15-494/694: Cognitive Robotics

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Lecture 4:

Advanced State Machine Concepts, and Introduction to Particle Filters

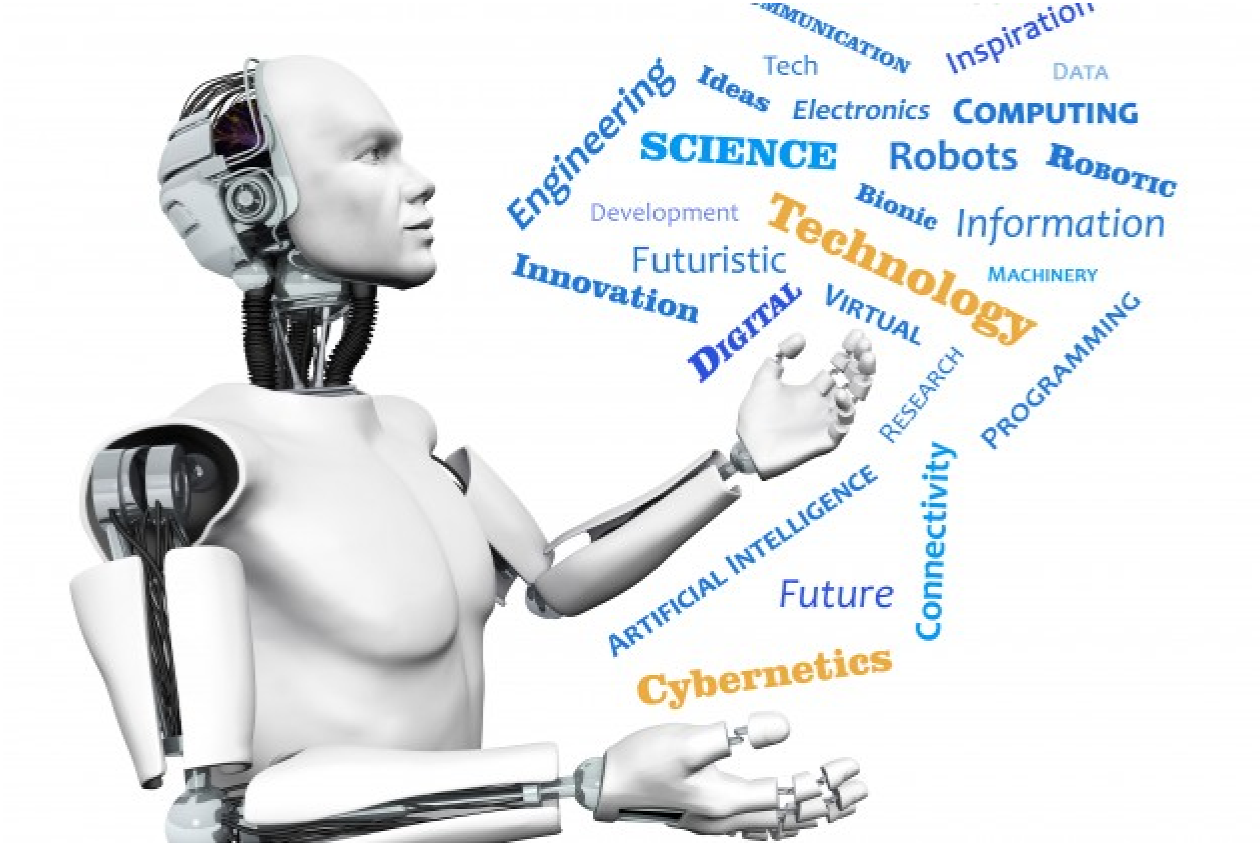


Image from http://www.futuristgerd.com/2015/09/10

Differences From Classical FSMs

1. **Multi-State:**
   – Multiple states can be active simultaneously (fork), and their completions can be synchronized (join).

2. **Hierarchical:**
   – State machines can nest.

3. **Message Passing:**
   – One state can send a message to another as part of a transition firing.

More On Hierarchy

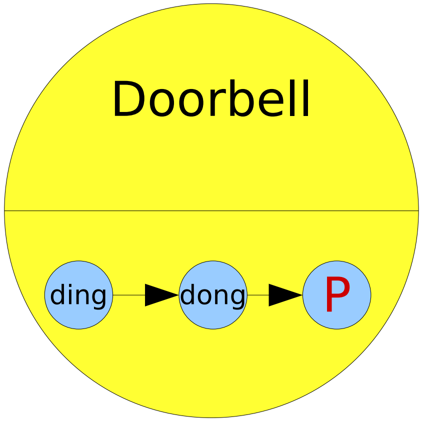
- A nested state machine is started automatically when its parent node starts.
- The nested machine can cause its parent to signal *completion* by:
  - Transitioning to a `ParentCompletes` node
  - Calling `self.parent.post_completion()` from inside one of its nodes.
- Similarly for signaling parent *success* or *failure*: ParentSucceeds or ParentFails.

Nested State Machines

Doorbell has an empty start() method,
but it has a setup() method.

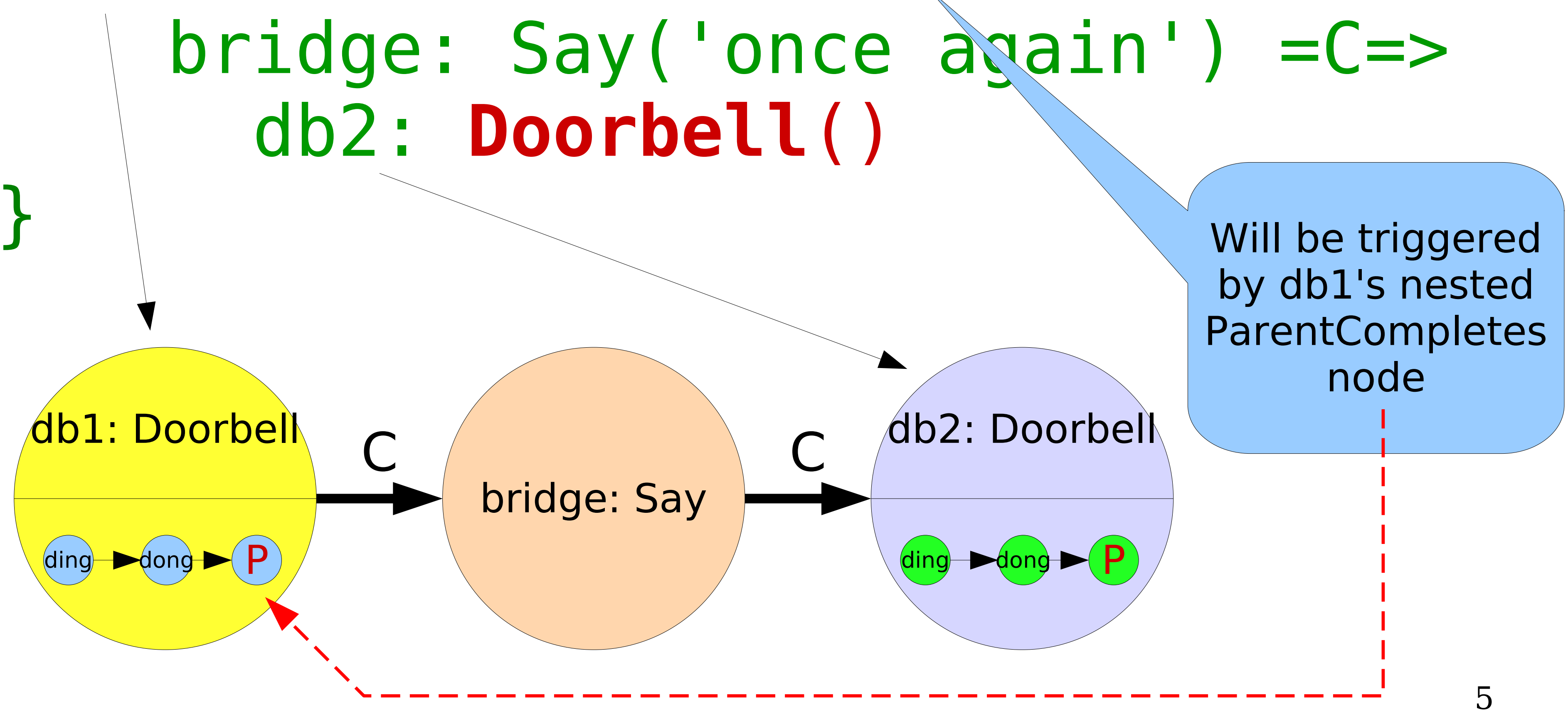
```
class Doorbell(StateNode):
  $setup {
    ding: Say('ding') =C=>
      dong: Say('dong') =C=>
        ParentCompletes()

  }
```



Nested State Machines

```
class Nested(StateMachineProgram):
  $setup {
    db1: Doorbell() =C=>
      bridge: Say('once again') =C=>
        db2: Doorbell()
  }
```



Message Passing

- Nodes can signal “data events” that data transitions look for:

```
self.post_data(5)
```

- Transitions can match the data item:

```
foo =D(5)=> draw_pentagram
foo =D(6)=> draw_hexagram
```

- Transitions can also do wildcard match:

```
foo =D=> draw_stuff
```

Pattern Matching in =D()=>

- You can specify a type in a data transition to match any data item of that type:

  =D(int)=>

- You can specify a regular expression and do pattern matching on string data:

  =D(re.compile('subtract \d+$'))=>

Message Passing (cont.)

- When an event-dependent transition activates a node, the node's start method is passed the event that triggered the transition.

- If this was a DataEvent, the start method can extract the data item and process it.

Sending Data

```
class Sender(StateNode):

    def start(self, event=None):
        super().start(event)
        value = random.random()
        self.post_data(value)
```

Receiving Data

```
class Receiver(StateNode):

  def start(self, event=None):
    super().start(event)
    if isinstance(event, DataEvent):
      value = event.data
      print('Value received:', value)
```

Sending and Receiving

```
class SendRecv(StateMachineProgram):
  $setup{
    Sender() =D=> Receiver()
  }
```

```
C> runfsm('SendRecv')
Value received: 0.380313711
```

Iteration

```
class IterDemo(StateMachineProgram):
  $setup{
    loop: Iterate(4)
    loop =D=> Print() =Next=> loop
    loop =C=> Print('Done!')
  }
```

Prints the data received from a DataEvent

Use =CNext=> instead of =Next=> to wait for completion.

Default Transitions

For data events and text message events, value matches take priority over defaults.

```
foo =TM('cat')=> Say('meow')
foo =TM('dog')=> Say('woof')
foo =TM=> Say('wacka-wacka')
```

How does this work? Default (wildcard) transitions have a slight time delay to allow any matching value transition to fire first.

The Event Loop

- While the SDK is connected to the robot and simple_cli is running, the value of `asyncio.get_event_loop()` is available in `robot.loop`.

- From simple_cli, in order to run a node we have to schedule it via this event loop.

- This is what the now() method does:

```
Forward(50).now()
```

Do It "Now"

```
class StateNode(EventListener):
  ...
  def now(self):
    self.robot.loop.
        call_soon(self.start)
```

EventListener

- EventListener is the parent class of both StateNode and Transition.
- Includes a polling feature: an instance can request that its poll() method be called every *t* seconds.
- Polling begins when the instance's start() method is called and ends when stop() is called.

Uses of Polling

- TimerTrans uses the polling interval to know when to fire.

- ArucoTrans uses polling to check if an Aruco marker has appeared in the camera image.

Named Transitions

- A complex state machine may have a lot of CompletionTrans, SuccessTrans, and TimerTrans transitions.
- This makes the trace confusing: what is `completiontrans5` doing?
- Solution: assign meaningful names to your transitions.

```
try_grab =grabbed:C=> open_it
try_grab =fumbled:F=> reposition
```

Writing Your Own Transitions

- Rarely necessary, unless you're developing new robot functionality.

- How to do it:
  - __init__() to store constructor parameters.
  - start() to subscribe to events if needed.
  - handle_event() to examine the events and call self.fire(event) if needed.
  - poll() if polling is needed.

InRange Transition

```
class InRange(DataTrans):
  def __init__(self, min_x, max_x):
    super().__init__()
    self.min_x = min_x
    self.max_x = max_x

  def handle_event(self, event):
    val = event.data
    if isinstance(val, (int,float)) and
        self.min_x <= val <= self.max_x:
      self.fire(event)
```

FilterNum.fsm

```
class FilterNum(StateMachineProgram):
  $setup {
    gen: GenerateNumber()
    gen =InRange(-inf,68)=> Say(‘cold’)
    gen =InRange(68,74)=> Say('good')
    gen =InRange(74,inf)=> Say(‘hot’)
  }
```

State Machine Misconceptions

What *not* to do when writing a state machine program.

Don’t Call SDK Actions Directly

```
class Forward75(StateNode):
    def start(self, event=None):
        super().start(event)
        self.robot.robot0.move_for(75, 0)
        self.post_completion()
```

This bypasses all the FSM machinery for keeping track of running actions and generating completion events.

Read the code for Forward in nodes.py to see how the Forward node actually works.

Do Use Subclass To Modify An Action’s Behavior

```
class Forward75(Forward):
    def __init__(self, **kwargs):
        super().__init__(**kwargs)
        self.distance_mm = 75
```

Don’t Try to Call Node Constructors in the Body of a start() Method

```
class TriangleLeg(StateNode):
    def start(self, event=None):
        Forward(50)
        Turn(120).now()
        self.parent.post_completion()
```

Do Use the State Machine Language

```
class TriangleLeg(StateNode):
  $setup {
      Forward(50) =C=> Turn(120) =C=>
          ParentCompletes()
  }
```

Constructors Are Only Called Once

Node constructors are only called once, when the state machine is being set up, not when the state machine is executing.

```
$setup {
   Turn(robot.pose.theta/2*180/pi)
}
```

This is not the robot's pose at the time the node is started; it's the pose at the time the node was created. See next slide for how to do it right.

Do Put Dynamic Logic in start()

```
class TurnMore(Turn):
    def start(self, event=None):
        heading = self.robot.pose.theta
        self.angle_deg = heading/2*180/pi
        super().start(event)
```

Bad Style: Spaghetti Code

```
$setup {
    rock: Say(“rock”)
    turn: Turn(180)
    and_roll: Say(“and roll”)

    rock =C=> turn =C=> and_roll
    turn =Hear(“go”)=> and_roll
}
```

Proper Style: Group Each Node’s Creation and Outgoing Transitions Together

```
$setup {
    rock: Say(“rock”) =C=> turn

    turn: Turn(180)
    turn =C=> and_roll
    turn =Head(“go”)=> and_roll

    and_roll: Say(“and roll”)
}
```

Follow Naming Conventions

1) Class names must begin with a capital letter.

2) Node labels in state machines should be lowercase.

3) The name of the StateMachineProgram class must match the name of the .fsm file.

simple_cli 'show' commands

- show active
  - Shows the currently active nodes and transitions.
- show objects
  - Shows the worldmap contents
- show pose
  - Shows the robot’s pose

Particle Filters

Intro to Particle Filters

- Odometry is unreliable.
  - Still useful for short trajectories.
  - But error inevitably accumulates.

- Solution: use visual landmarks to correct for odometry error.

- But vision is unreliable too!
  - Landmark pose estimation is noisy.
  - Landmarks aren't always available.

Probabilistic Robotics

- Probabilistic robotics is based on the idea that we should embrace the noisiness.
- Instead of discrete values, think in terms of *probability distributions*.
- Robot's location is not (x,y), but a *distribution* of possible locations, some more likely than others.

Modeling Location Distributions

- Particle filters are a way to model distributions.
- Think of each particle as a “guess” (hypothesis) about the robot's location.
- Assume we have a map with landmarks.
- Each guess predicts how the landmarks should look from that location.

Modeling Location Distributions

- Particles representing good guesses will accurately predict the landmark locations.
  - Good predictions earn a high weight.

- Bad guesses lead to poor predictions.
  - Poor predictions result in a low weight.

- As we accumulate sensor data, we can figure out which particles are the good guesses.

Particle Filter Demos

- particle_filter_demo is linked from the class schedule and can be found in the Class/demos directory.
- It shows the robot wandering in a maze; walls are landmarks.
- The estimated location (white or green circle) is the average of all the particles.
- pfdemo.py is another demo you can try.

Resampling

- Bad guesses are a waste of resources.
- When we've accumulated enough data, we can generate a new set of particles to try to concentrate resources in the region of good guesses.
- Particles with high scores are chosen to spawn new particles.
- Low-scoring particles are unlikely to spawn.

Motion Model

- So far we have a robot that is standing still, receiving sensor data, and trying to figure out its location on the map.

- But the robot needs to move.
  - Stationary robots aren't useful.
  - Motion allows the robot to see more landmarks.

Motion Model (cont.)

- How can we accommodate motion?
- Solution:
  - As the robot moves, drag the particles along with it.
- But odometry is noisy!
  - Add noise (via a motion model) to the particle locations because we know that motion is unreliable, so our estimates become less and less certain.

SLAM

- What if we don't have a world map?
- SLAM: Simultaneous Localization And Mapping.
- Now each particle represents a slightly different map of the world, plus the robot's estimated location on that map.
- We will look at this in the next lecture.