15-494/694: Cognitive Robotics

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Lecture 4:

Advanced State Machine Concepts, and Introduction to Particle Filters

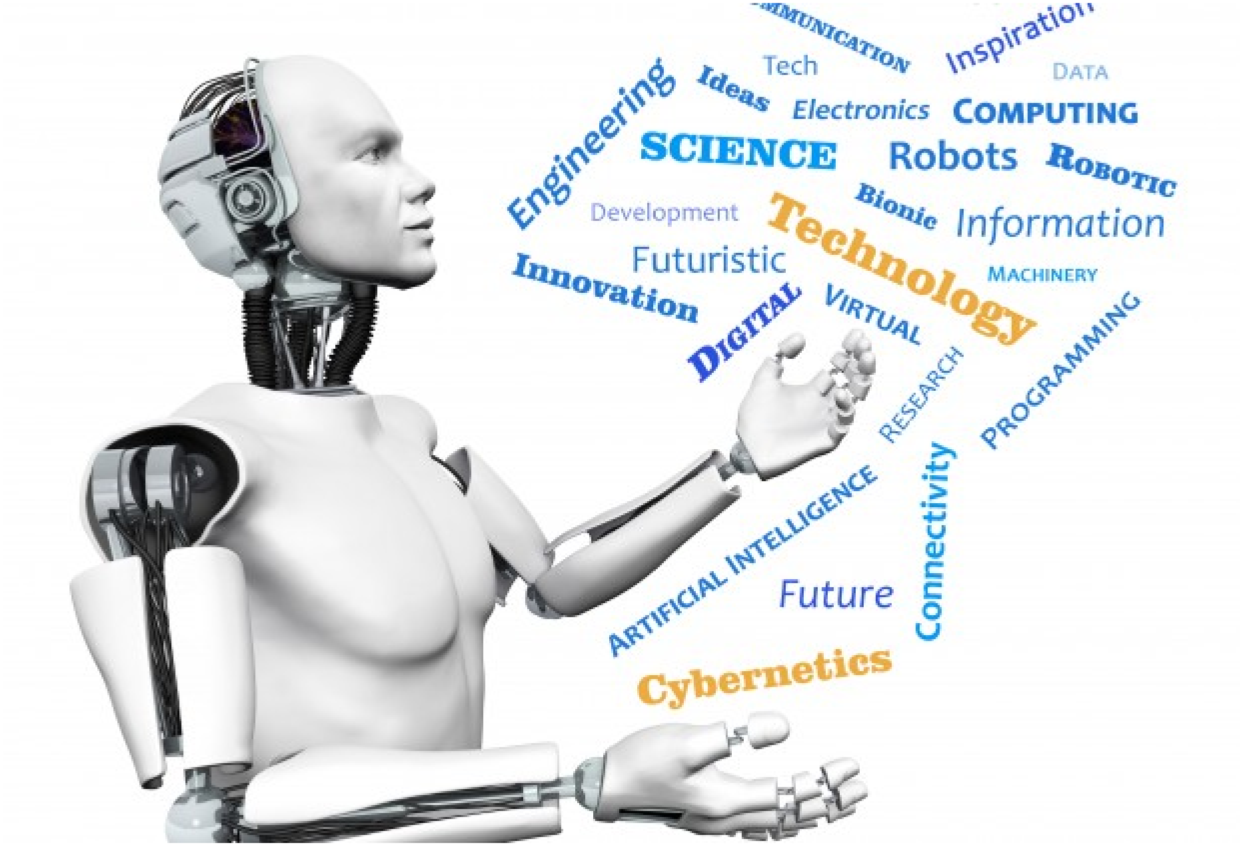


Image from http://www.futuristgerd.com/2015/09/10

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

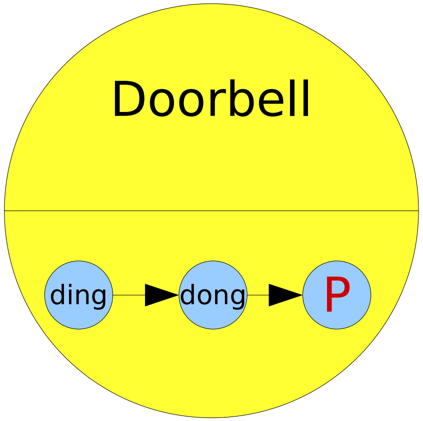
- A nested state machine is started automatically when its parent node starts.
- The nested machine can cause its parent to signal *completion* by:
  - Transitioning to a `ParentCompletes` node
  - Calling `self.parent.post_completion()` from inside one of its nodes.
- Similarly for signaling parent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

Nested State Machines

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

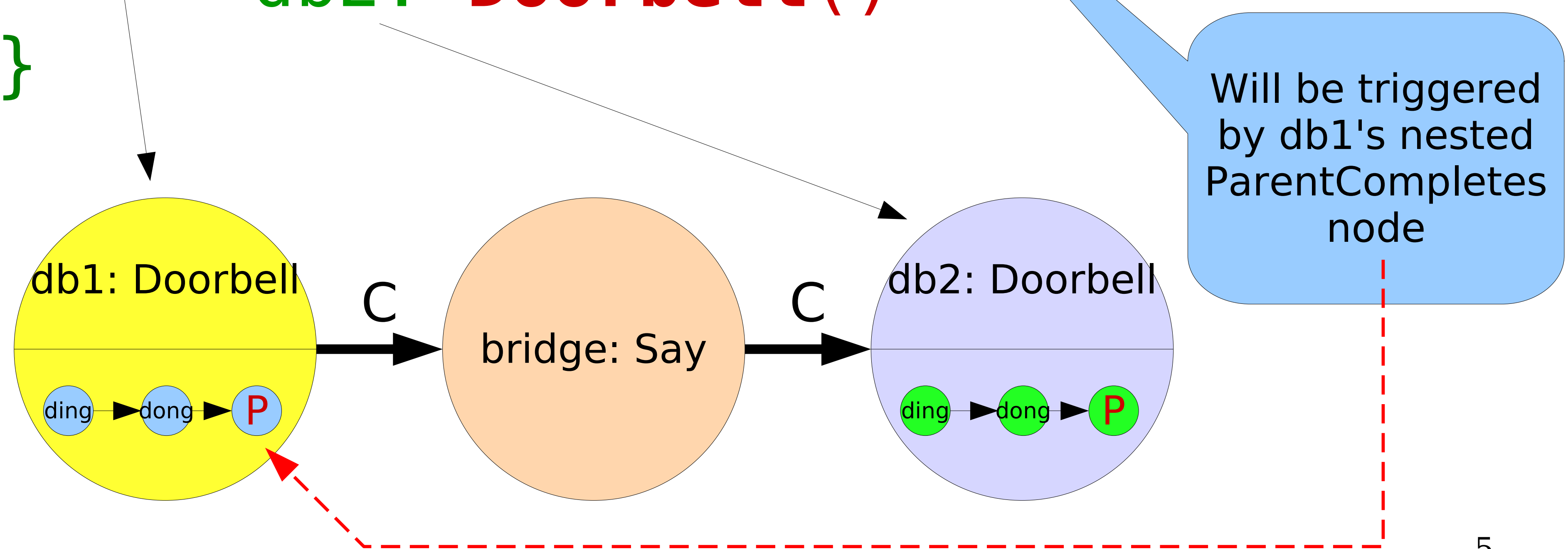
```
class Doorbell(StateNode):
  $setup {
    ding: Say('ding') =C=>
      dong: Say('dong') =C=>
        ParentCompletes()

  }
```



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
```

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.

Tap Events

- The SDK generates tap events when someone taps on a cube.
- We turn these into cozmo_fsm TapEvents that can be matched by a =Tap=> transition:

```
=Tap(cube2)=>
=Tap=>
```

- We need to check the tap intensity to reject false positives.

Face Events

- The SDK generates face events whenever a face is detected in the camera image.
- We turn these into cozmo_fsm FaceEvents that can be matched by a =Face=> transition:

```
=Face('Dave')=>
=Face=>
```

- Should probably provide separate cases for FaceAppeared and FacePresent.

The Event Loop

- While the SDK is connected to the robot and simple_cli is running, the value of `asyncio.get_current_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

- 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

- DriveForward and DriveTurn use polling to check the robot's progress and decide when to stop.
- TimerTrans uses the polling interval to know when to fire.
- ArucoTrans uses polling to check if a marker has appeared in the camera image.

Animation and Trigger Nodes

- Animation nodes take an animation name as a string argument. There are over 900 to choose from.

```
AnimationNode('anim_bored_01')
```

- AnimationTriggerNodes take an _AnimTrigger object as an argument.

```
AnimationTriggerNode(
        cozmo.anim.Triggers.
            CubePouncePounceNormal
                          )
```

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.

SeeBoth Transition

```
class SeeBoth(Transition):
  def __init__(self,thing1,thing2):
    super().__init__()
    self.thing1 = thing1
    self.thing2 = thing2
    self.set_polling_interval(0.1)

  def poll(self):
    if self.thing1.is_visible and
         self.thing2.is_visible:
      self.fire()
```

See12.fsm

```
class See12(StateMachineProgram):
  $setup {
    StateNode()
      =SeeBoth(cube1,cube2)=>
         Say('I saw both')
  }
```

simple_cli 'show' commands

- show active
  - Shows the currently active nodes and transitions.
- show viewer
  - Shows the camera viewer
- show worldmap_viewer
  - Shows the worldmap viewer

Particle Filters

Intro to Particle Filters

- Odometry is unreliable.
  - Still useful for short trajectories.
  - But error accumulates quickly.
- 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 <u>likely</u> 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 robot’s estimated location (white 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.