APPROACH HAS A NUMBER OF PROBLEMS

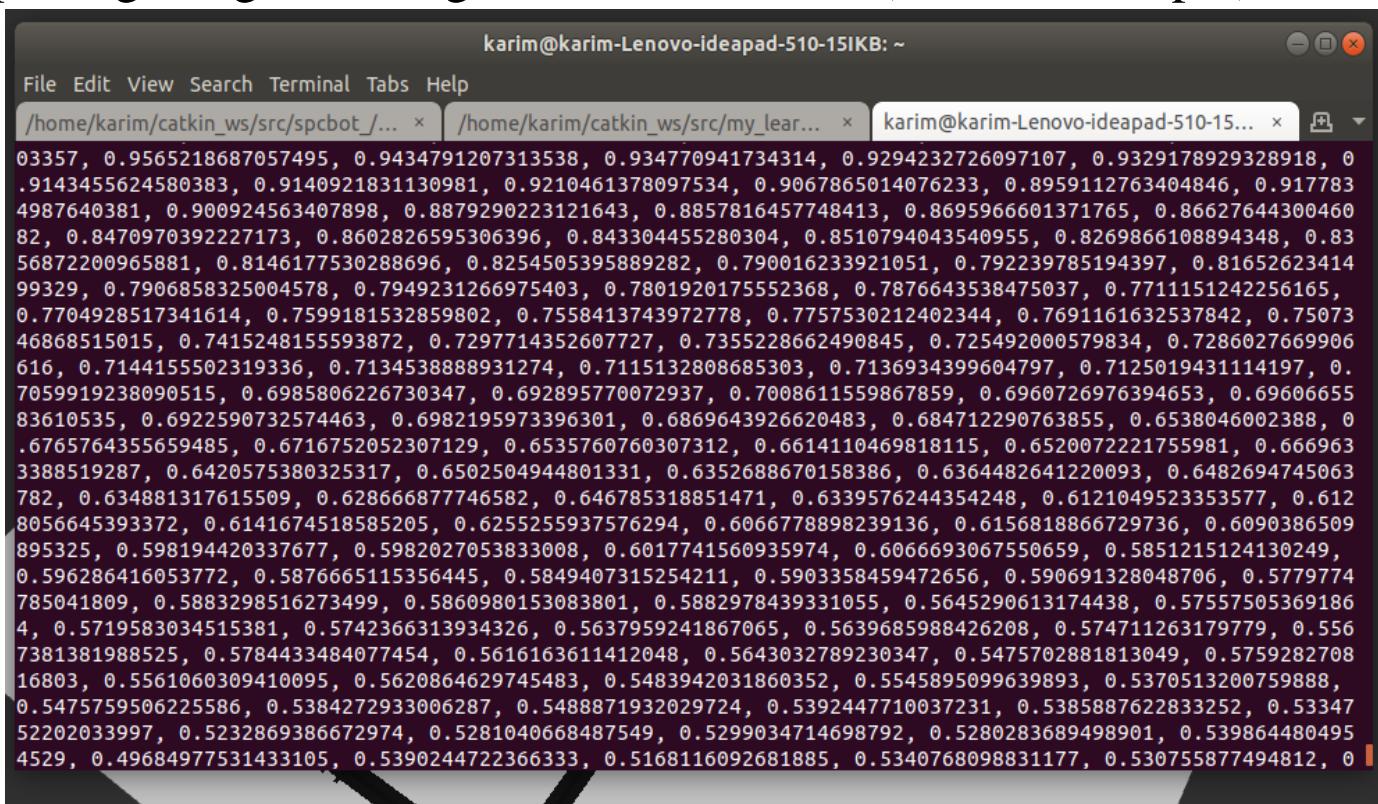
- The number of nodes in the resulting distance graph will be huge
- As neighboring pixels have been transformed into neighboring graph nodes and therefore only support turning angles that are multiples of  $\pm 45^\circ$  (eight nearest neighbors) or multiples of  $\pm 90^\circ$  (four nearest neighbors).

# USING A QUADTREE WILL IMPROVE THIS SITUATION ON BOTH COUNTS



# 2D GRID MAP USING LIDAR

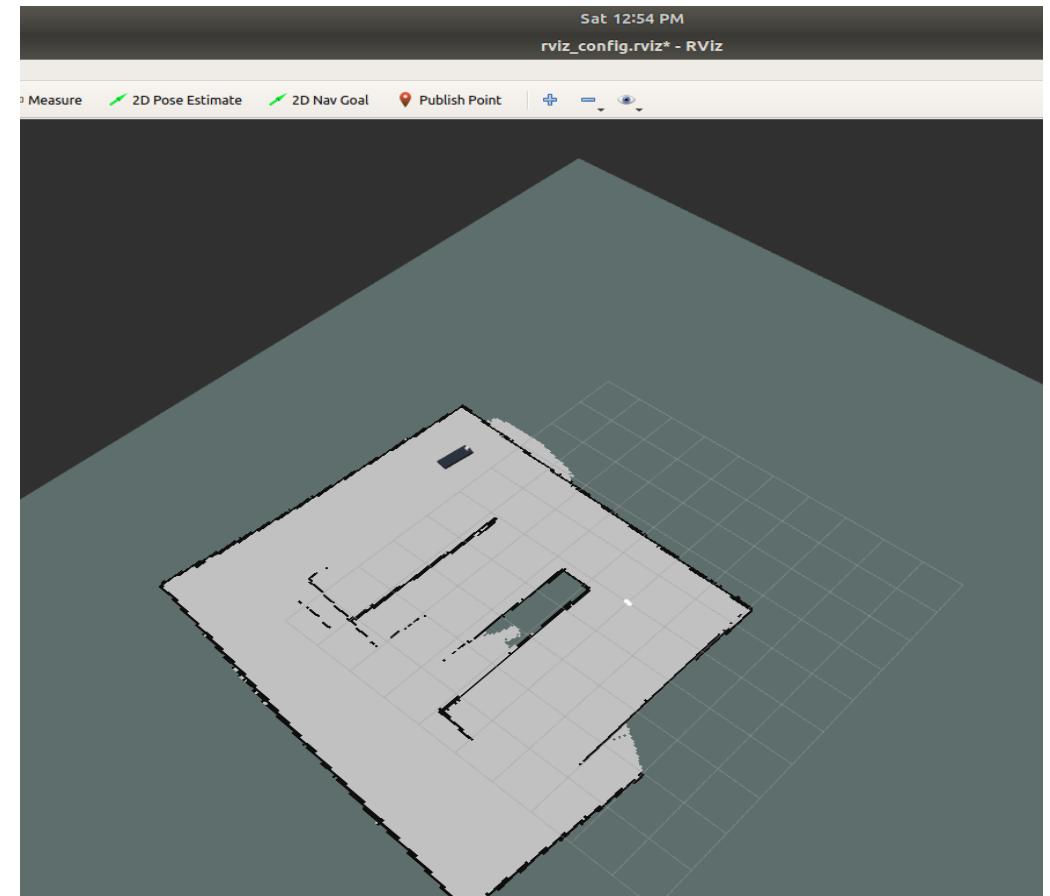
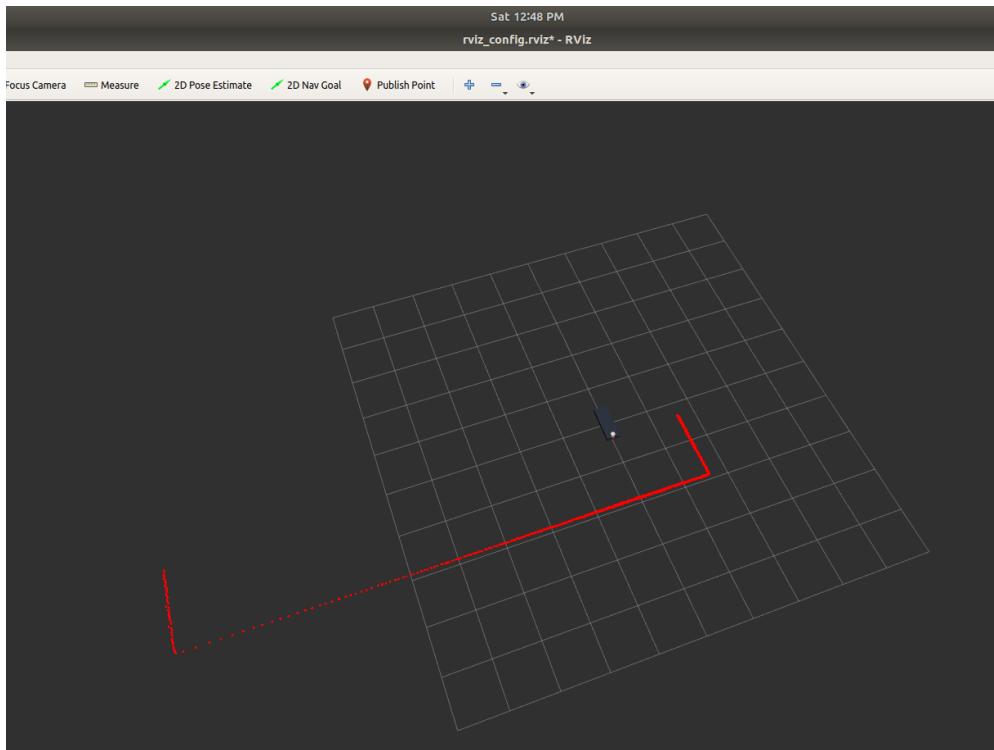
- First we use YDLIDAR ROS package to get readings from the LIDAR (laser\_scan topic)



The screenshot shows a terminal window titled "karim@karim-Lenovo-ideapad-510-15IKB: ~". The window has three tabs open: "/home/karim/catkin\_ws/src/spcbot\_... ", "/home/karim/catkin\_ws/src/my\_lear... ", and "karim@karim-Lenovo-ideapad-510-15... ". The main pane displays a long list of numerical values representing lidar scan data. The data consists of approximately 1000 entries, each containing two sets of coordinates and a distance value. The first set of coordinates is (0.9565218687057495, 0.9434791207313538) and the second is (0.934770941734314, 0.9294232726097107). The distance values range from 0.5390244722366333 to 0.9329178929328918.

```
03357, 0.9565218687057495, 0.9434791207313538, 0.934770941734314, 0.9294232726097107, 0.9329178929328918, 0  
.9143455624580383, 0.9140921831130981, 0.9210461378097534, 0.9067865014076233, 0.8959112763404846, 0.917783  
4987640381, 0.900924563407898, 0.8879290223121643, 0.8857816457748413, 0.8695966601371765, 0.86627644300460  
82, 0.8470970392227173, 0.8602826595306396, 0.843304455280304, 0.8510794043540955, 0.8269866108894348, 0.83  
56872200965881, 0.8146177530288696, 0.8254505395889282, 0.790016233921051, 0.792239785194397, 0.81652623414  
99329, 0.7906858325004578, 0.7949231266975403, 0.7801920175552368, 0.7876643538475037, 0.7711151242256165,  
0.7704928517341614, 0.7599181532859802, 0.7558413743972778, 0.7757530212402344, 0.7691161632537842, 0.75073  
46868515015, 0.7415248155593872, 0.7297714352607727, 0.7355228662490845, 0.725492000579834, 0.7286027669906  
616, 0.7144155502319336, 0.7134538888931274, 0.7115132808685303, 0.7136934399604797, 0.7125019431114197, 0.  
7059919238090515, 0.6985806226730347, 0.692895770072937, 0.7008611559867859, 0.6960726976394653, 0.69606655  
83610535, 0.6922590732574463, 0.6982195973396301, 0.6869643926620483, 0.684712290763855, 0.6538046002388, 0  
.6765764355659485, 0.6716752052307129, 0.6535760760307312, 0.6614110469818115, 0.6520072221755981, 0.666963  
3388519287, 0.6420575380325317, 0.6502504944801331, 0.6352688670158386, 0.6364482641220093, 0.6482694745063  
782, 0.634881317615509, 0.628666877746582, 0.646785318851471, 0.6339576244354248, 0.6121049523353577, 0.612  
8056645393372, 0.6141674518585205, 0.6255255937576294, 0.6066778898239136, 0.6156818866729736, 0.6090386509  
895325, 0.598194420337677, 0.5982027053833008, 0.6017741560935974, 0.6066693067550659, 0.5851215124130249,  
0.596286416053772, 0.5876665115356445, 0.5849407315254211, 0.5903358459472656, 0.590691328048706, 0.5779774  
785041809, 0.5883298516273499, 0.5860980153083801, 0.588297843931055, 0.5645290613174438, 0.57557505369186  
4, 0.5719583034515381, 0.5742366313934326, 0.5637959241867065, 0.5639685988426208, 0.574711263179779, 0.556  
7381381988525, 0.5784433484077454, 0.5616163611412048, 0.5643032789230347, 0.5475702881813049, 0.5759282708  
16803, 0.5561060309410095, 0.5620864629745483, 0.5483942031860352, 0.5545895099639893, 0.5370513200759888,  
0.5475759506225586, 0.5384272933006287, 0.5488871932029724, 0.5392447710037231, 0.5385887622833252, 0.53347  
52202033997, 0.5232869386672974, 0.5281040668487549, 0.5299034714698792, 0.5280283689498901, 0.539864480495  
4529, 0.49684977531433105, 0.5390244722366333, 0.5168116092681885, 0.5340768098831177, 0.530755877494812, 0
```

- Then, we use gmapping ROS package which uses readings from the LIDAR by subscribing to laser\_scan topic which is now published by the YDLIDAR ROS package



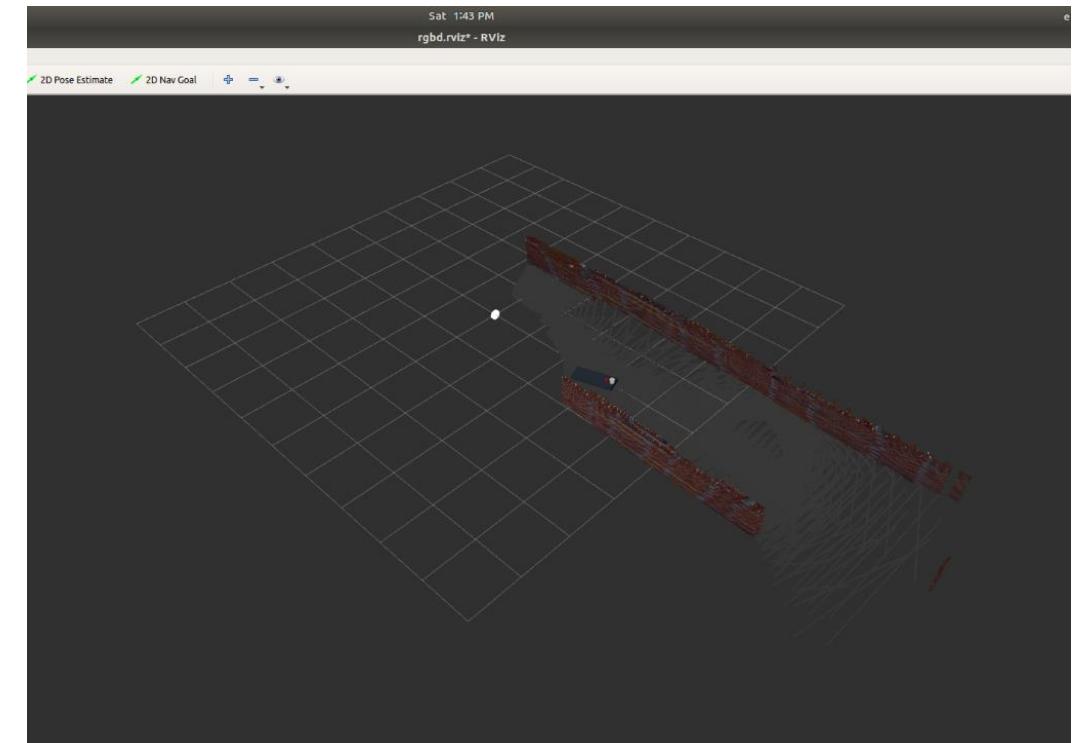
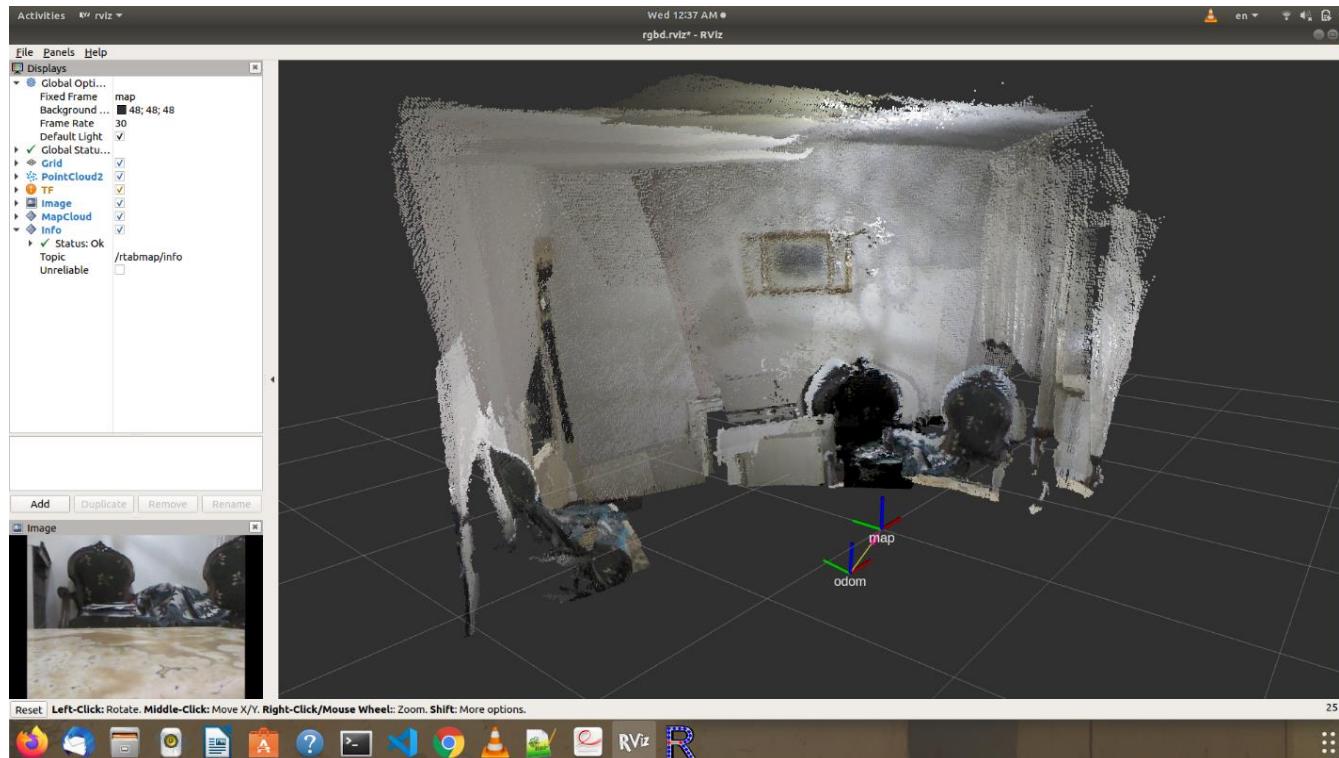
# **ILLUSTRATING VIDEO (BUILDING 2D MAP BY LIDAR)**

- **VIDEO 1**

# **3D MAPPING USING RGB-D SENSOR (XBOX360 KINECT)**

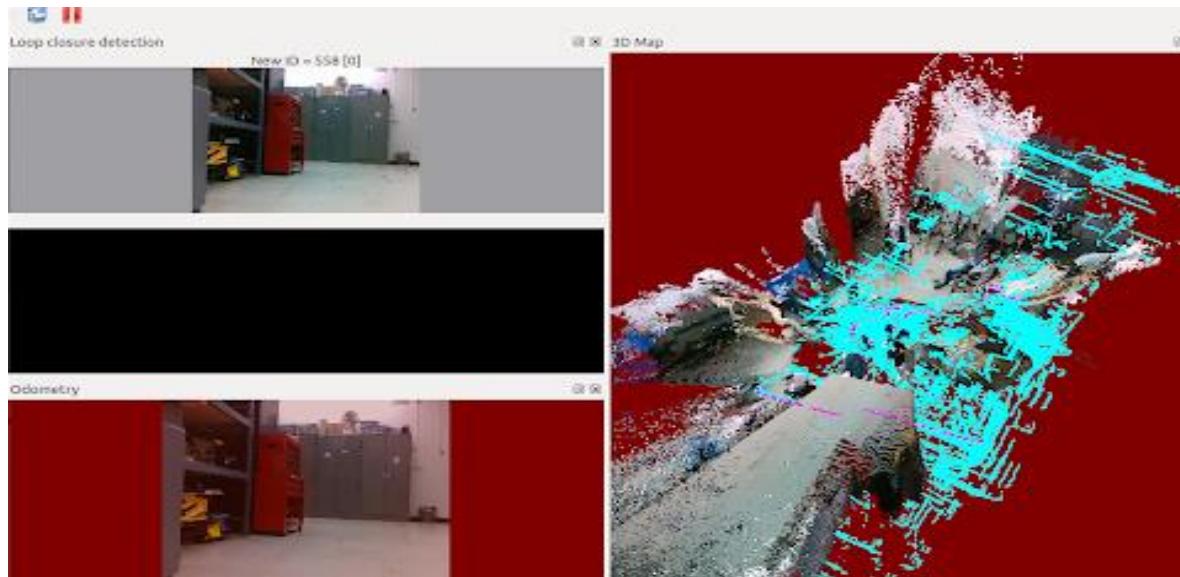
- First we use OpenNI ROS package to get readings from the Kinect camera

- The second package used is RTABmap\_ros (Real-Time Appearance-Based Mapping). It uses this reading that we get from the Kinect camera and perform RGB-D SLAM on it

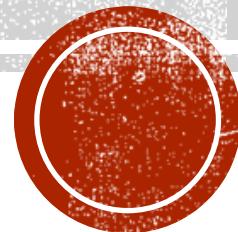


# 5. COMPARISON BETWEEN 2D AND 3D MAPS

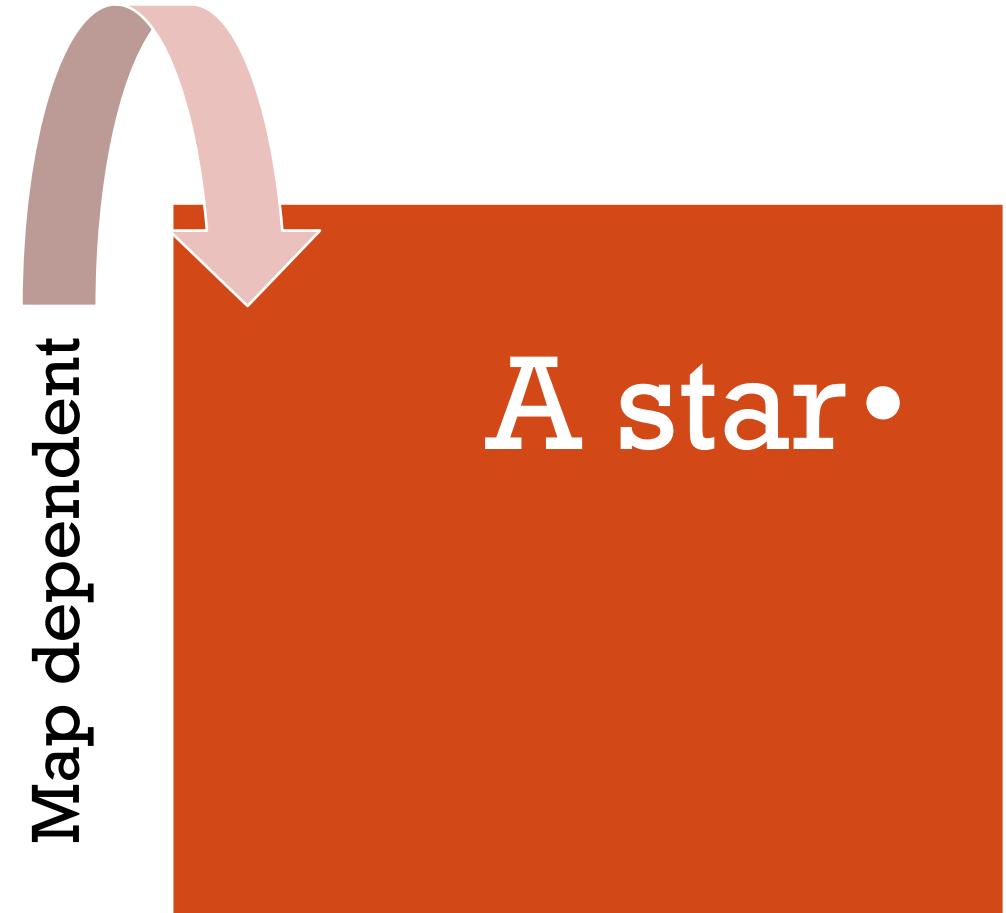
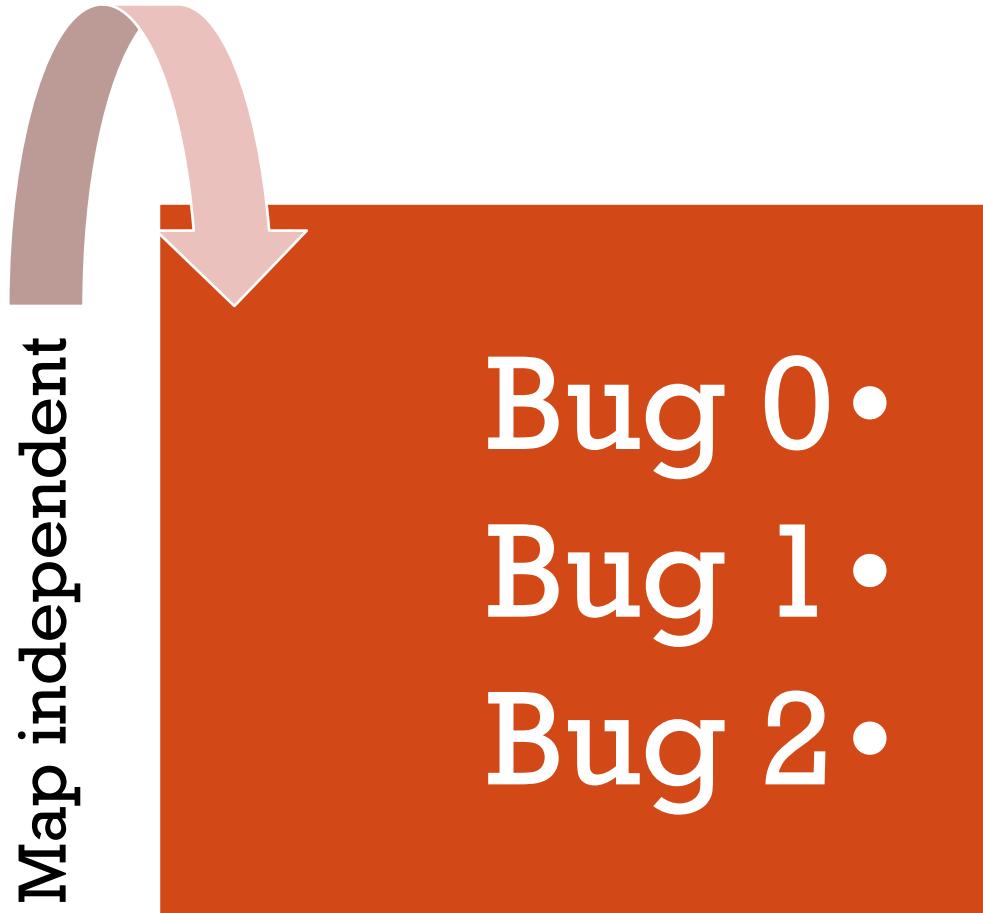
- 2D LIDAR sensor is more accurate than Kinect sensor, covers more distance and covers an angle of 360° of the surroundings. The Kinect sensor covers only about 57°.
- Kinect camera is better for obstacle avoidance as it detects the height of the obstacle
- The Kinect camera has much noises and larger errors than LIDAR sensor.
- Kinect camera needs to move much slower to avoid loop closure failure on creating the map.



# MOTION PLANNING



# MOTION PLANNING



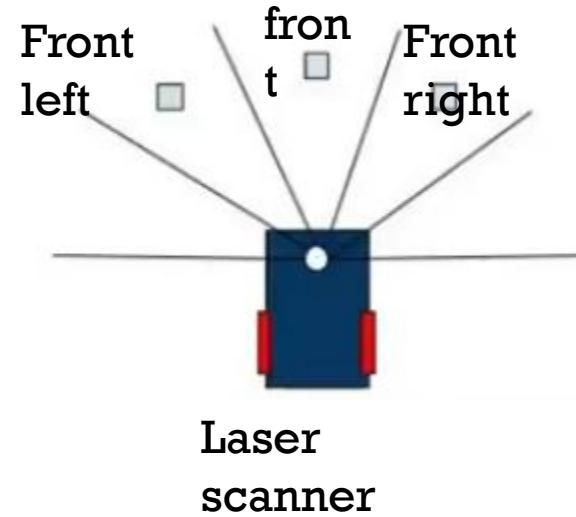
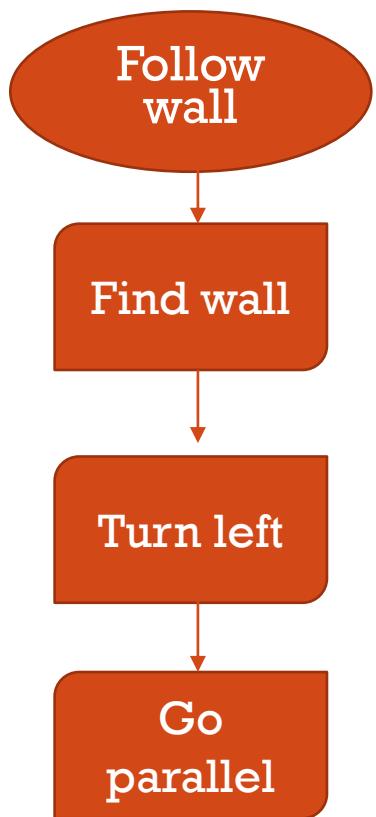
# BASIC ALGORITHMS NEEDED FOR BUGS

## ■ Go To point

- Givens : start point and goal point



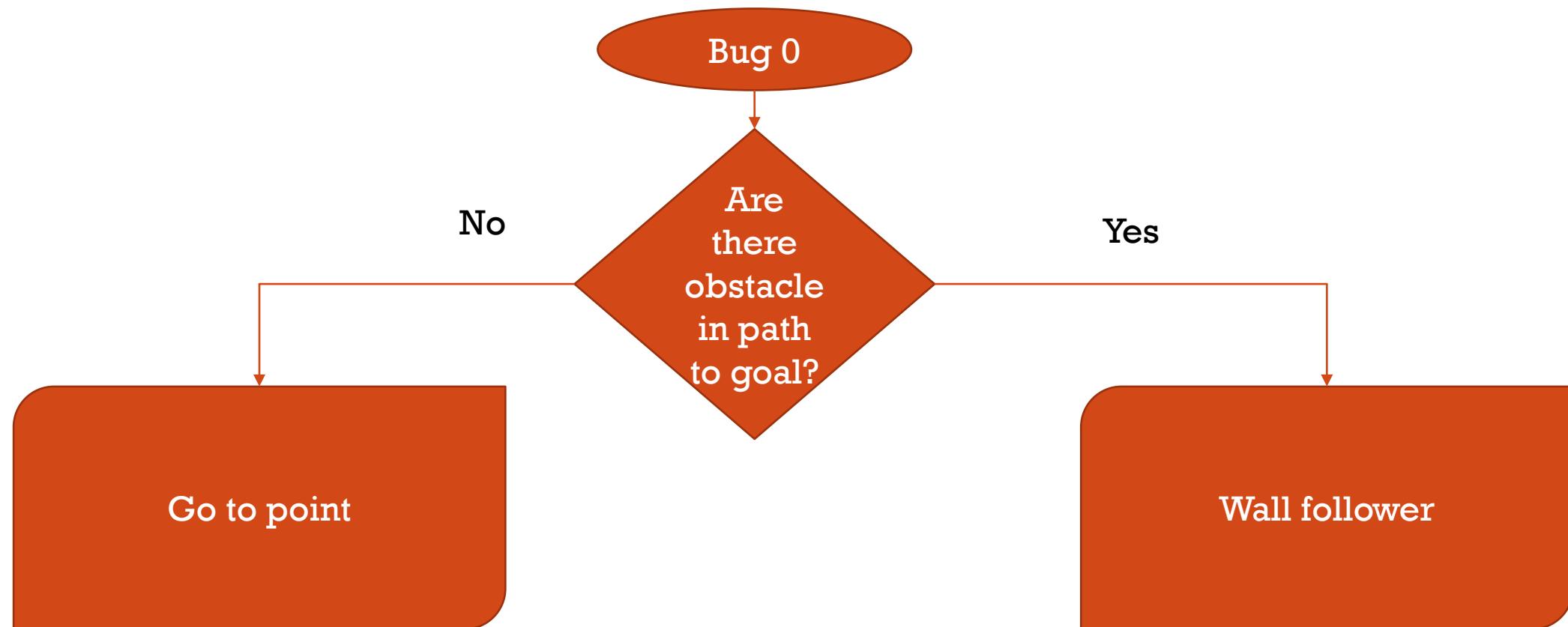
# \* FOLLOW WALL



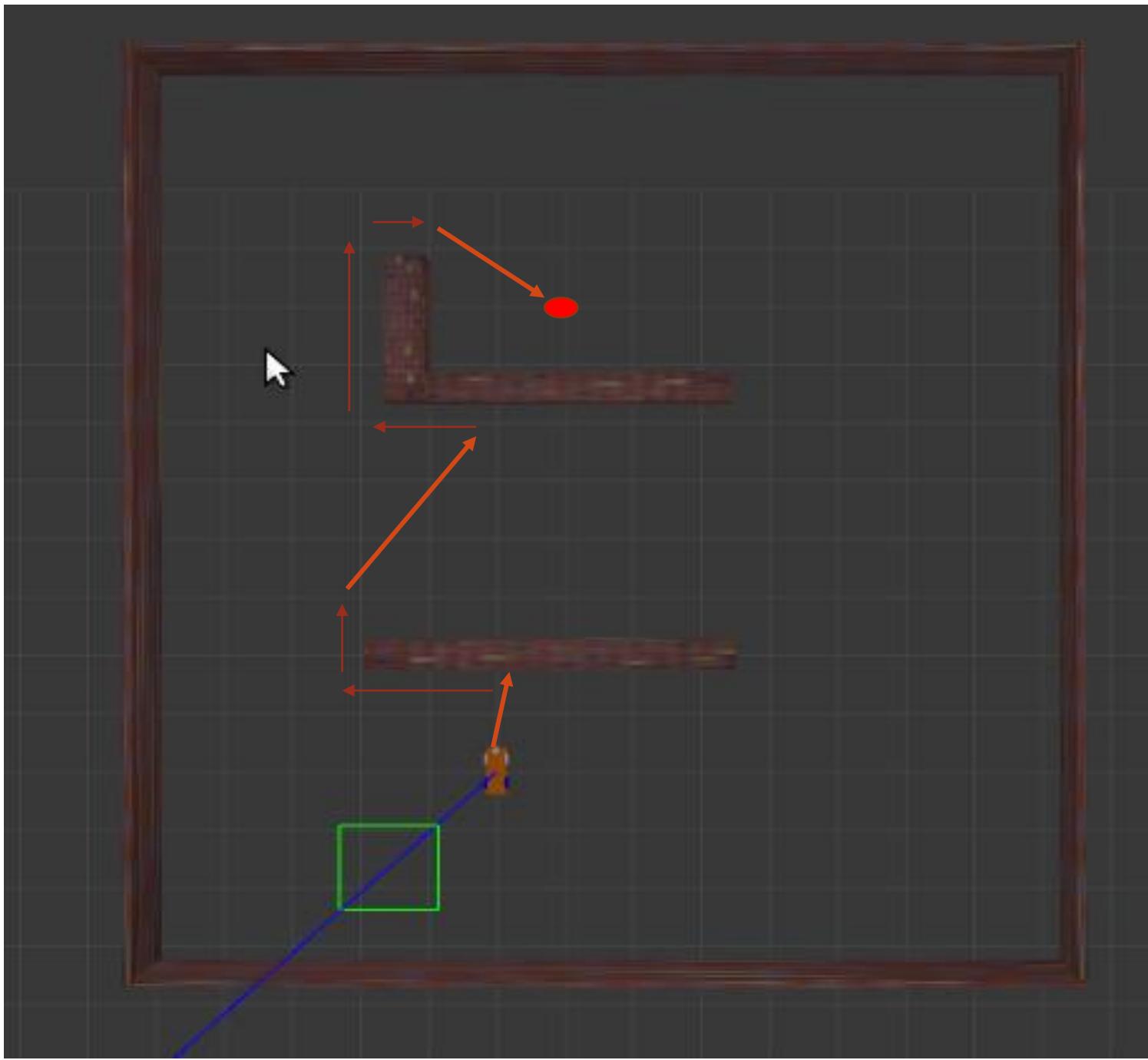
Case	Front left	Front	Front right	Task
1				Find wall
2		X		Turn left
3			X	Go parallel
4	X			Find wall
5		X	X	Turn left
6	X	X		Turn left
7	X	X	X	Turn left
8	X		X	Find wall

Tasks for different cases

# BUG 0 ALGORITHM

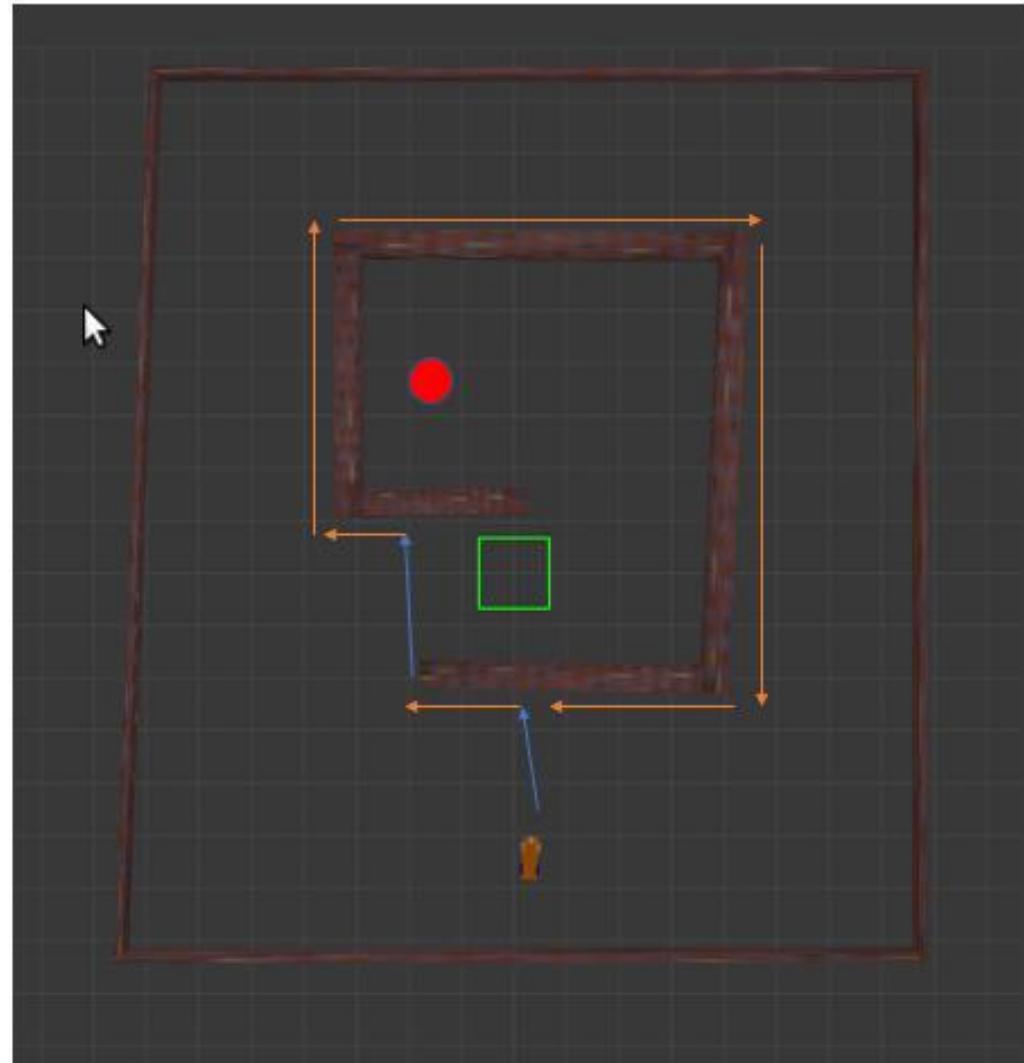


- Goal point
- Wall Follower
- Go to point

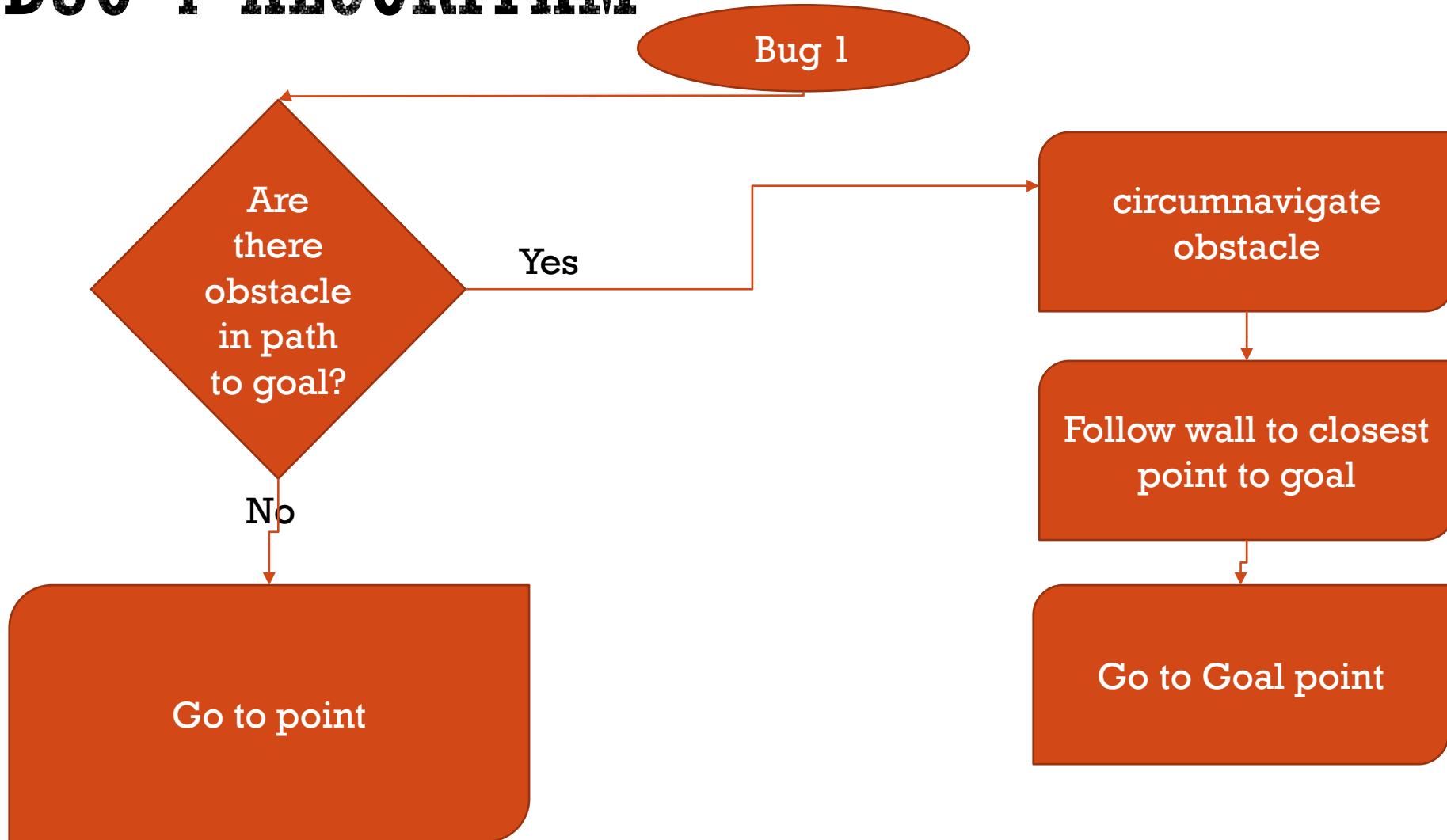


# BUG 0 FAILURE

- Goal
- ← Go to point
- ← Follow wall



# BUG 1 ALGORITHM



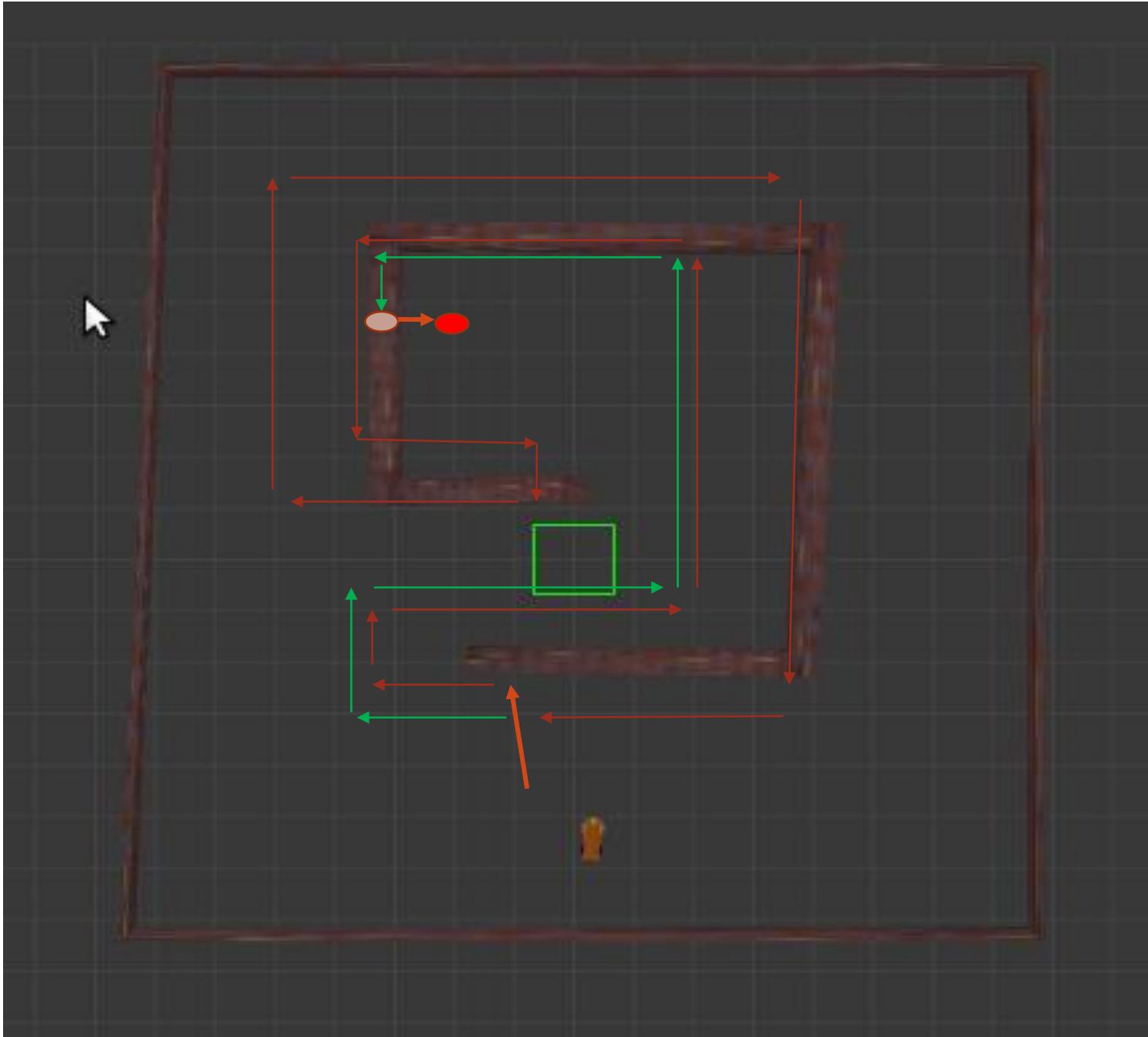
● Goal point

● Closest point

→ Go to point

→ circumnavigate

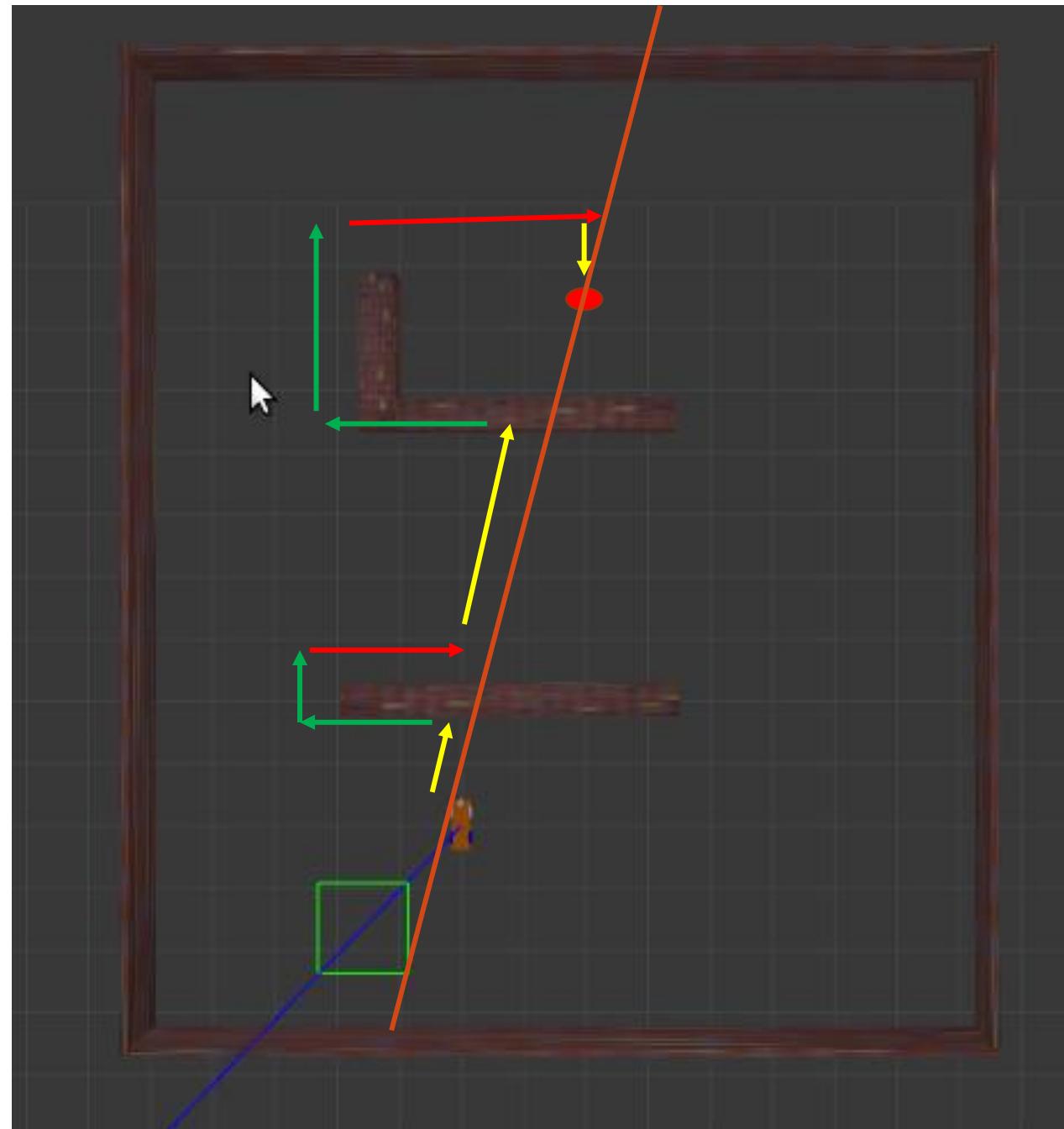
→ Go to  
closest  
point



# BUG 2 ALGORITHM



- Goal point
- Global pathway
- Go to point
- Follow wall
- Go to pathway



# CONCLUSION

- Bugs algorithms are not efficient to use for autonomous vehicles like rovers, as it shown before from test cases, so we need for more advanced algorithms to depend on it in automation of our rover but also bugs algorithms are not useless

## exploration



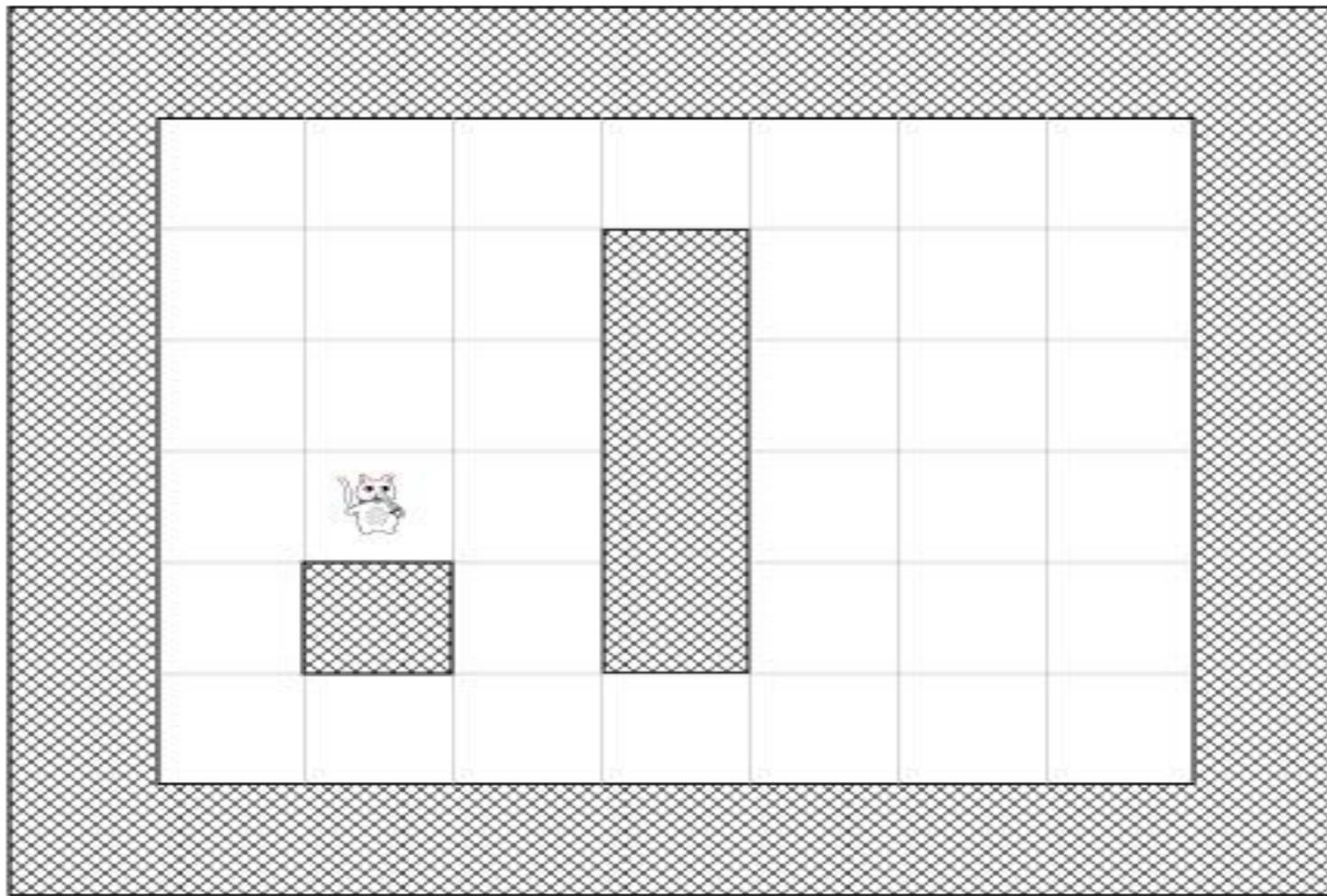
# A STAR ALGORITHM

- $F(n) = g(n) + h(n)$
- $F$  : total cost to reach next node
- $g$  : the movement cost to move from the starting point to a given square on the grid, following the path generated to get there.
- $h$  : the estimated movement cost to move from that given square on the grid to the final destination

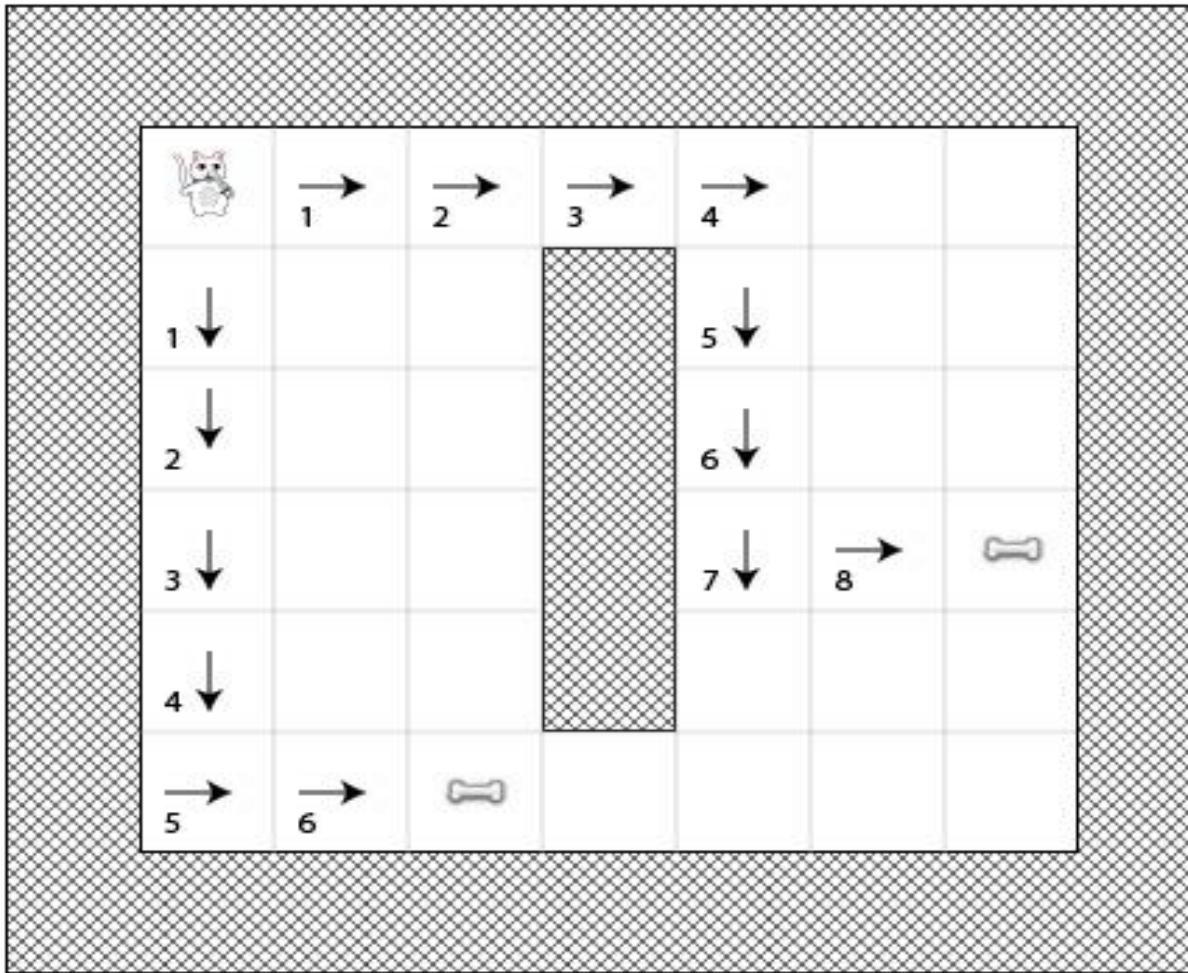


# A\* TUTORIAL

“GRID”

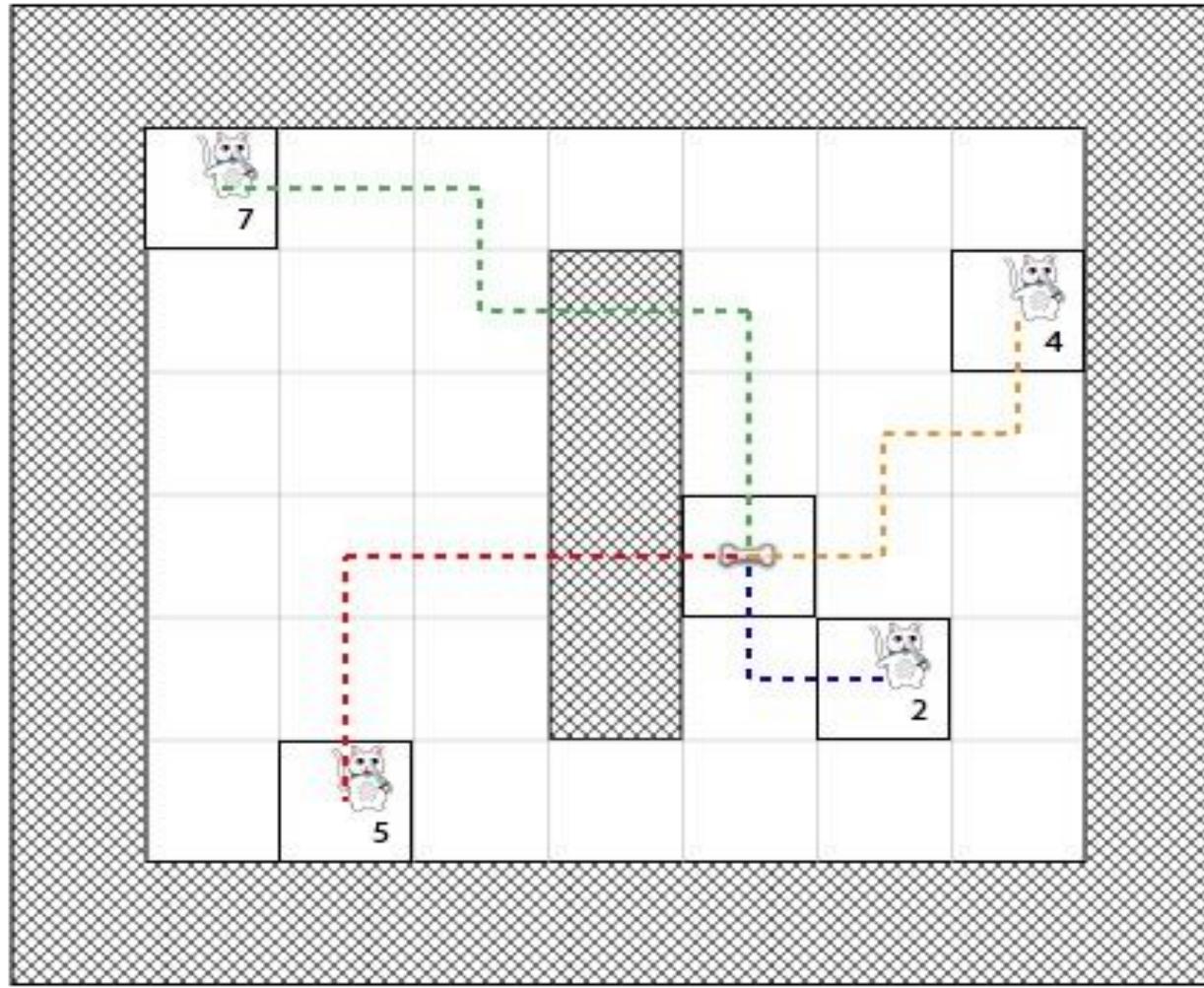


# G CALCULATION



# H CALCULATION

"MANHATTAN LENGTH"

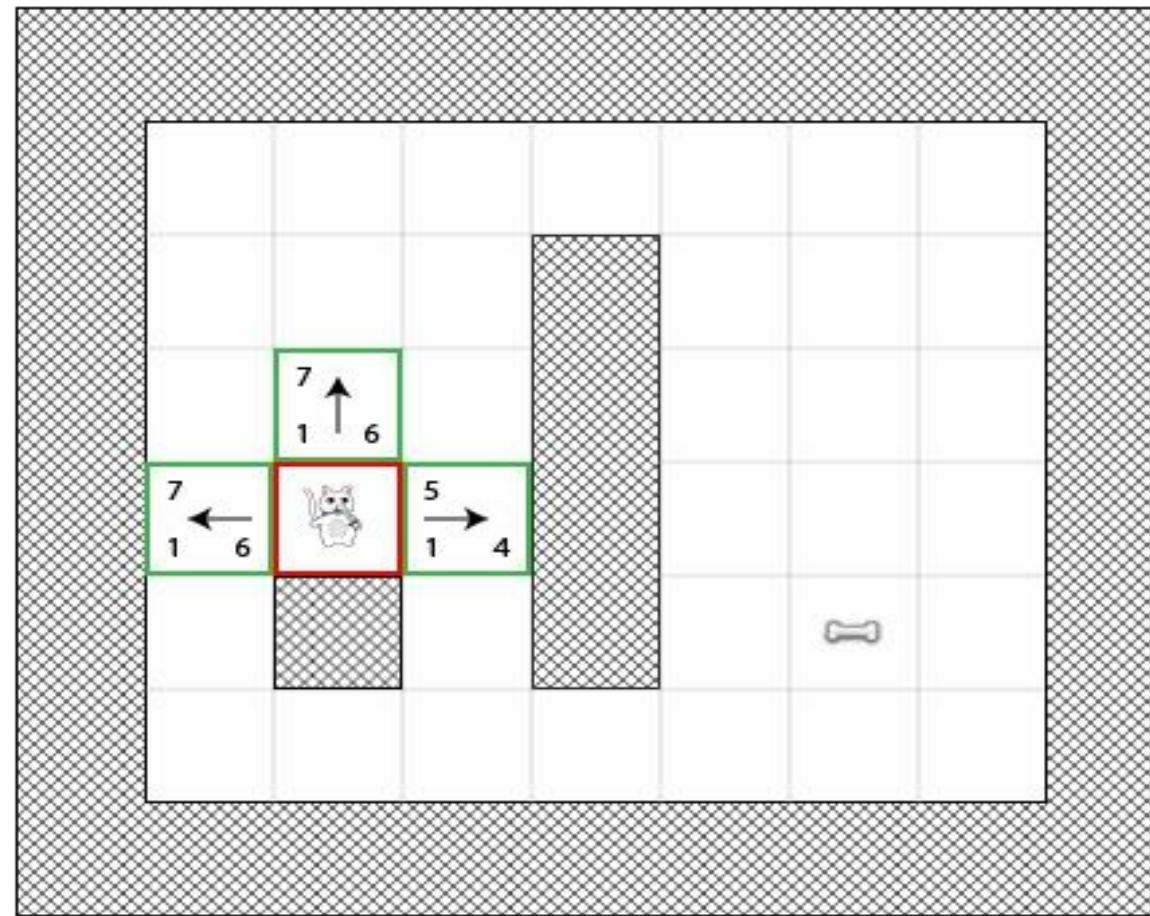


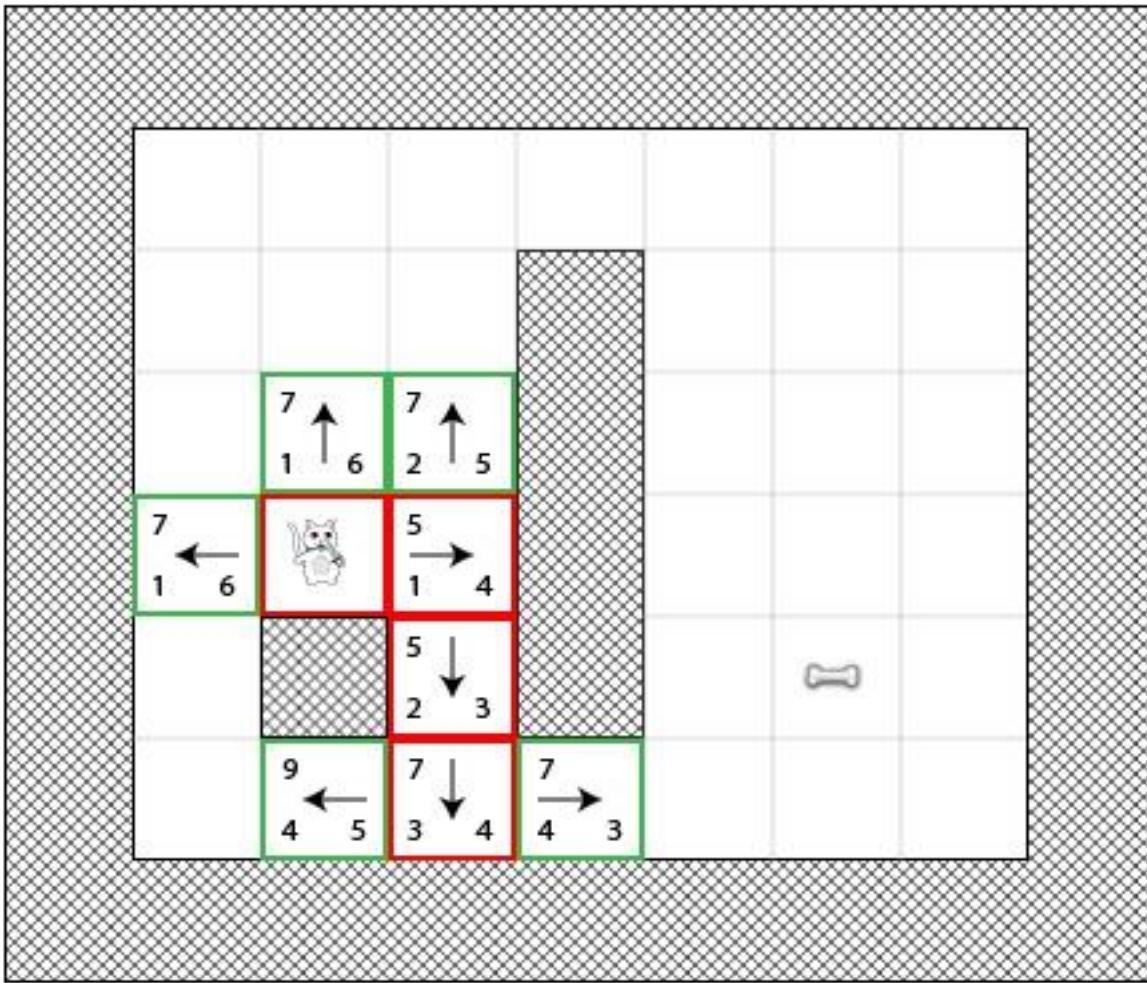
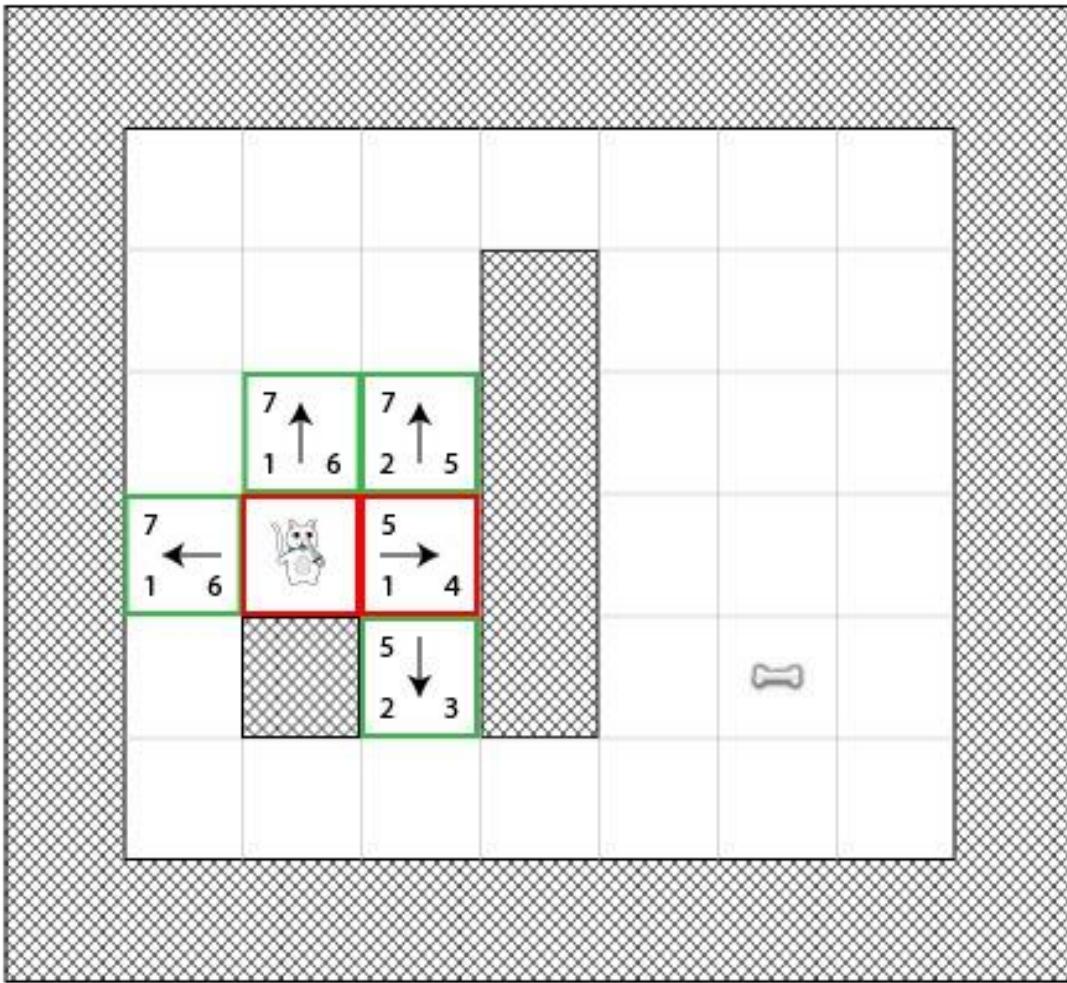
# TEST CASE

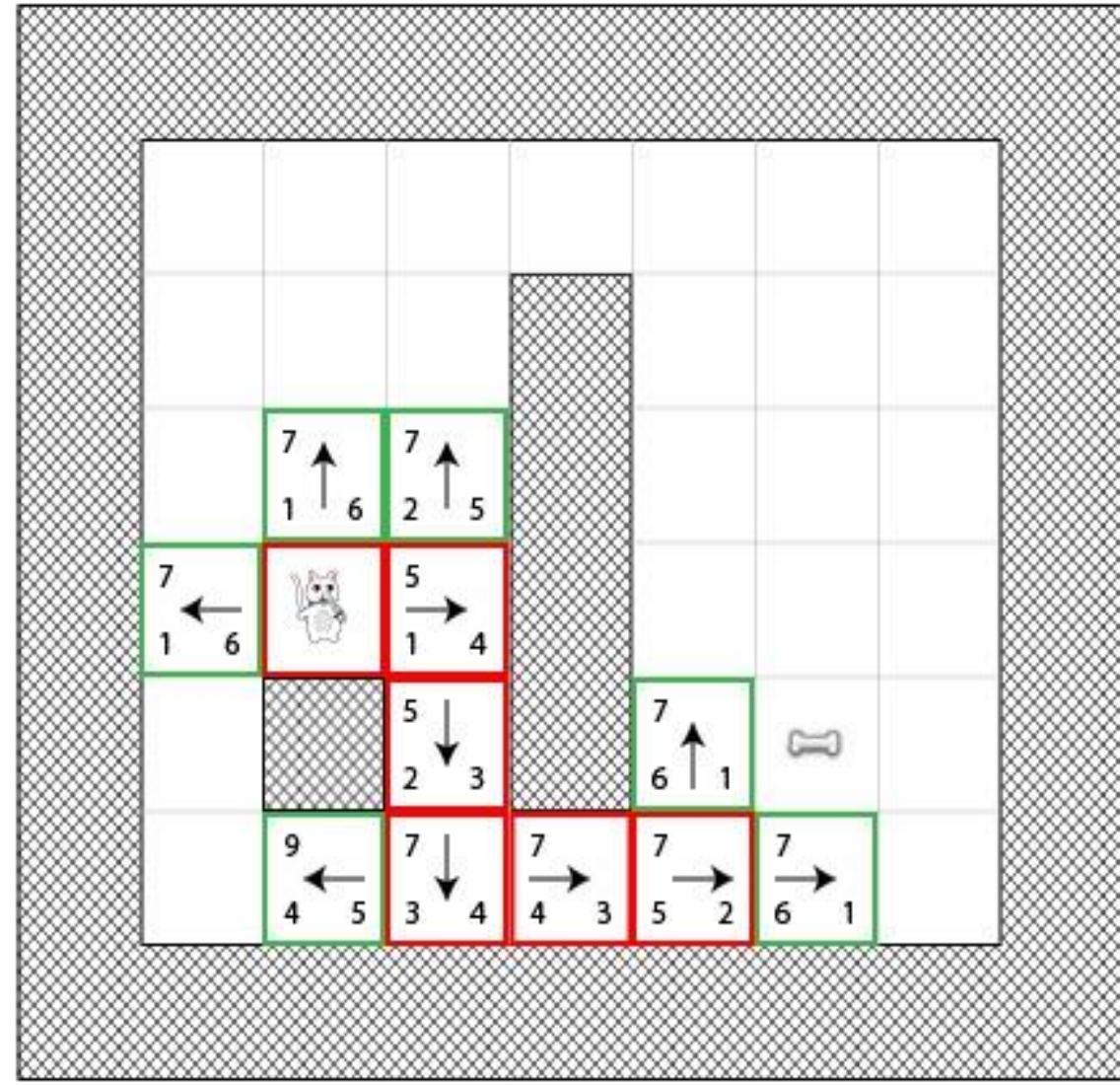
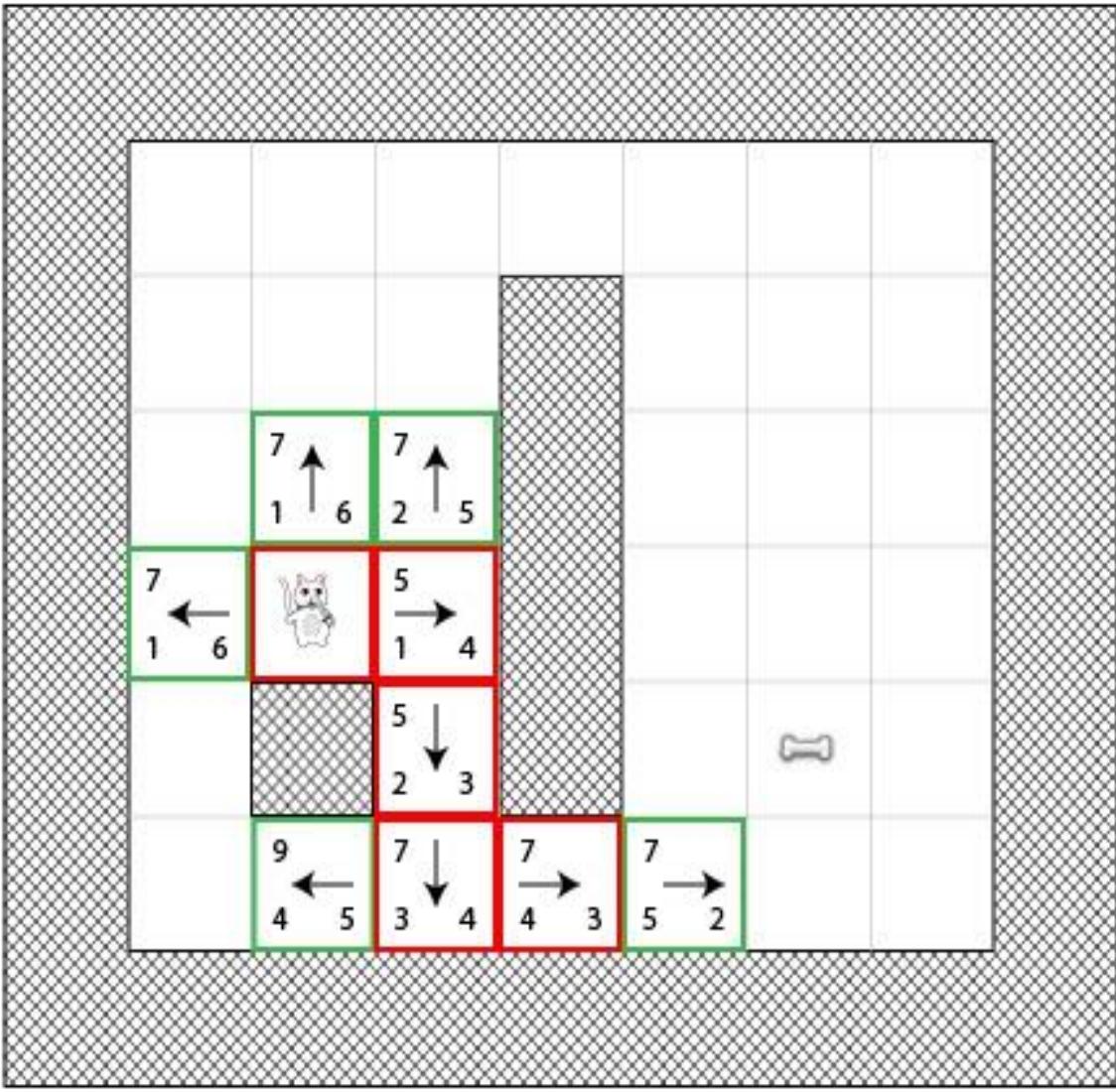
“CAT TO BONE”

F  
G   H

Key

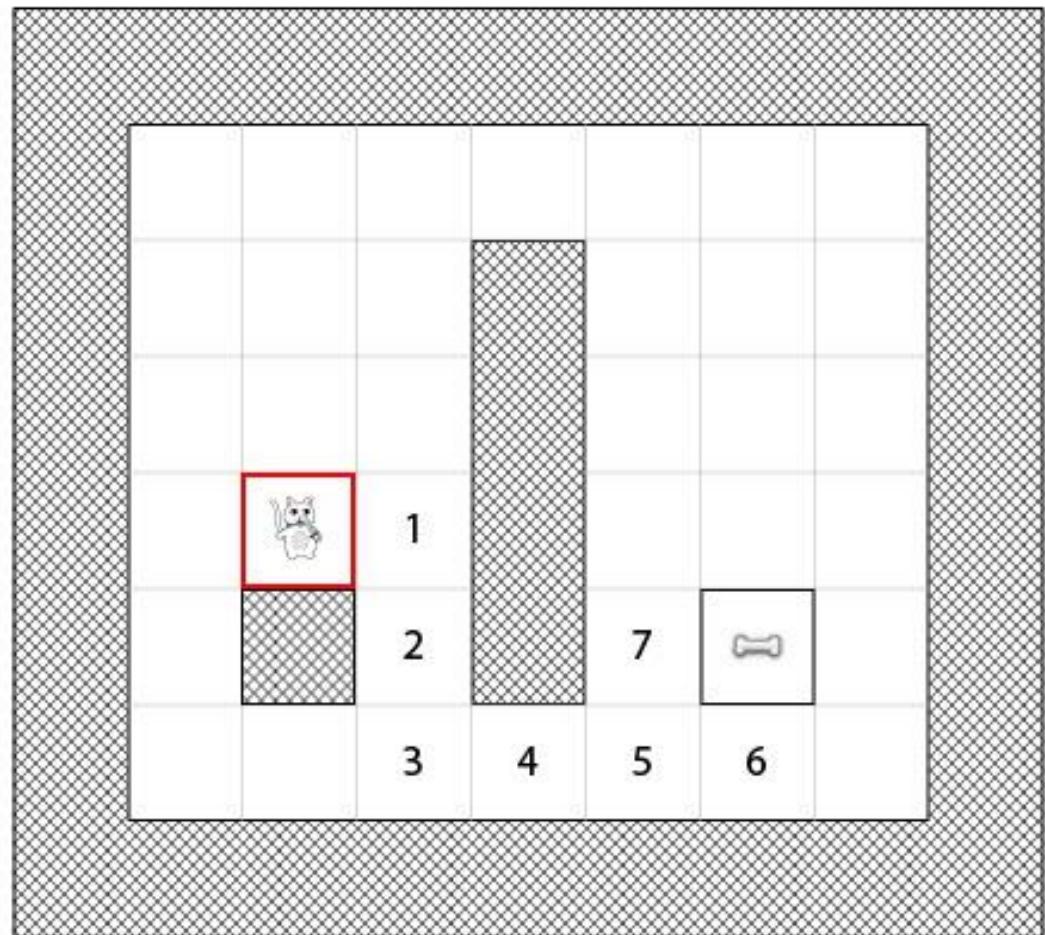


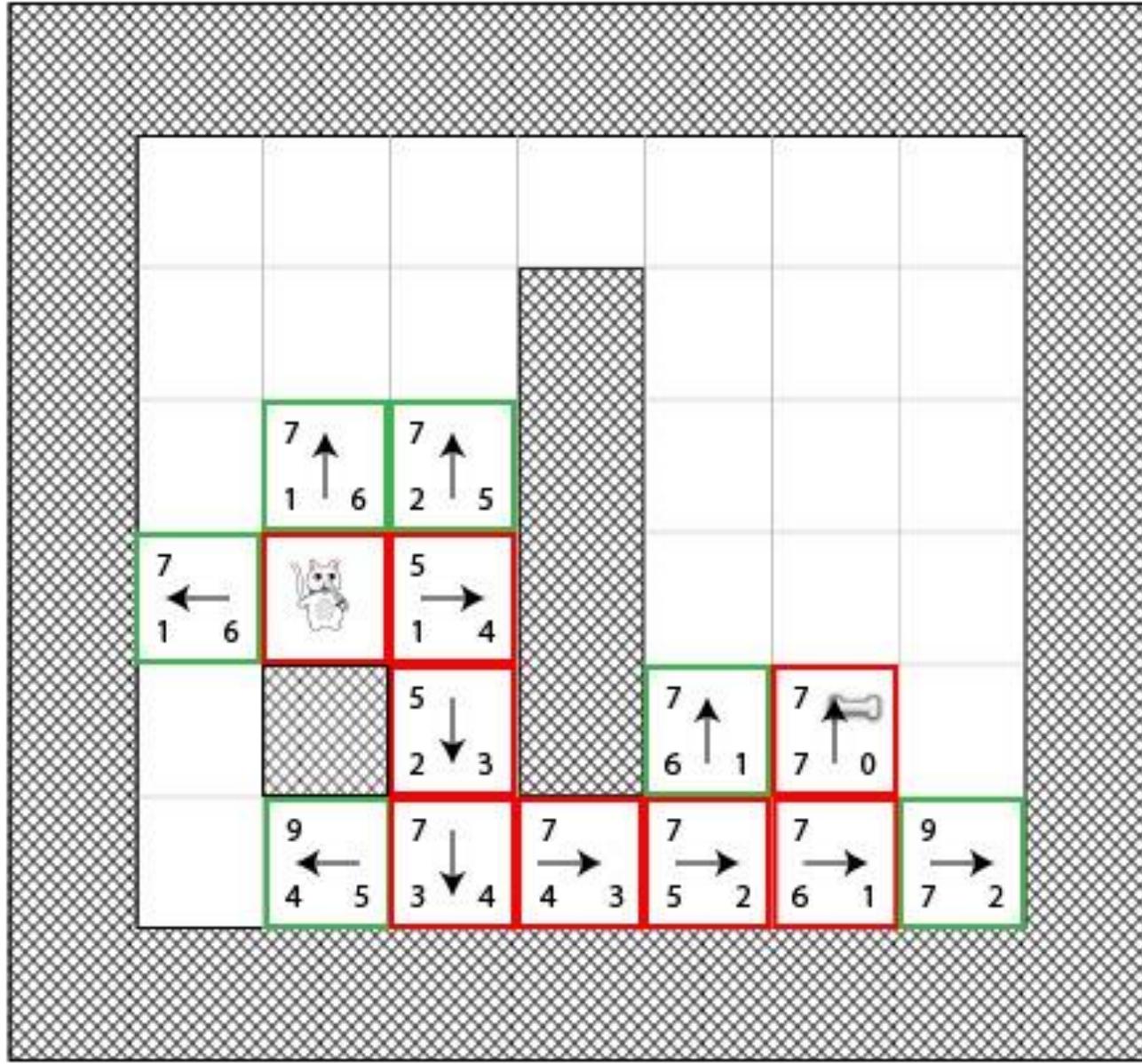




The two paths:

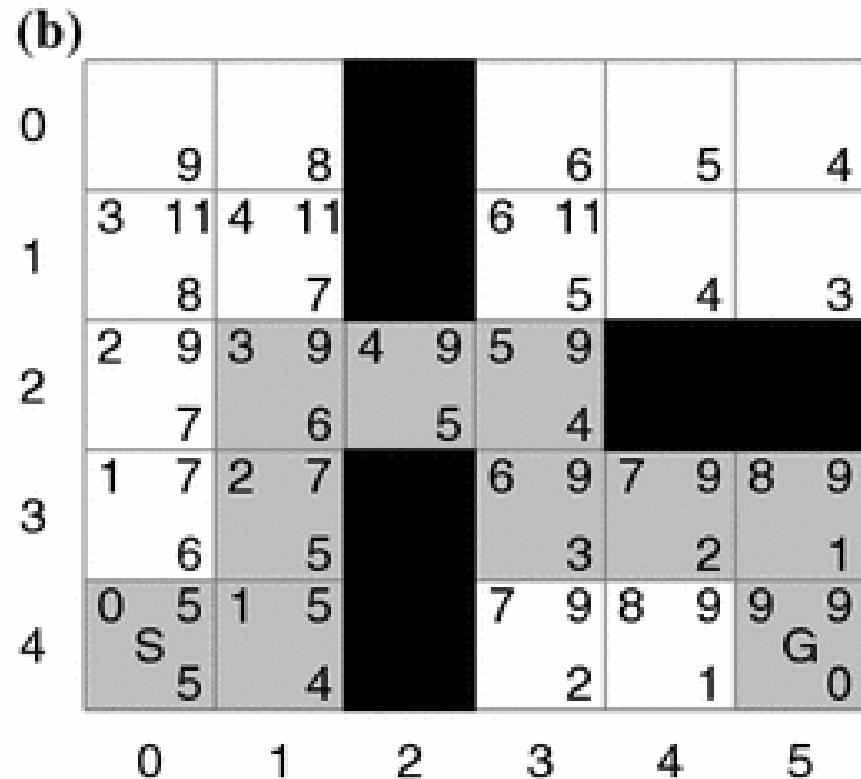
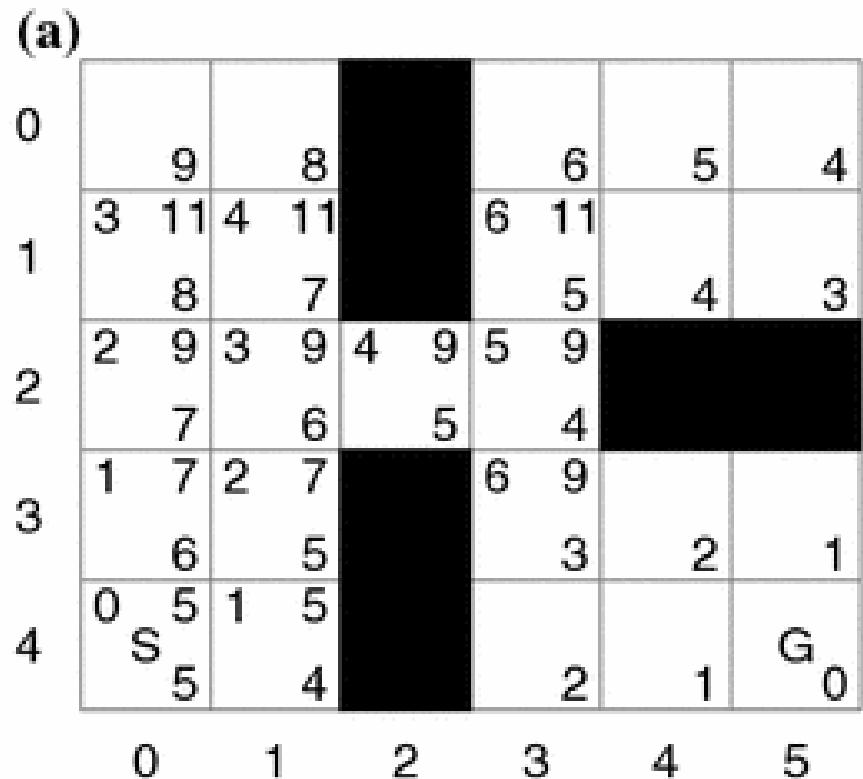
- 1-2-3-4-5-6-Bone
- 1-2-3-4-5-7-Bone





$g$	$f$
$h$	

Keys



Cost map and pass from start(s) to Goal(G)



# ACTUAL IMPLEMENTATION

