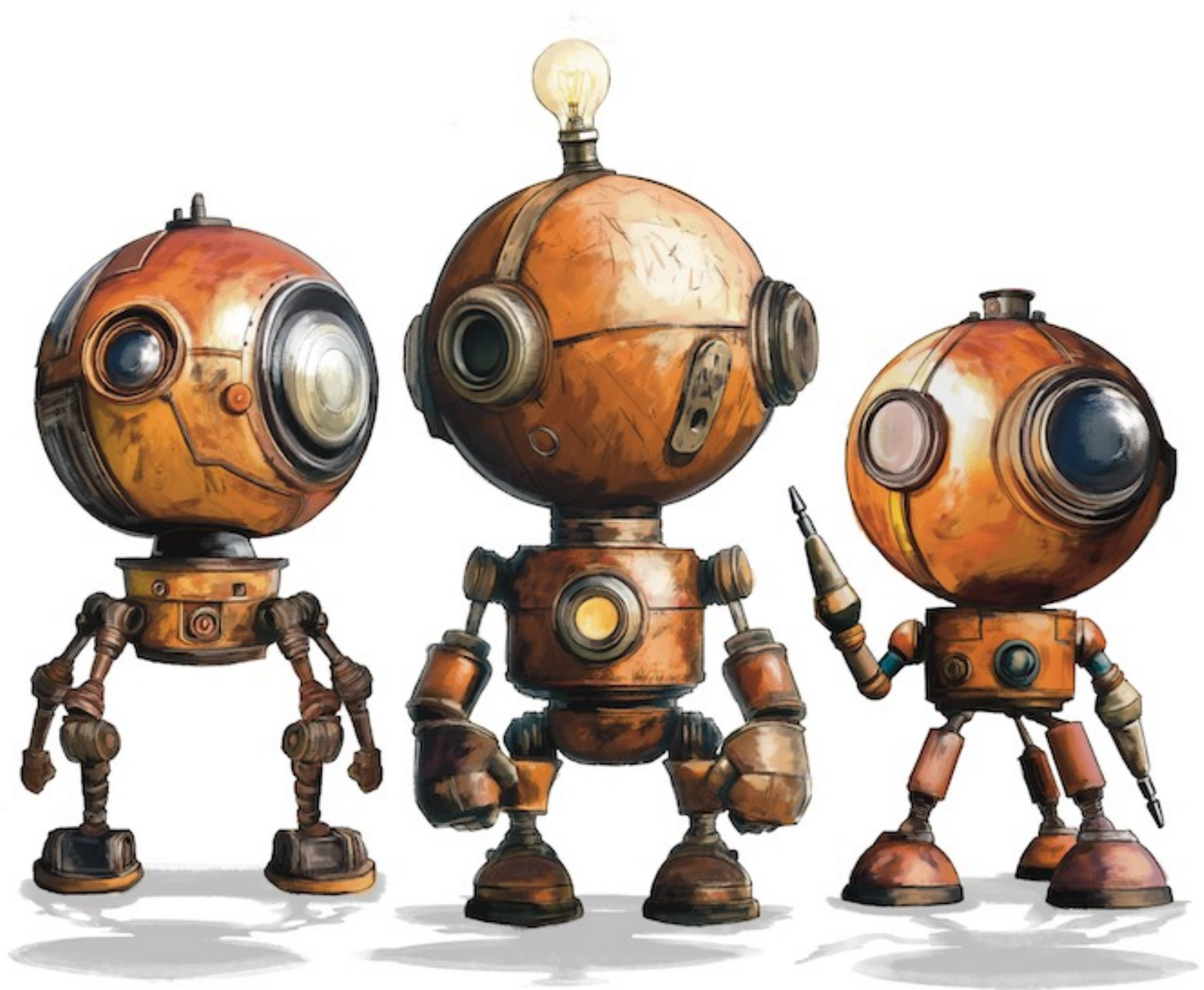
CS 3630



Introduction to Robotic Systems

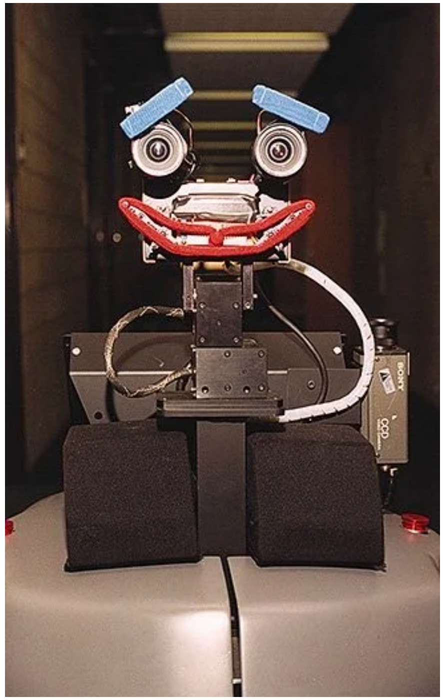
A Taxonomy of Robotics Topics

For each module in this class, we'll consider six distinct aspects of robotics:

1. **State:** How does the robot represent its world, and itself?
2. **Actions:** What can the robot do, and how to represent this?
3. **Sensors:** What information about the world can be ascertained via sensing, and how do we model this process?
4. **Perception:** How can we combine sensor data with contextual knowledge to understand the current state?
5. **Planning:** What actions should the robot execute to transform the state of the world into a desired goal state?
6. **Learning:** How can the robot improve its knowledge over time, using information that it acquires during operation?

Each chapter of the book includes seven sections, corresponding to these 6 topics, and a summary.

Robots in the real world



For specific applications, these topics correspond to specific problems that robots must solve to operate effectively.

For example, a museum guide robot:

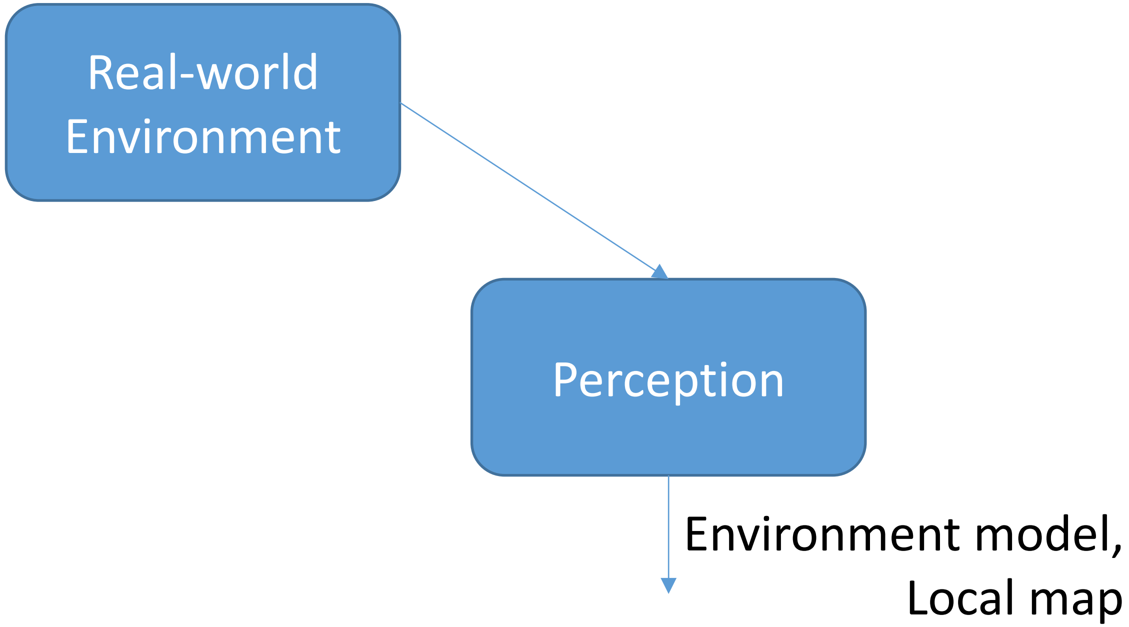
- State: where is the robot, and where are the humans to be guided?
- Actions: move from room to room
- Sensors: cameras
- Perception: use computer vision to understand human intention, and to localize
- Planning: what path to take in order to guide humans to their desired exhibit
- Learning: which parts of the museum are crowded, and when to avoid these?

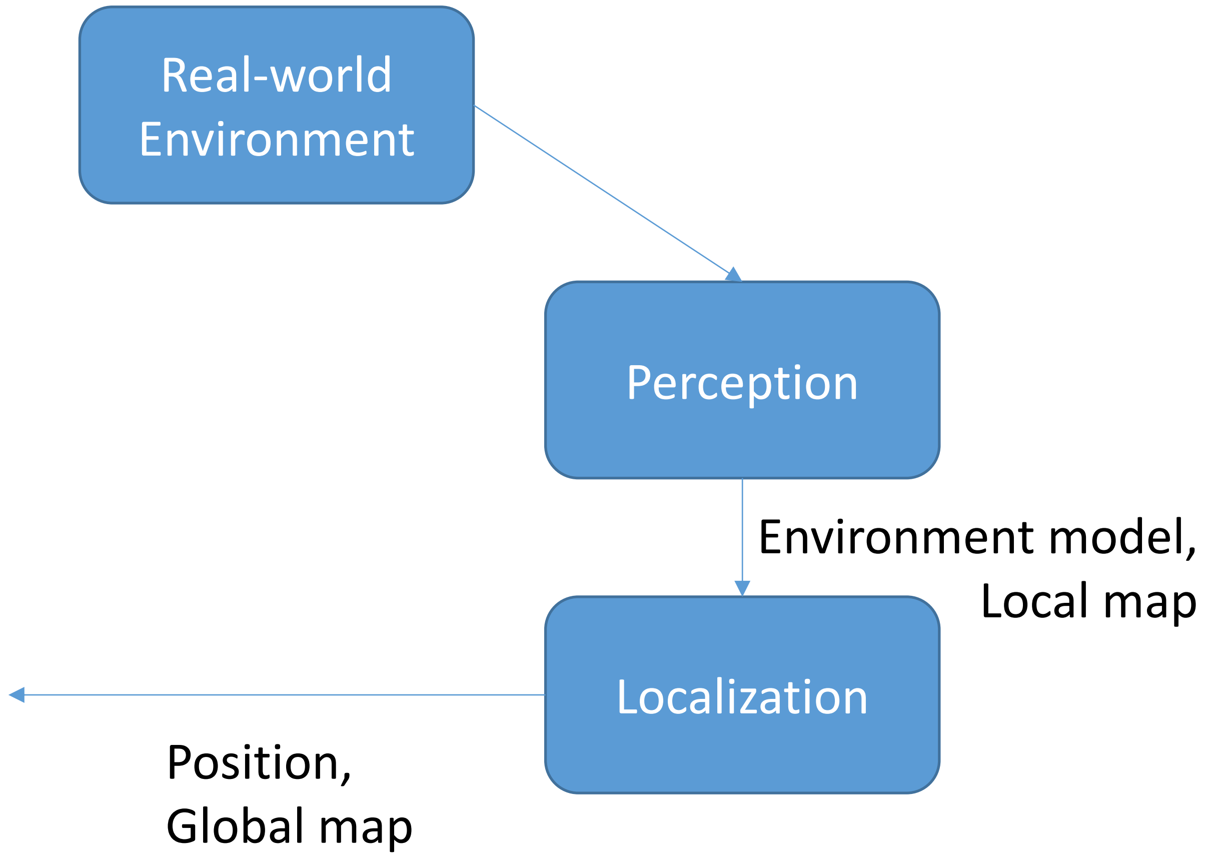
How do robots function in the world

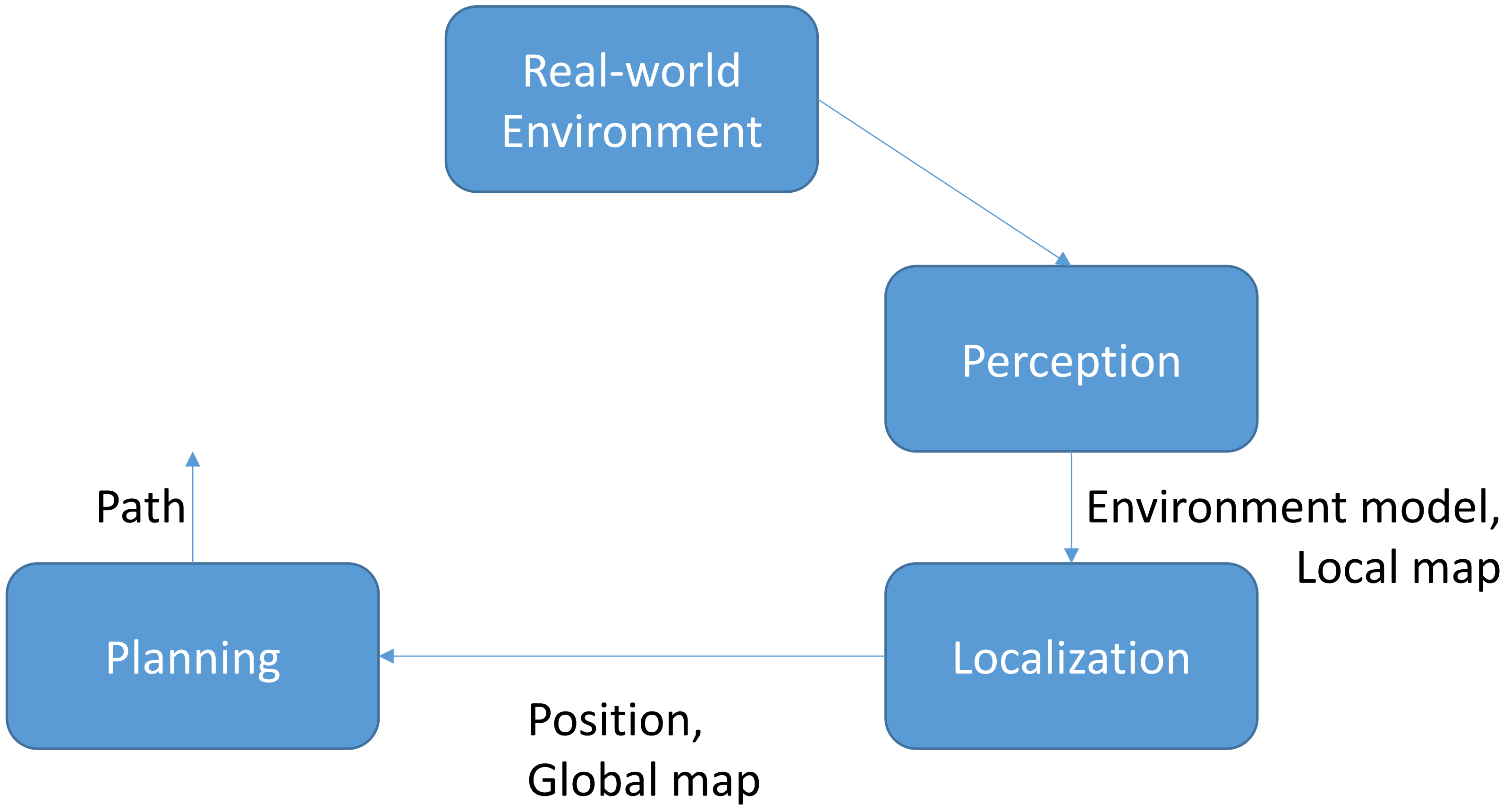
When they are deployed in the world, most robots use the so-called ***Sense-Think-Act*** paradigm of operation.

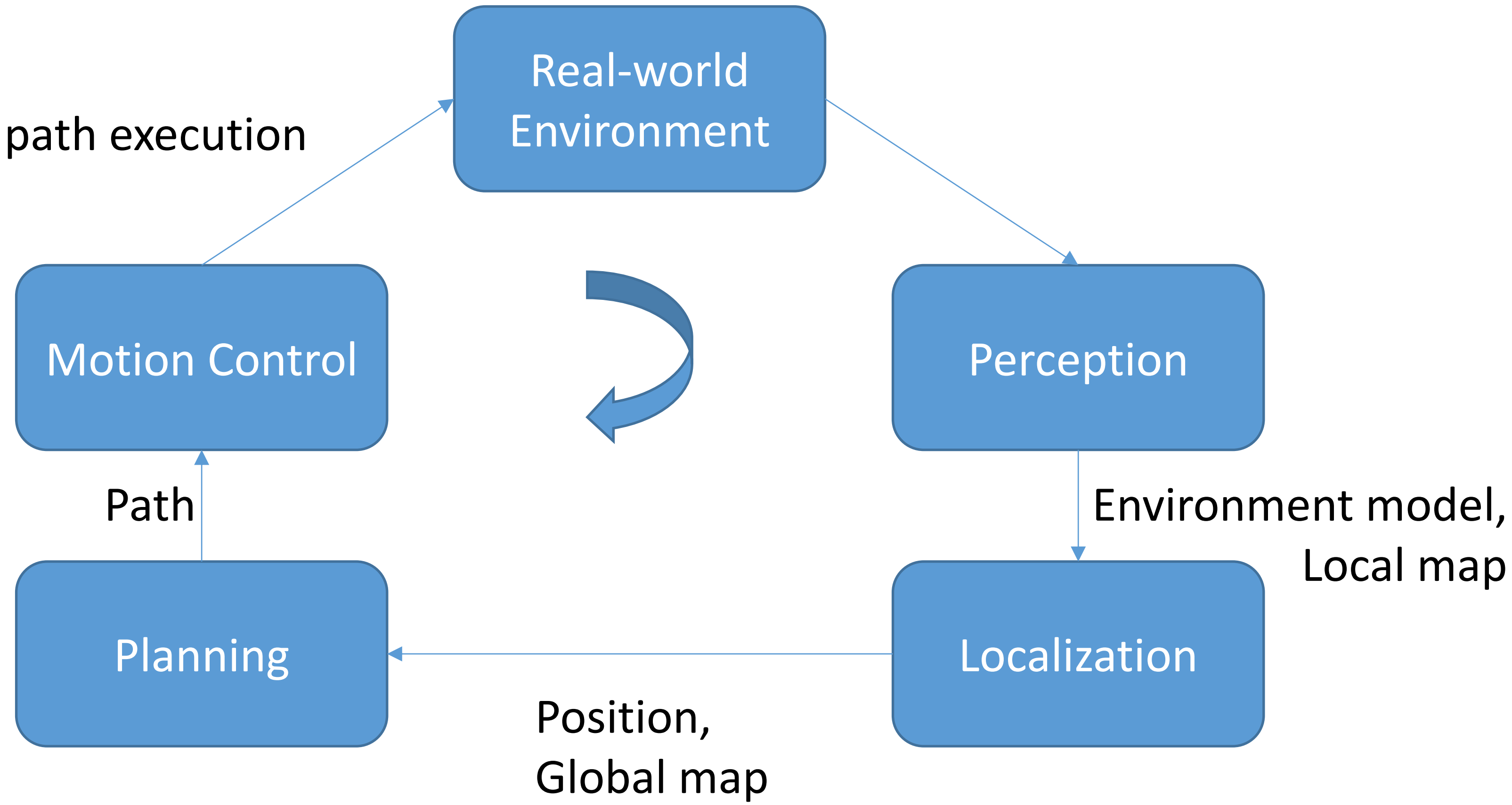
This can be viewed as an overall control structure, in which state, actions, sensors, perception, planning, and learning play specific roles.

Real-world
Environment


Real-world Environment
Perception
Environment model,
Local map


Real-world
Environment
Perception
Environment model,
Local map
Localization
Position,
Global map


Real-world
Environment
Perception
Environment model,
Local map
Localization
Position,
Global map
Planning
Path


Real-world Environment
Perception
Environment model,
Local map
Localization
Position,
Global map
Planning
Path
Motion Control
path execution

Sense, Think, Act

Suppose you are given a task: *Rearrange the chairs in the room into a circle.* How would you proceed?

1. Look around the room and evaluate the situation.
   Where are the chairs? How many chairs are there?
2. Make a plan:
   1. Go the first chair, pick it up, place it in the desired position
   2. Repeat for all N chairs.
3. Execute the plan.

This is the basic strategy followed by almost all robots.

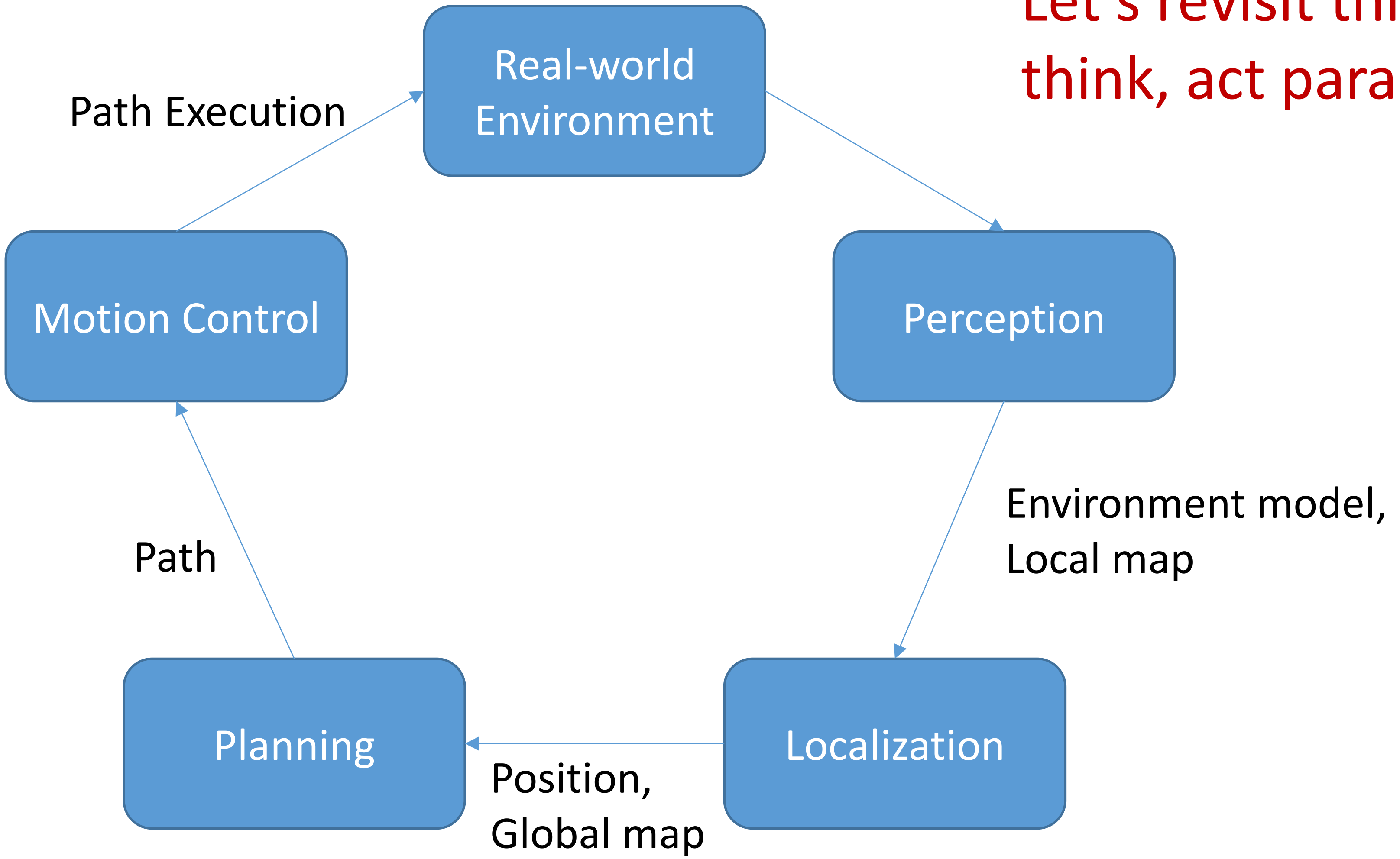
Sense, Think, Act

Suppose you are given a task: *Rearrange the chairs in the room into a circle.* How would you proceed?

1. Look around the room and evaluate the situation. Where are the chairs? How many chairs are there?	Sense
2. Make a plan: 1. Go the first chair, pick it up, place it in the desired position 2. Repeat for all N chairs.	Think
3. Execute the plan.	Act

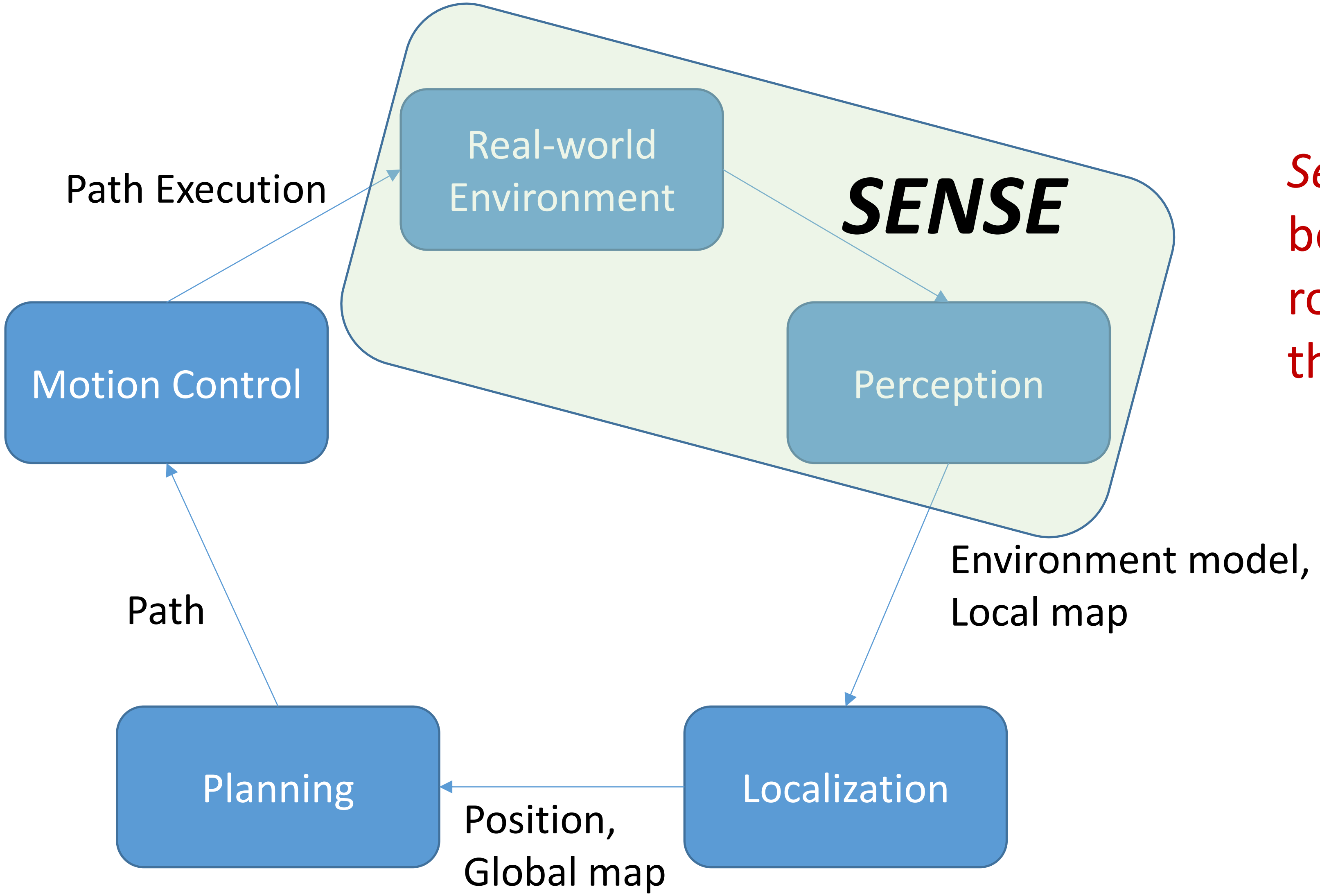
This is the basic strategy followed by almost all robots.

Example: Navigation in a Known Environment



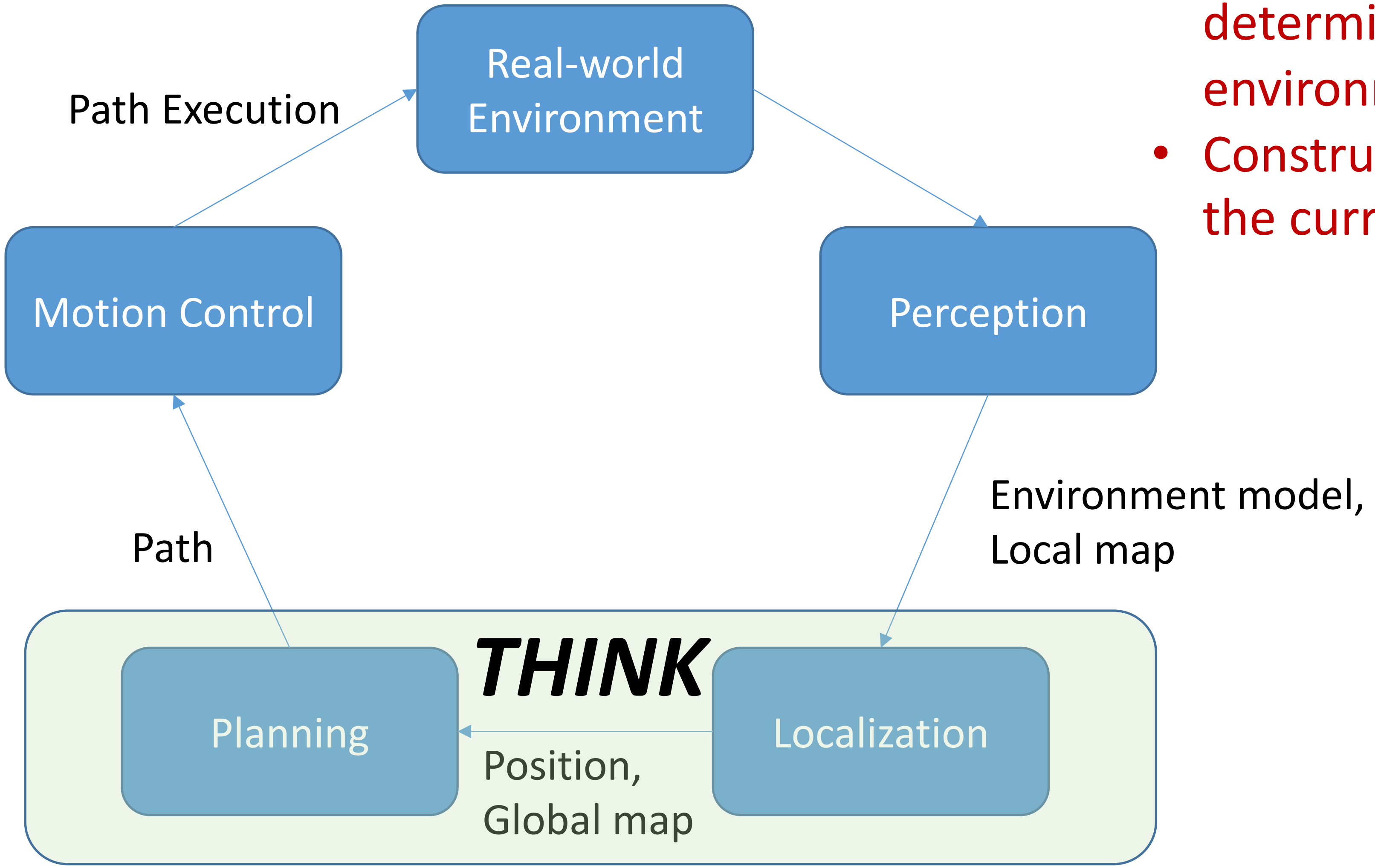
Let's revisit this in terms of the sense, think, act paradigm.

Example: Navigation in a Known Environment



Sensing provides a connection between the real world and the robot's internal representation of the world.

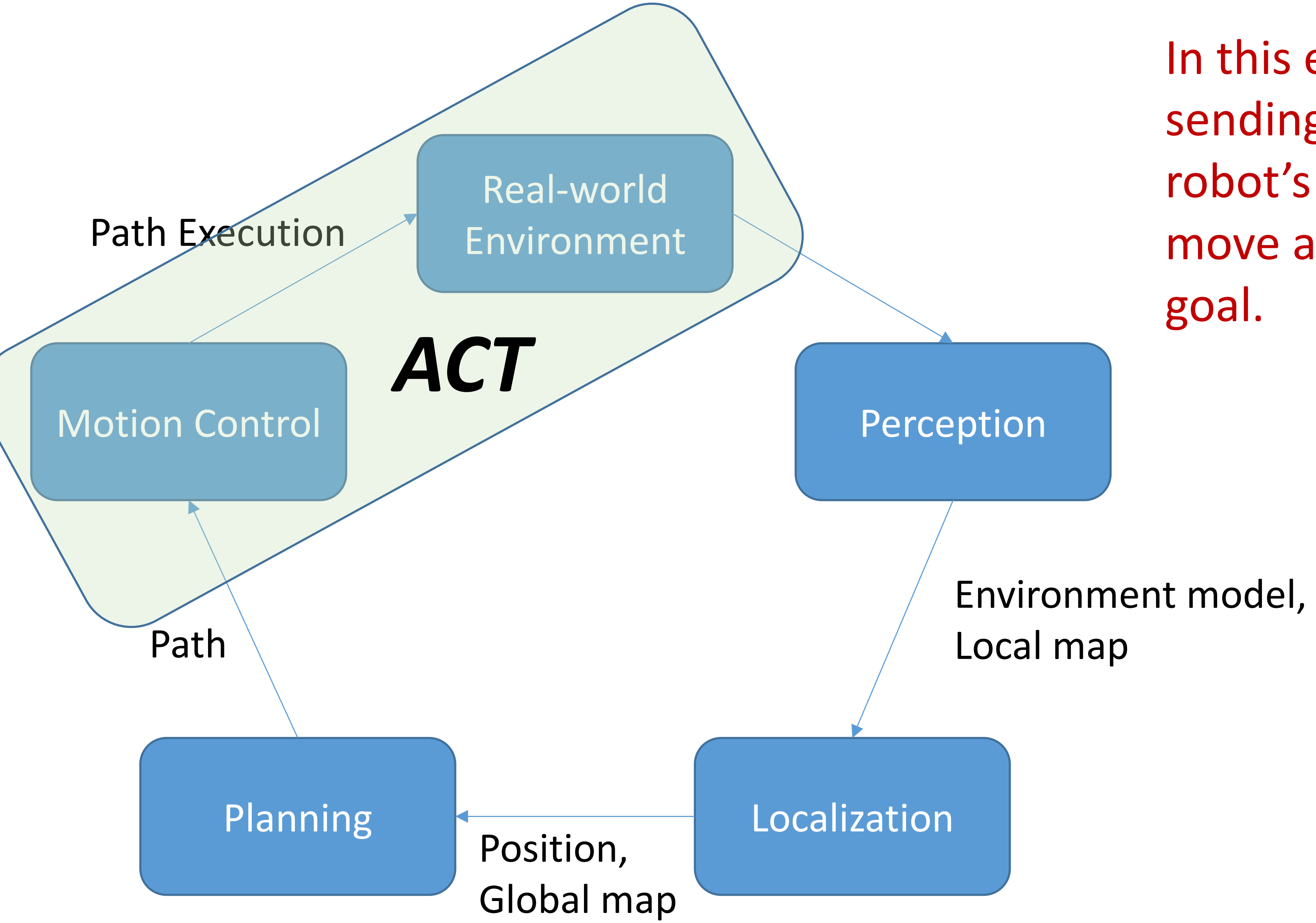
Example: Navigation in a Known Environment



In this example, *thinking* involves:

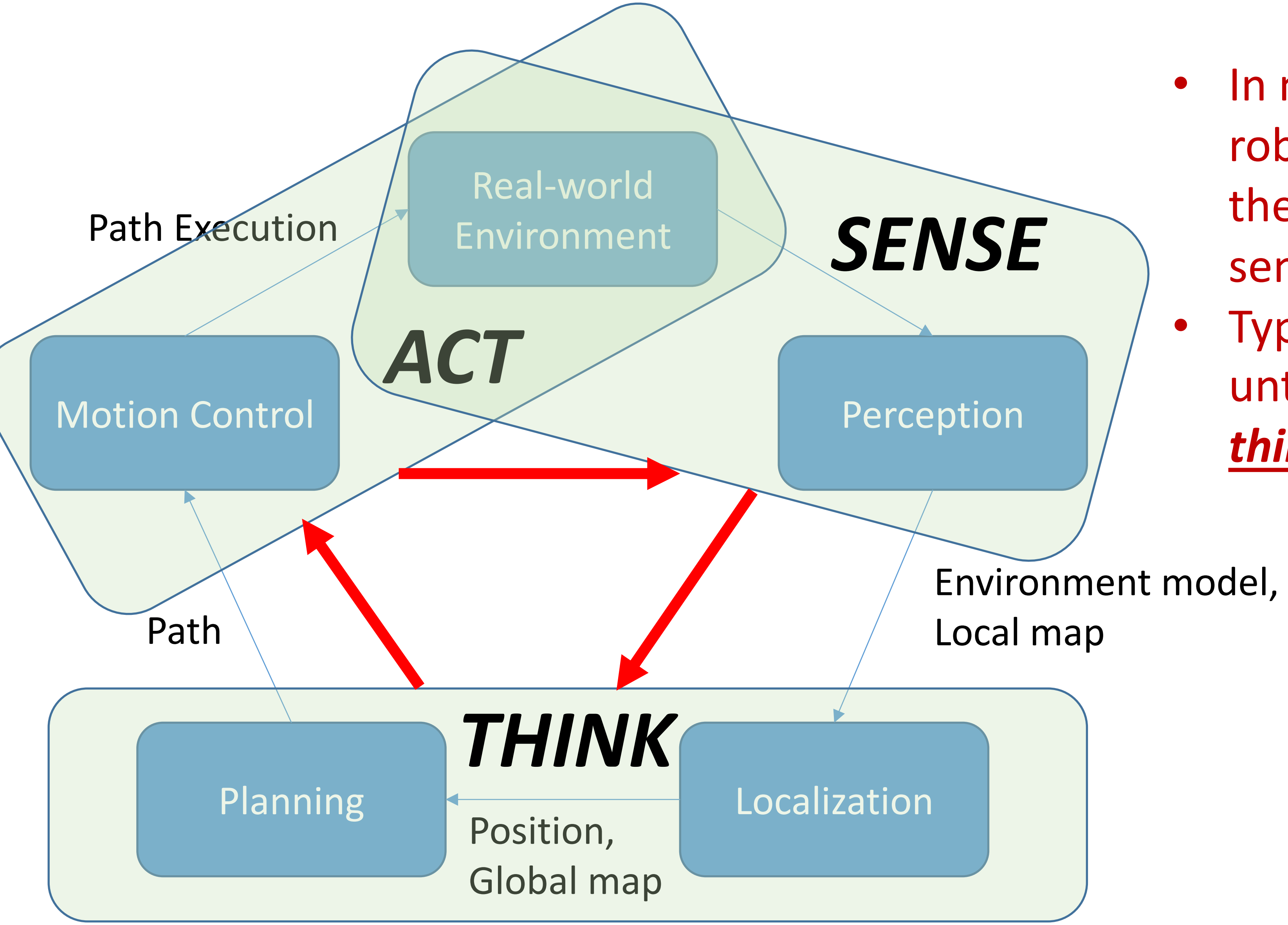
- Processing perceptual information to determine the position of the robot in its environment
- Constructing a motion plan to move from the current position to the goal position.

Example: Navigation in a Known Environment



In this example, *acting* involves sending motion commands to the robot's motors, so that the robot will move along the desired path to its goal.

Example: Navigation in a Known Environment

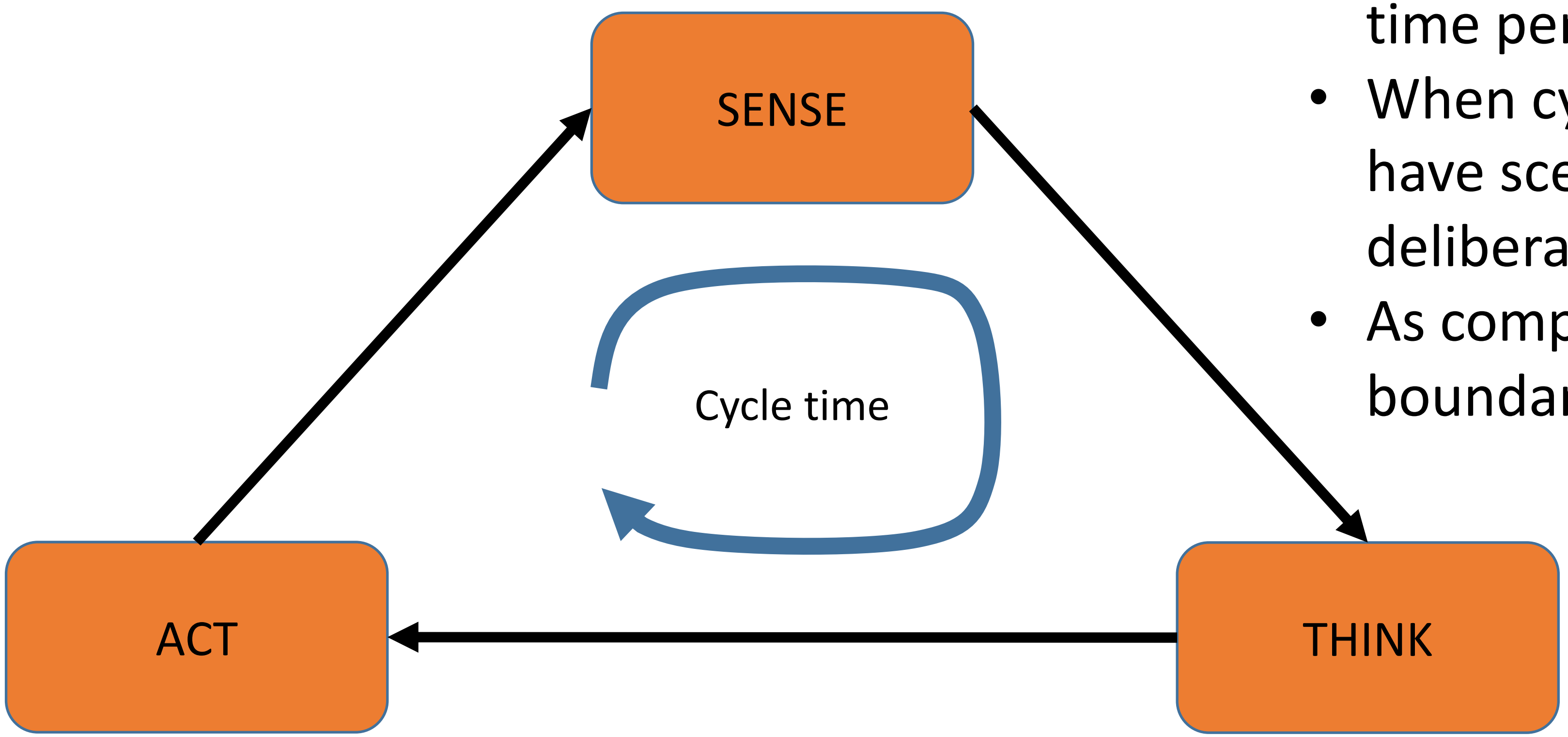


- In most robotics applications, the robot does not succeed to perform the task using a single episode of sense, think, act.
- Typically, these stages are repeated until the task is achieved: the ***sense, think, act loop.***

Sense, Think, Act at Different Time Scales

The time to complete one cycle of this loop depends on the task:

- Playing chess: minutes
- Hand-eye coordination: 30 Hz
- Force controlled robot: Order of KHz



- When cycle time is very fast, we use tools from control theory, and model systems using differential equations (continuous time performance).
- When cycle time is very slow, we might have scene understanding and deliberative planning.
- As computers become faster, the boundary between these begins to blur.

State

Representing the Robot and the World

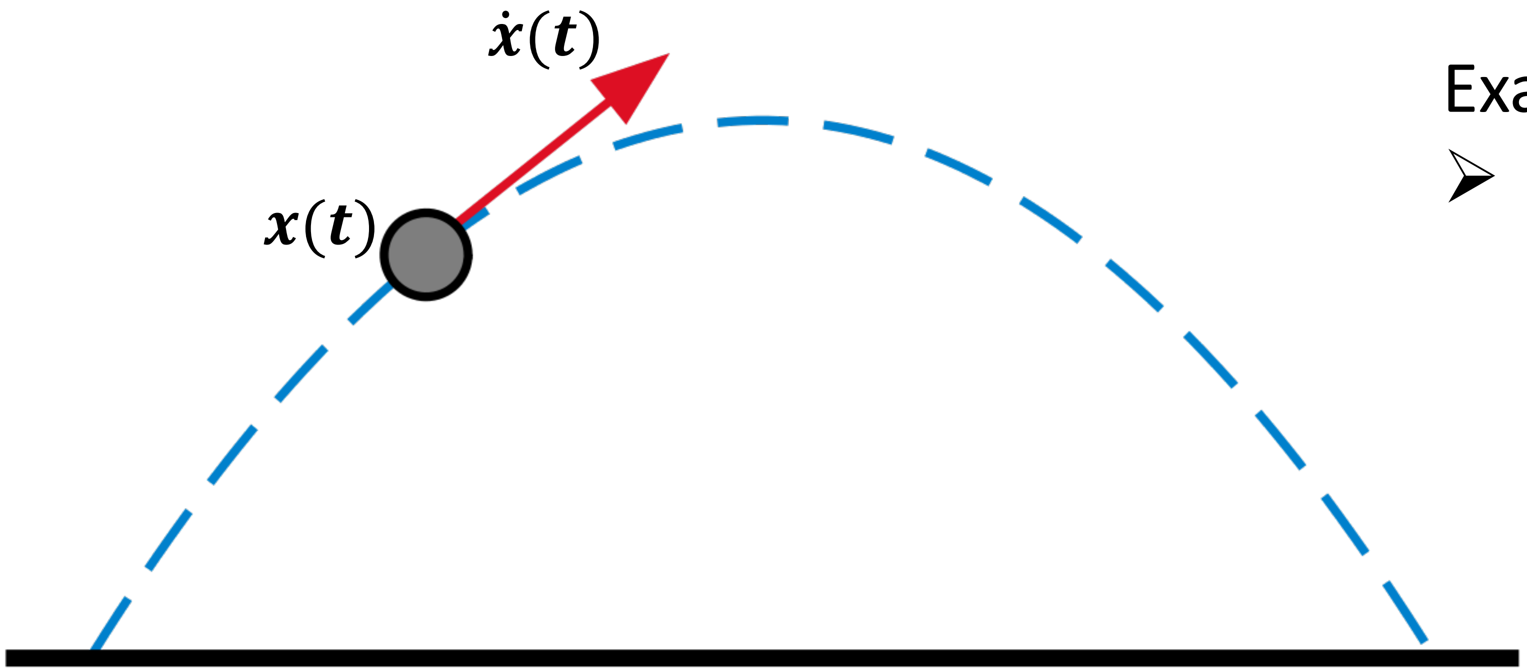
- Perception has the responsibility of converting sensor measurements into a representation of the world and of the robot’s current situation.
- Planning uses these representations to reason about the effects of actions in the world.

These representations define the robot’s ***state***, and the world ***state***.

State

The term ***state*** is used in the study of dynamical systems to describe the relevant aspects of an objects motion.

If we know the state x at time t_0 along with the system input for all $t \geq t_0$, then we can predict the state at all future times.



Example:

- If we know the position and velocity of a projectile at a given time, we can compute its entire trajectory.

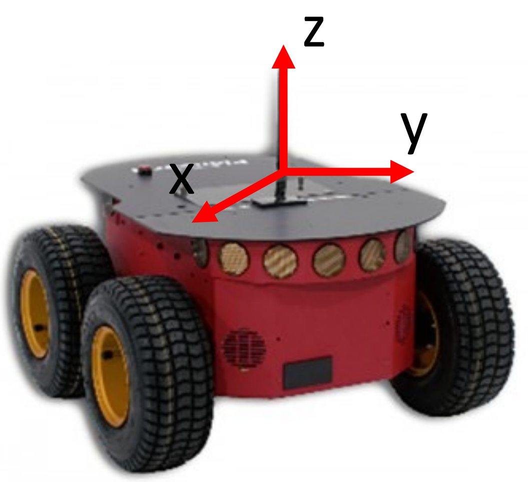
Geometric Representations

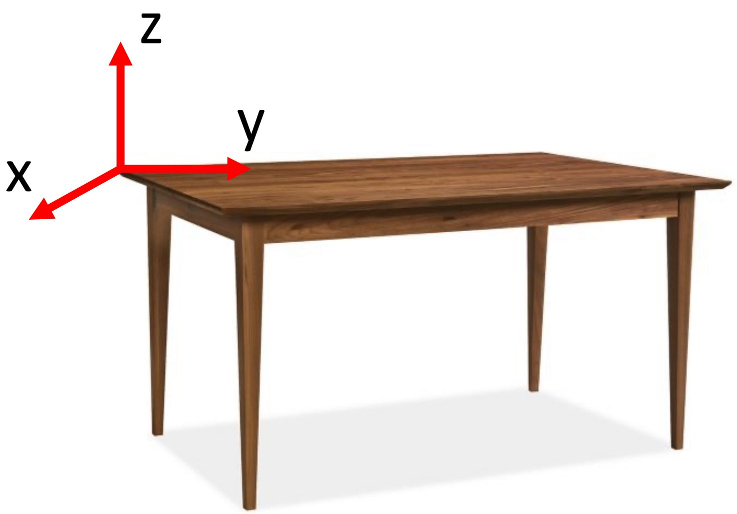
In robotics, we often require specific geometric information.

To describe an object's position:

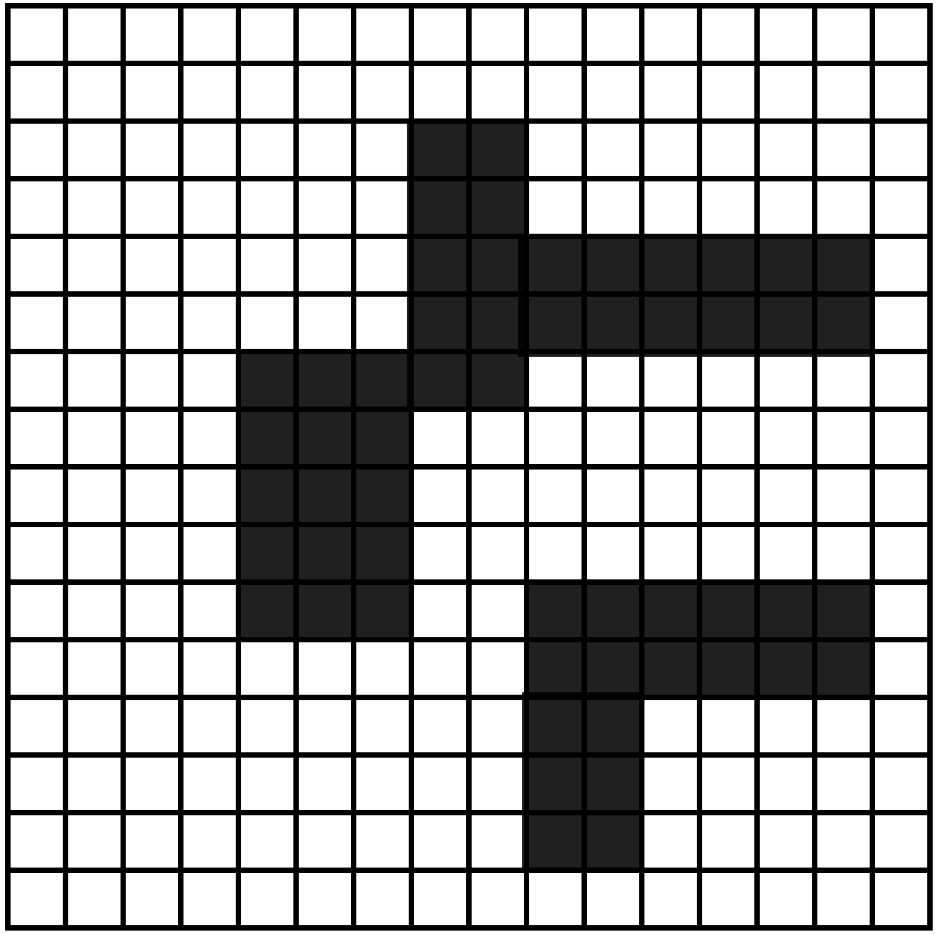
- Attach a coordinate frame to the object (rigidly attach frame to the object)
- Specify the position and orientation of the coordinate frame.

If we know this information, we know everything about the object's position!





Grid World



- For many mobile robotics applications, one can represent the world as a grid.
- The robot state is defined by its current grid cell location.
- Each grid cell is either free or occupied by an obstacle (world state).
- There are many variations, e.g., assign to each cell in the grid a *probability* that it is occupied by an obstacle.

Symbolic Representations

For high-level task planning, it is often sufficient to represent the world using symbolic descriptions.

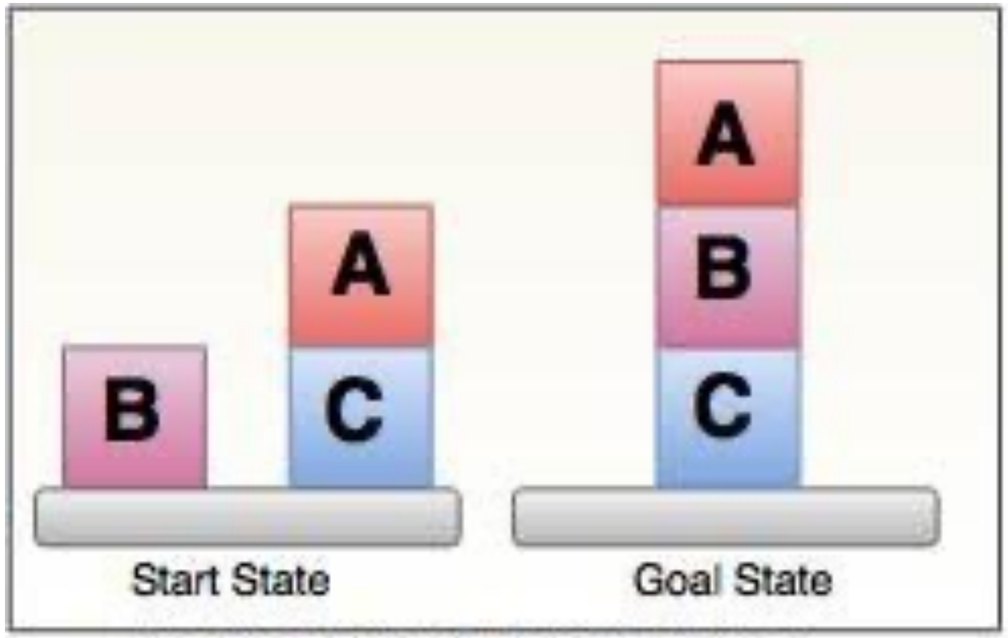


Fig: Blocks-World Planning Problem

Representation of Blocks World using simple predicates

Initial State:

- On(table,B)
- On(table,C)
- On(A,C)
- Clear(B)
- Clear(A)

Goal State:

- On(table,C)
- On(A,B)
- On(B,C)
- Clear(A)

Actions and Planning

High-Level Planning

A high-level planner uses a symbolic representation of actions:

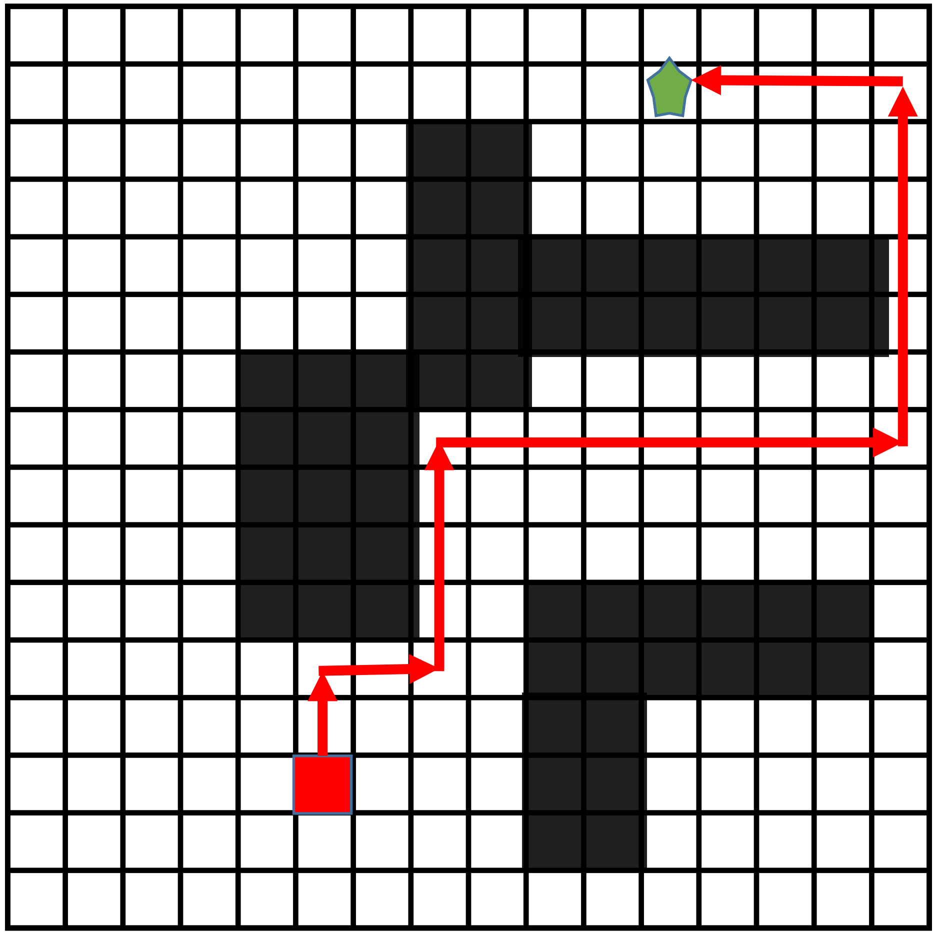
- Preconditions: what must be true in the world before the action is applied?
- Effects: what changes occur in the world after the action occurs?

Pickup(?X):
  Preconditions: Gripper(empty)
  Effects: Gripper(full), Holding(?X)

If the goal is to be holding Block B, the planner can instantiate the variable ?X to B

Pickup(B):
  Preconditions: Gripper(empty)
  Effects: Gripper(full), Holding(B)

Grid World: Path Planning

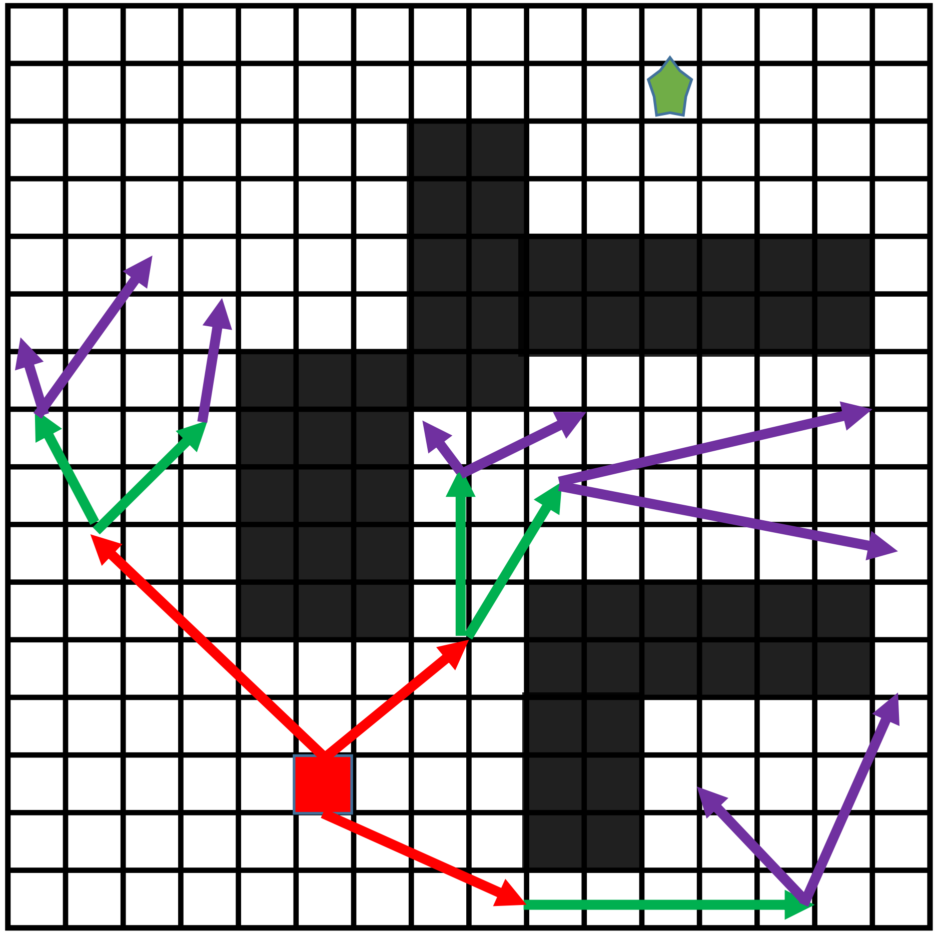


Actions: move to an adjacent cell

The path planning problem is to find a free path from start to goal.

- How can we effectively find any path from start to goal?
- How should we decide which path to take?

Grid World



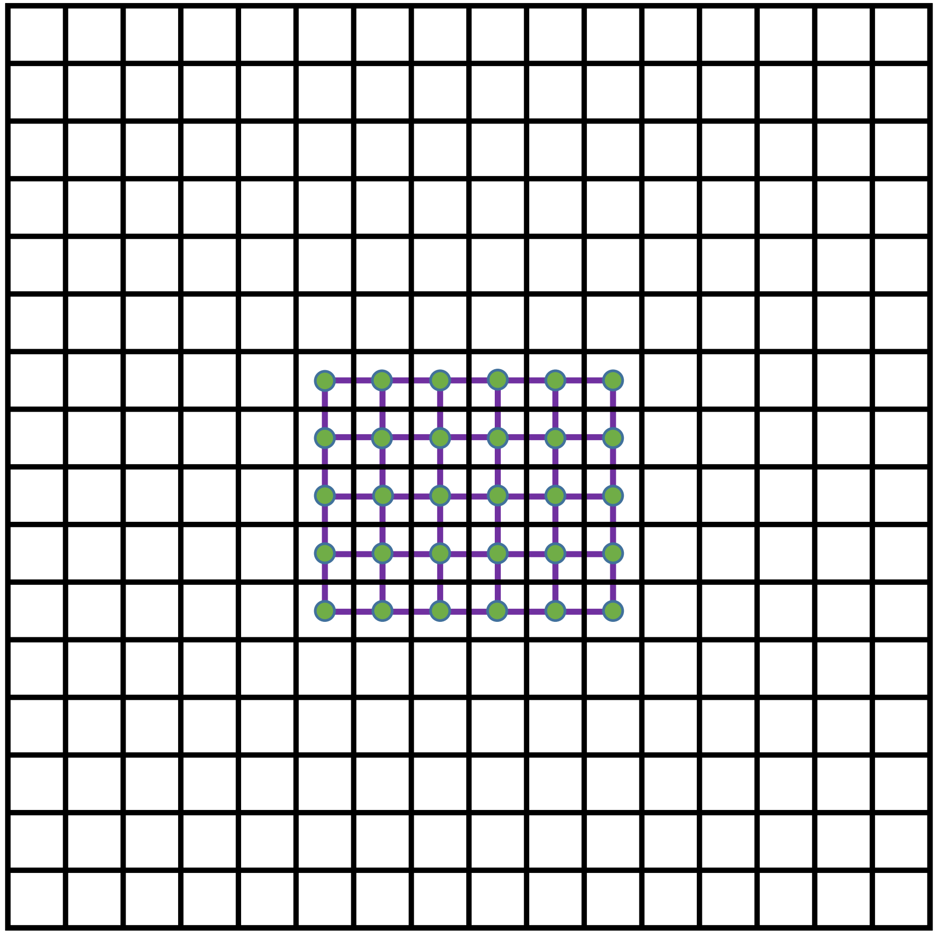
 **Start position**

 **Goal position**

One strategy is to systematically explore various possible solution paths.

This raises the question:
What strategies should we use to explore alternative paths?

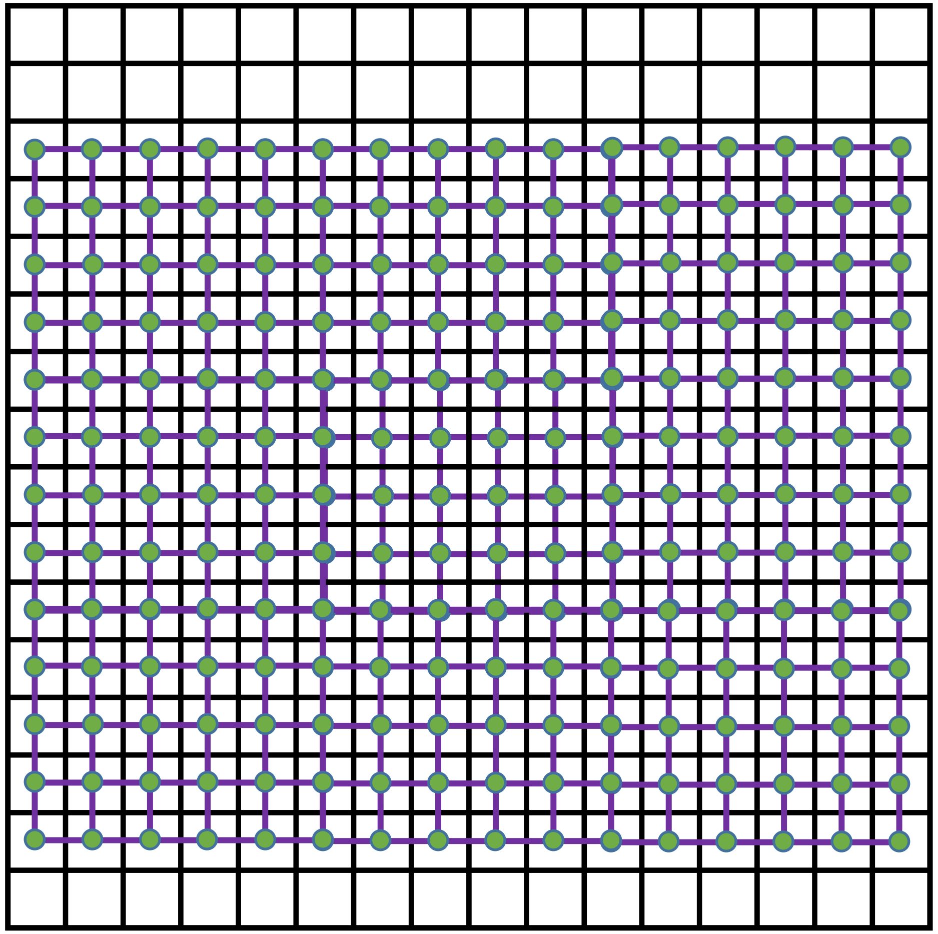
Grid World



A grid can be represented as a graph:

- Each cell in the grid corresponds to a vertex in the graph
- Vertices that correspond to adjacent grid cells are connected by an edge.

Grid World



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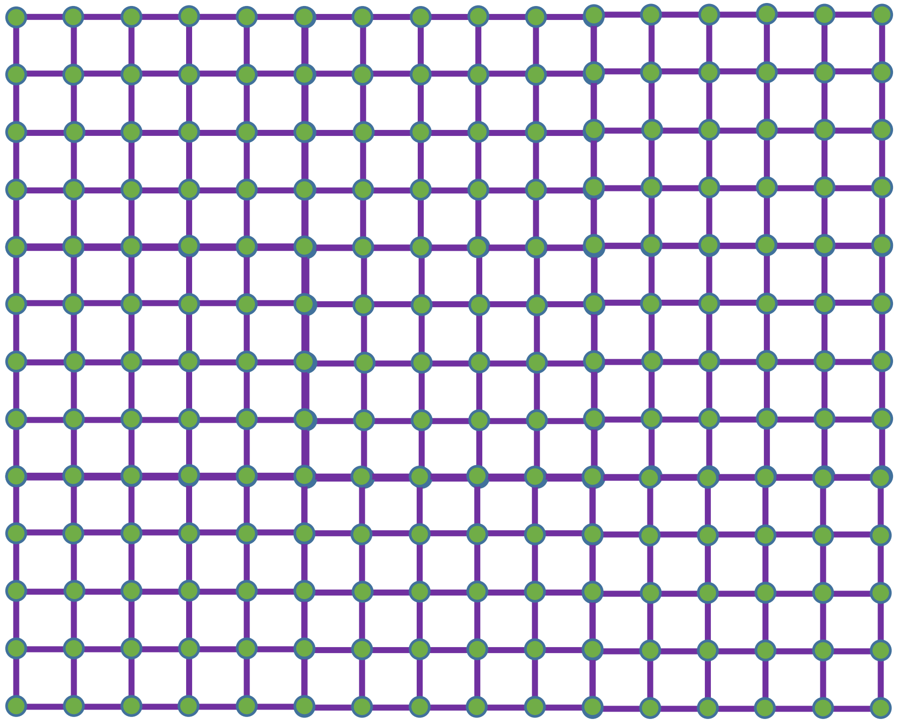
Grid World

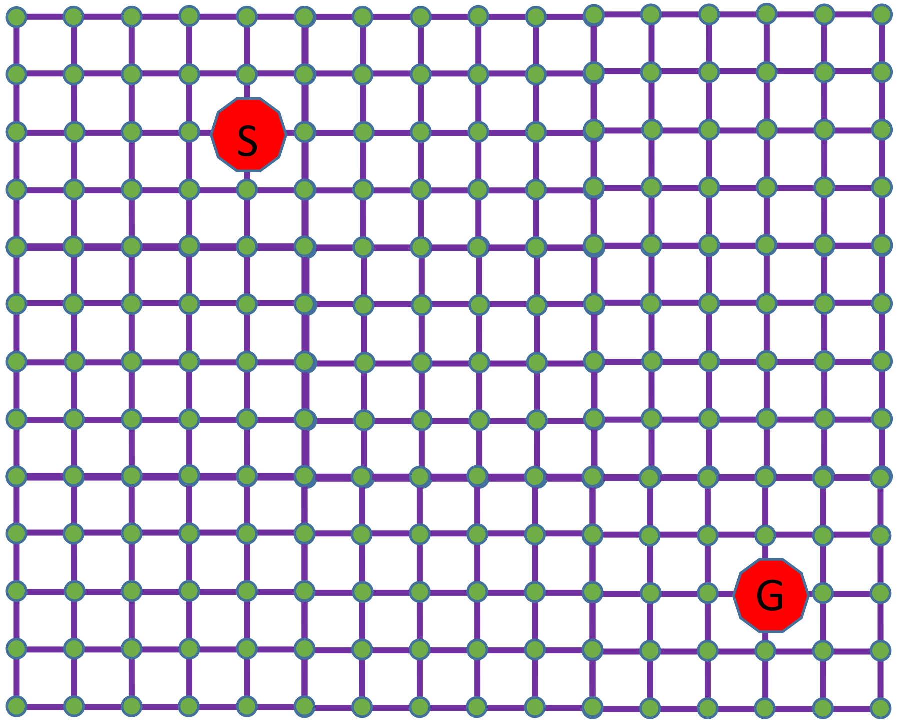


A grid can be represented as a graph:

- Each cell in the grid corresponds to a vertex in the graph
- Vertices that correspond to adjacent grid cells are connected by an edge.

And now, we can use graph search algorithms to find a path!

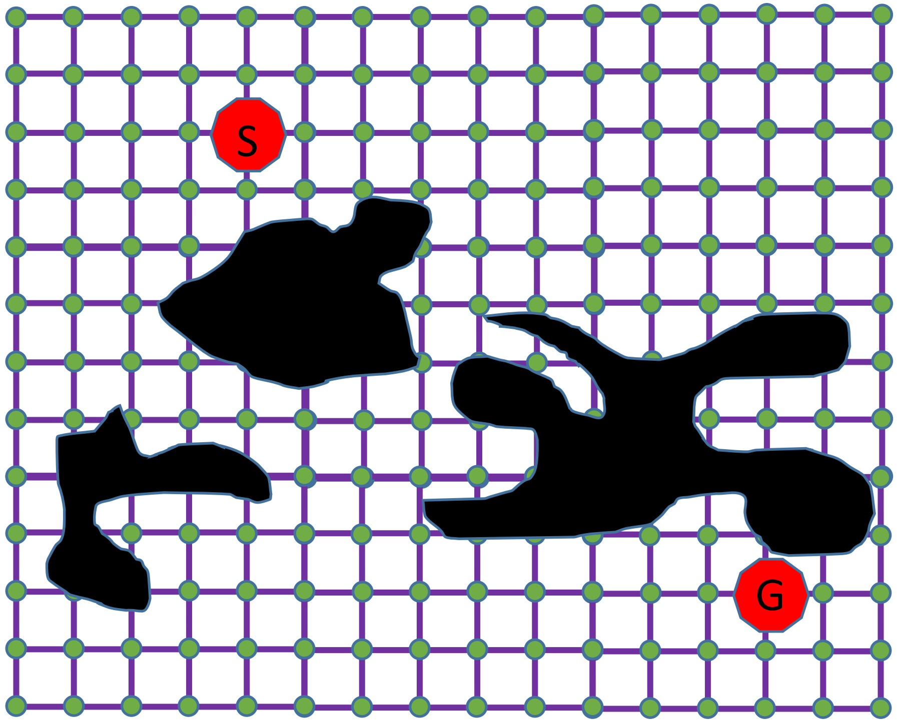
Grid World



Define a Starting state and a Goal state, and use your favorite graph search algorithm to find a path.

When there are no obstacles, it’s easy.

Grid World

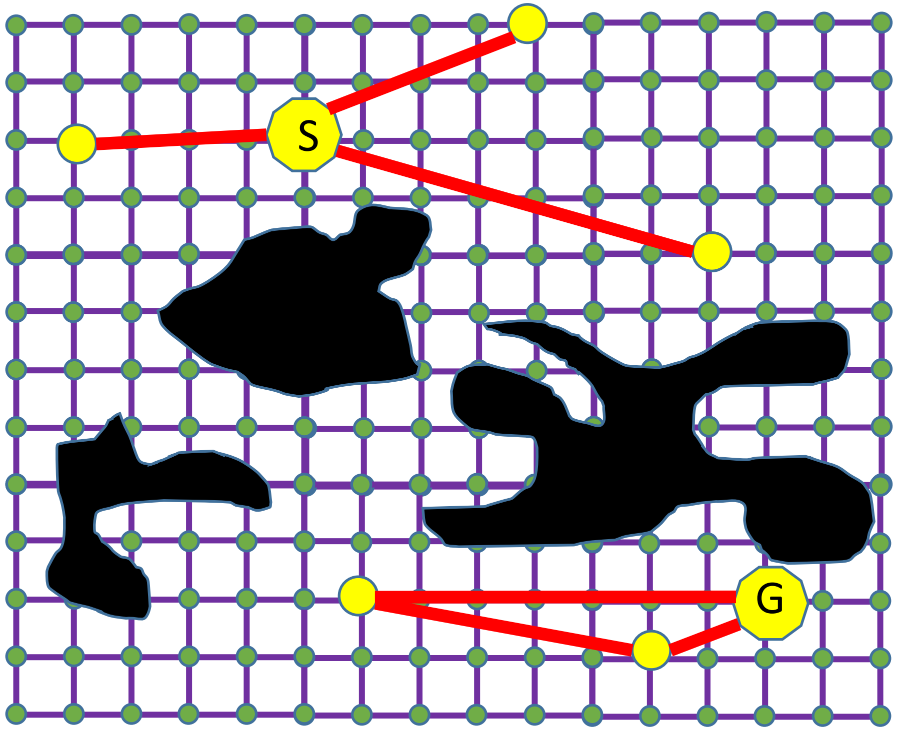


Define a Starting state and a Goal state, and use your favorite graph search algorithm to find a path.

When there are no obstacles, it's easy.

When there are obstacles, it becomes (only) slightly more difficult.

Sampling-based algorithms



- Don't build the entire grid a priori.
- Build the grid incrementally by generating random grid samples.
- Connect near-by samples when a collision-free path exists.
- No need for paths to stay on the grid.
- Stop sampling when we can find a path that satisfies the problem

Planning under uncertainty

- For many robotics applications, the world state is not known with certainty.
- In such cases, we use **probability theory** to characterize uncertainty.
- Planning typically involves maximizing some reward, or minimizing some cost, on average, over many trials.
- If we don’t know the relevant probabilities, we can often apply machine learning techniques to develop good estimates for these.
- Planning can look like: optimization, theorem proving (logic), geometry, stochastic control, optimal control, etc. – depending on the problem to be solved, the representation of state, and the nature of uncertainties.

Sensing and Perception

Some Sensors

Pan-Tilt Camera

Intel’s RealSense
Depth Camera

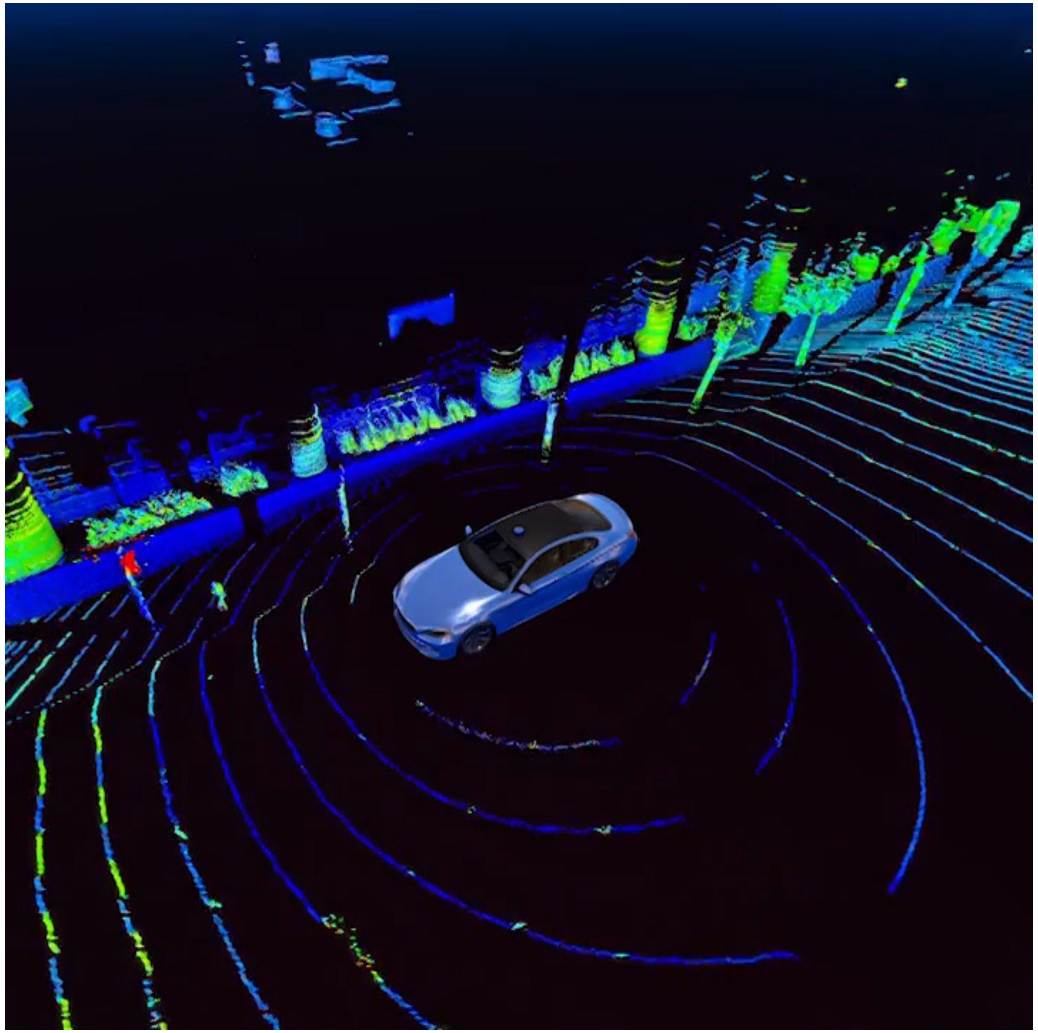
Velodyne LIDAR

LIDAR

LIght Detection And Ranging
aka Laser Scanning
aka 3D scanning

1. Emit light wave pulse
2. Measure time to return
3. Compute distance

Do this a few million times per second, and voila!



Perception

- Sensor readings are subject to noise and other errors.
- Sensor readings alone are not sufficient to reconstruct the state of the world:
  - A depth sensor reads 10m… what does that imply about the world?
  - Along a corridor there are many office doors. How can we know where we are when all doors look the same?
- Perception uses contextual information (e.g., maps, other sensor readings) to reason about state using sensor data as input.
- Bayesian inference is a key tool for this.

Learning

Machine Learning

- Maybe the hottest topic in robotics, and all of AI, today.
- Many methods have been developed:
  - Simple parameter estimation.
  - Reinforcement Learning (RL)
  - Deep Learning (using convolutional neural nets)
  - Deep RL
  - Transformer-based methods (super-hot!)

We won’t go into great depth with ML, but we’ll look at a few methods for specific cases.