

# Agent-based modeling workshop

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2022-03-24



# Disclaimer

- All content here is my personal understanding.
- Main intention is to open up the floor for discussion and trade concepts and ideas.
- Some code here is still under development so be patient and donate some coffee if you can. Nespresso red pods are suggested but Kopi O Kosong Peng does the job (UTown >>> Techno Edge).

# ABM - RL - ABM vs RL - OpenAI - ComfortLearn

## Agent-based modeling (ABM)

- Agent = Computational mechanism that exhibits a high degree of **autonomy**, performing **actions** in its environment based on **information** (sensors, feedback) received from the **environment**.

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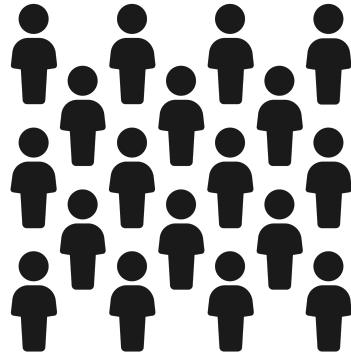


- But what for? How are they useful?
  - Helps us understand the effect of “multiple agents” **interacting** with **each other** and with their **environment**.

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## Examples

- Simulate occupancy for HVAC design and sizing. (**space-based approach**)



Impact of **aggregated** occupant behavior in a space of a certain category.

Erickson, V. L., Lin, Y., Kamthe, A., Brahme, R., Surana, A., Cerpa, A. E., Sohn, M. D., & Narayanan, S. (2009). Energy efficient building environment control strategies using real-time occupancy measurements. *BUILDSYS 2009 - Proceedings of the 1st ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Held in Conjunction with ACM SenSys 2009*, 19–24. <https://doi.org/10.1145/1810279.1810284>

Li, Z., Heo, Y., & Augenbroe, G. (2009). HVAC DESIGN INFORMED BY ORGANIZATIONAL SIMULATION Georgia Institute Of Technology , Atlanta , United States. *Ashrae Standard*, 2198–2203.

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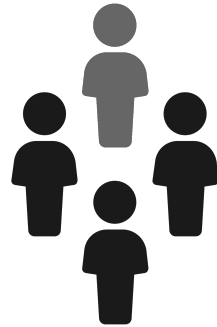
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## Examples

- Simulate occupancy at the urban-level for energy demand (**person-based approach**)



Impact of the presence of a **specific person** in a certain space

Erickson, V. L., Lin, Y., Kamthe, A., Brahme, R., Surana, A., Cerpa, A. E., Sohn, M. D., & Narayanan, S. (2009). Energy efficient building environment control strategies using real-time occupancy measurements. *BUILDSYS 2009 - Proceedings of the 1st ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Held in Conjunction with ACM SenSys 2009*, 19–24. <https://doi.org/10.1145/1810279.1810284>

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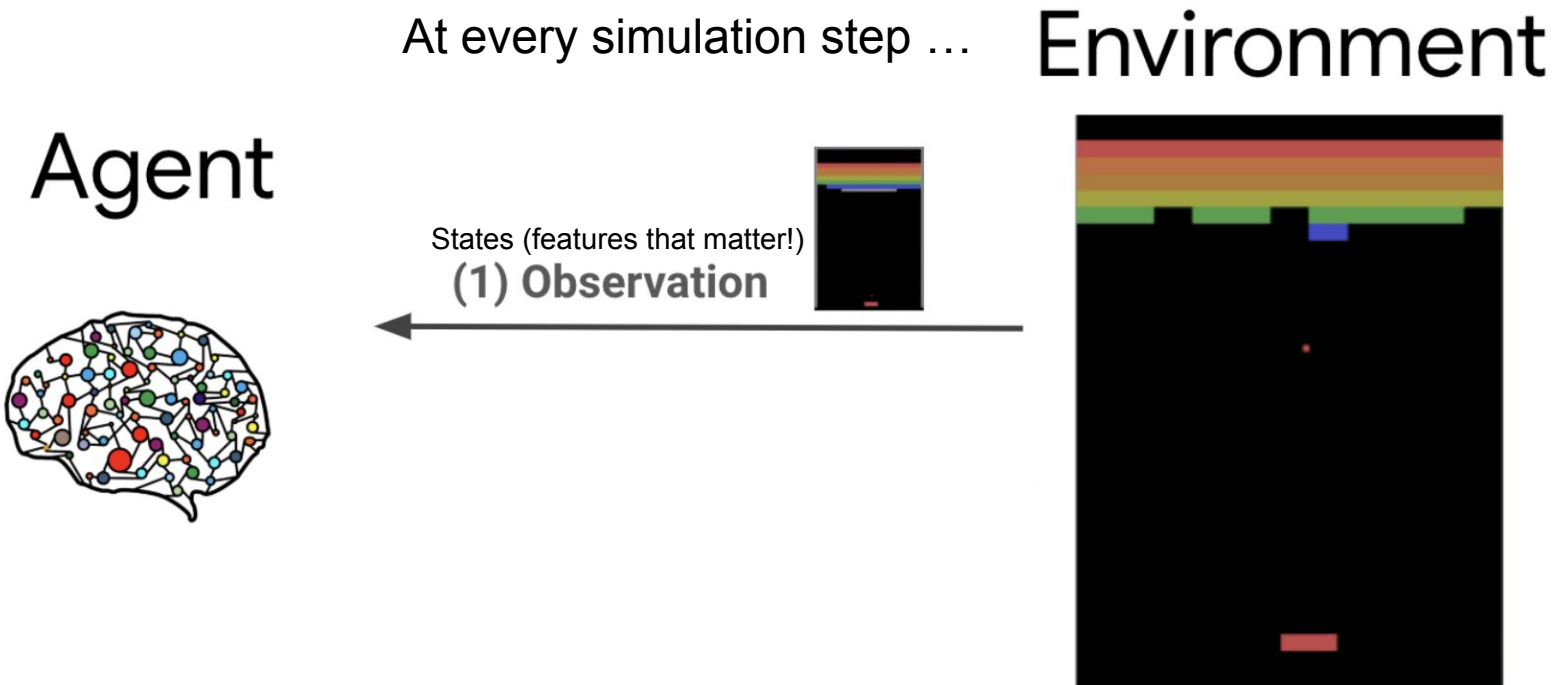
## Reinforcement Learning (RL)

- Framework where an *agent* learns to perform **actions** in an **environment** (that has **states**) so as to maximize a **reward**.
- Main components
  - Environment (problem to be solved)
  - Agent (entity that learns an algorithm)

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## Reinforcement Learning (RL)

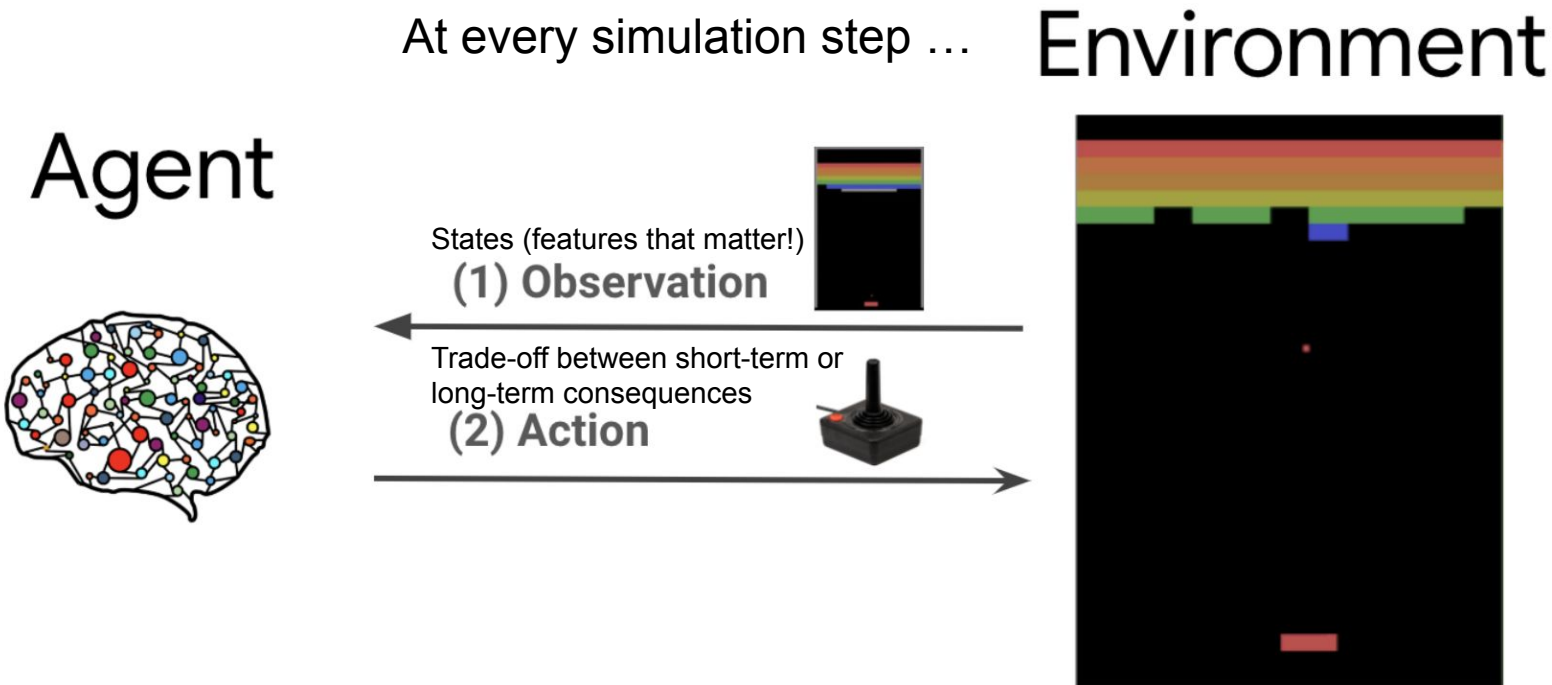
- How exactly does it work?



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## Reinforcement Learning (RL)

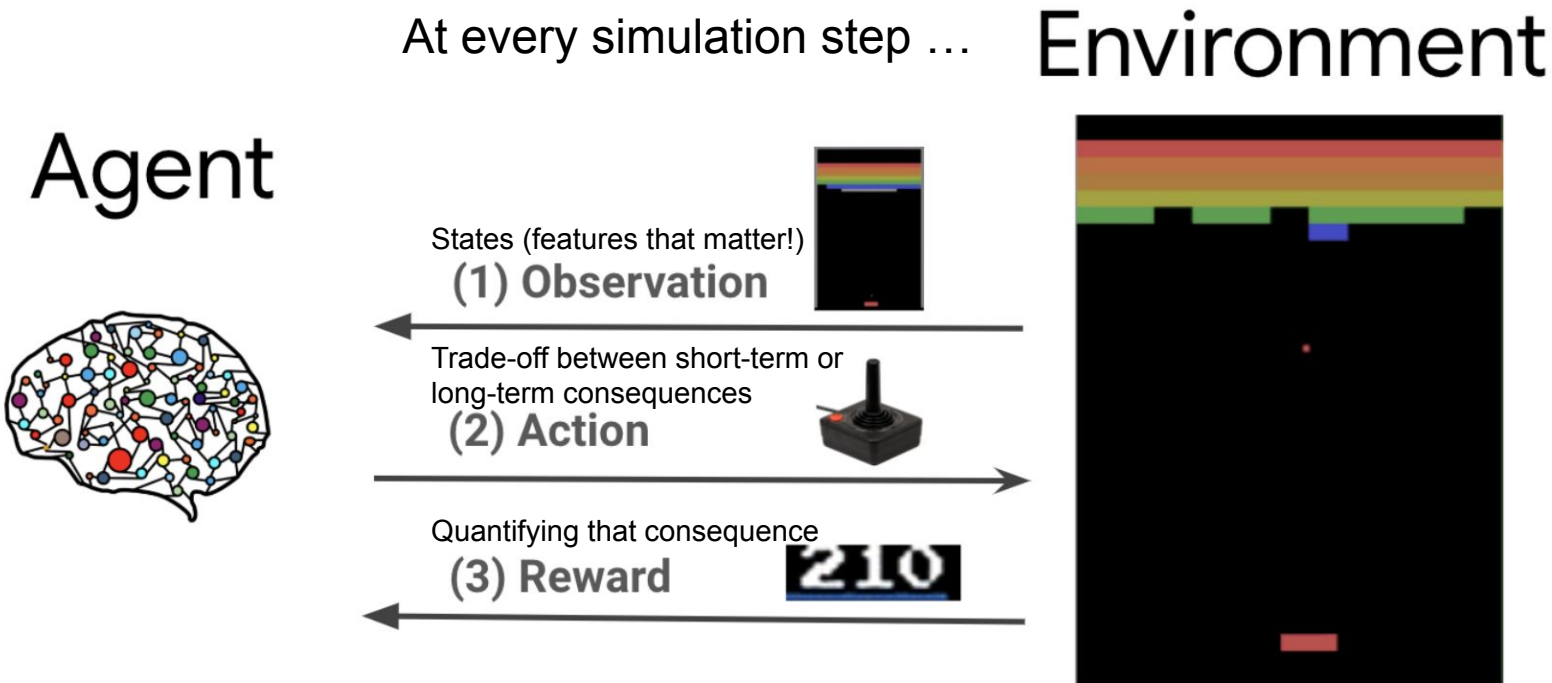
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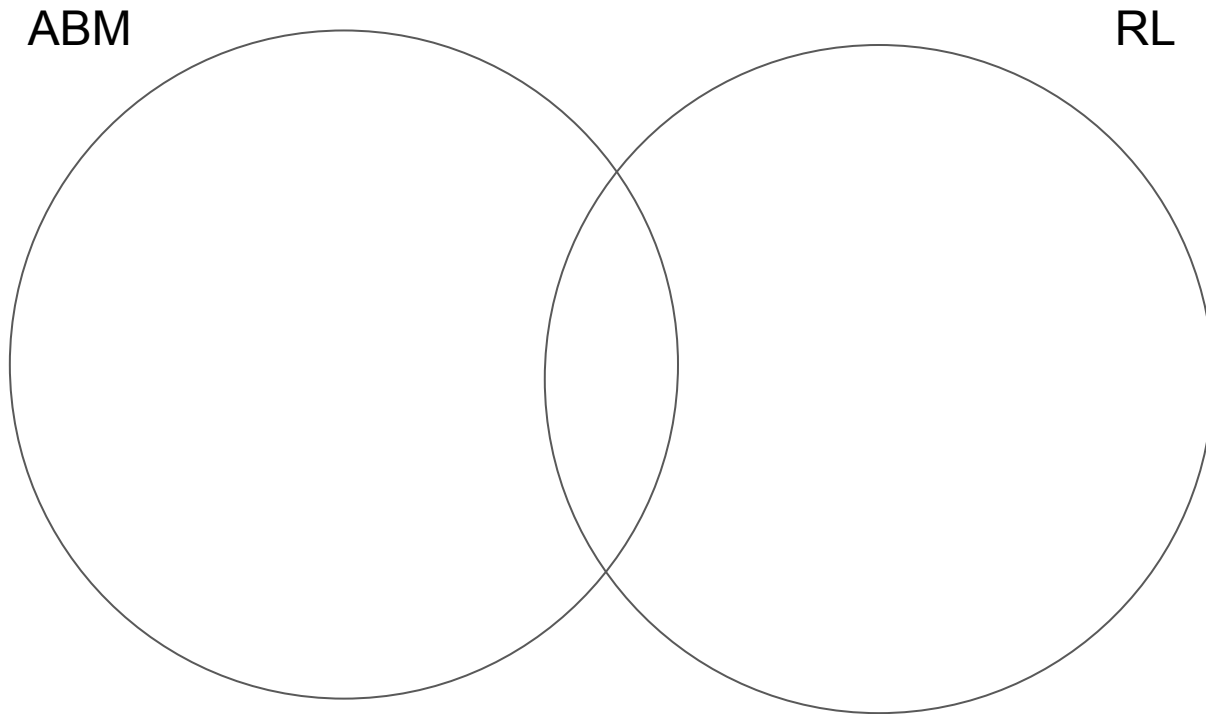
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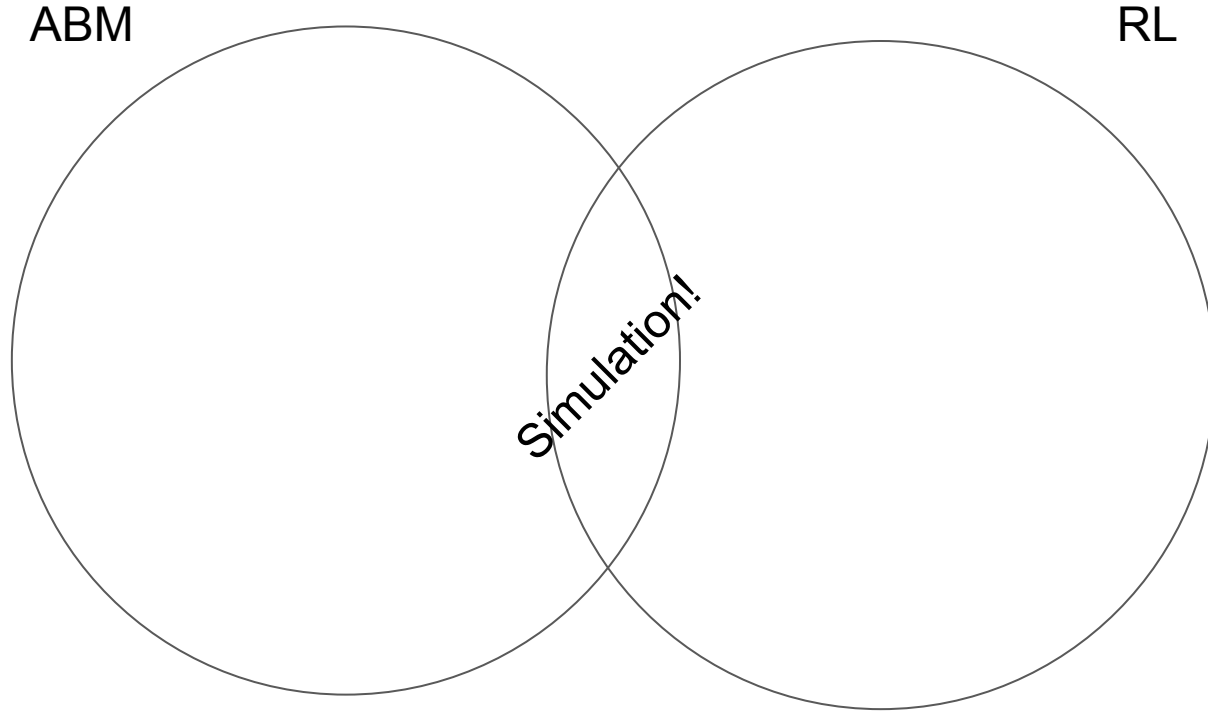
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## ABM vs RL



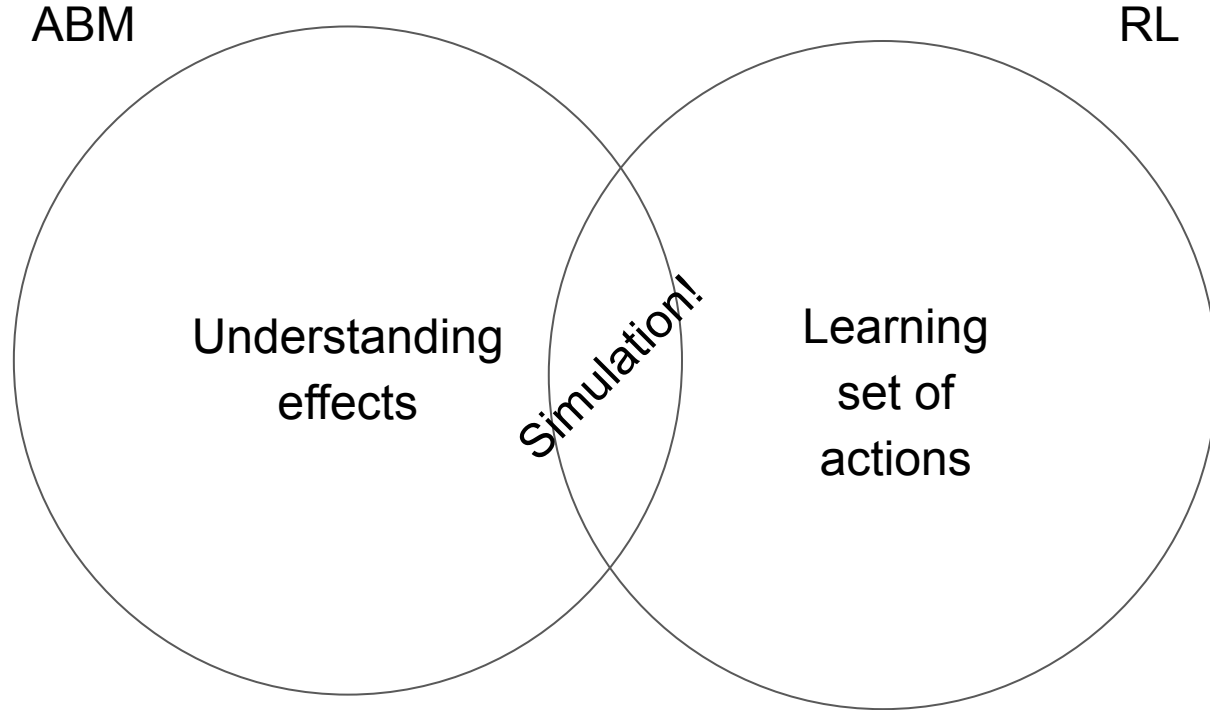
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## ABM vs RL



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## ABM vs RL





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## OpenAI gym



Open source interface to reinforcement learning tasks.

The **gym** library provides an easy-to-use suite of reinforcement learning tasks.

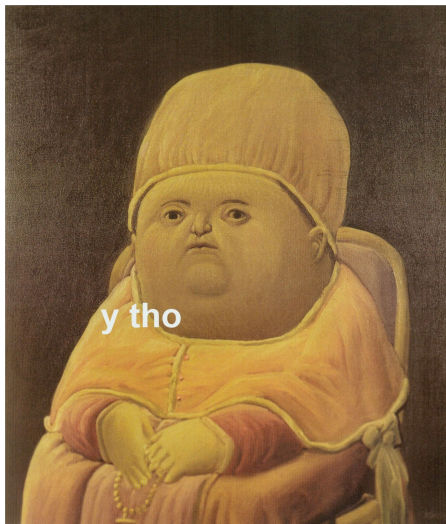
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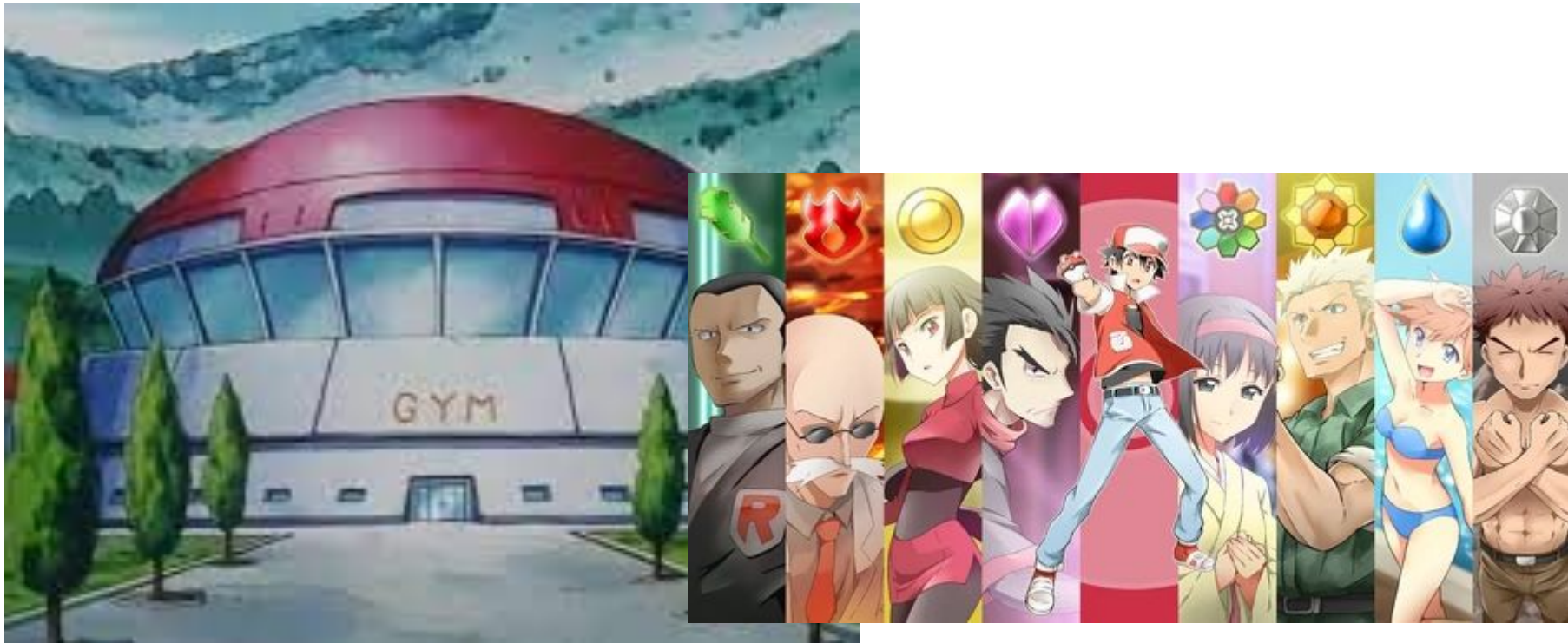
RL it's pretty damn cool:

- RL is **very general**, encompassing all problems that involve making a **sequence of decisions**
- RL algorithms have started to achieve **good results** in many **difficult environments**.

BUT! Research slowed down because ...

- There's a need for **better benchmarks**
- Lack of **standardization of environments** used in publications

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Here is where “gym” comes into play

(**Pokemon gen1 is the best gen, don't come at me**)

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## Overall structure of an openAI gym project

```
import gym
from gym import spaces

class CustomEnv(gym.Env):
    """Custom Environment that follows gym interface"""
    metadata = {'render.modes': ['human']}

    def __init__(self, arg1, arg2, ...):
        super(CustomEnv, self).__init__()    # Define action and observation space
        # They must be gym.spaces objects    # Example when using discrete actions:
        self.action_space = spaces.Discrete(N_DISCRETE_ACTIONS)    # Example for using image as input:
        self.observation_space = spaces.Box(low=0, high=255, shape=(
            HEIGHT, WIDTH, N_CHANNELS), dtype=np.uint8)

    def step(self, action):
        # Execute one time step within the environment
        ... def reset(self):
        # Reset the state of the environment to an initial state
        ... def render(self, mode='human', close=False):
        # Render the environment to the screen
        ...
```

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Hands on !

1. Clone the github repository <https://github.com/buds-lab/abm-demo>
2. Install the environments
  - a. `conda env create --file environment.yaml`
  - b. `pip install -r requirements.txt`
3. Let's just launch the environment doing some random actions. From `openai-gym/` Let's run `cartpole_example_1.py`
4. Now let's observe the environment's state at each time step, still with random actions though. From `openai-gym/` Let's run `cartpole_example_2.py`
5. But we want to LEARN! From `openai-gym/` Let's run `cartpole_example_3.py`

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Cool learning and all, but what about the more traditional ABM? What about CitySim? MATSim?

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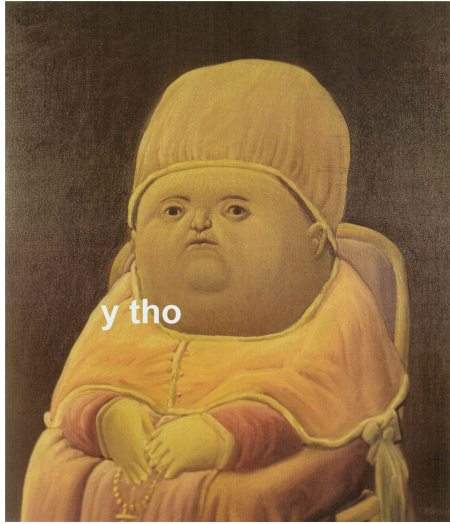
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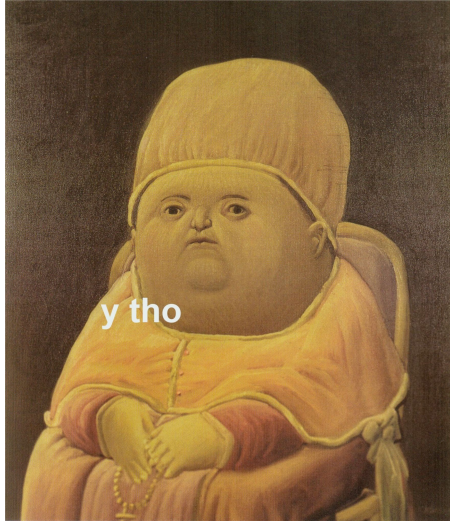
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We can simply define “agents”  
(without learning) to perform  
actions at each step of the  
simulation!

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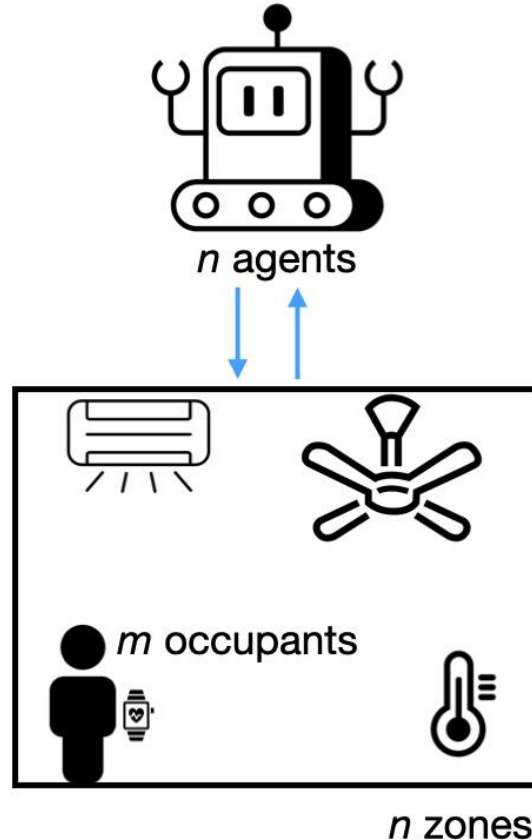
Gym environments are becoming more popular for standardised benchmarking in the built environment

- [CityLearn](#)
- [GridLearn](#)
- [Gym-Eplus](#)

“Need for more benchmarking of control algorithms”

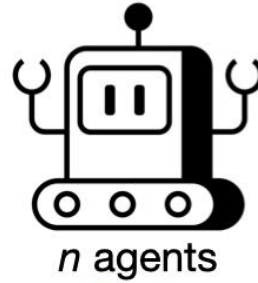
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So what is ComfortLearn?

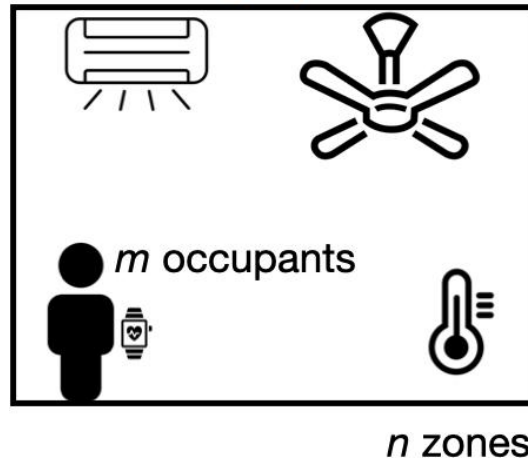


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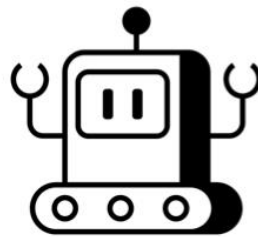
RL agent that learns  
set-points and occupant  
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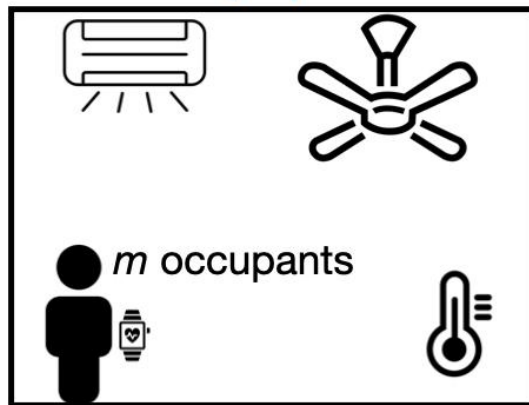
Agent-based occupants from  
real occupant longitudinal  
data

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So what is ComfortLearn?



$n$  agents



$n$  zones

RL agent that learns  
set-points and occupant  
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Agent-based occupants from  
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# ABM - RL - ABM vs RL - OpenAI - ComfortLearn

Hands on (again!)!

1. From the same github repository go to [comfortlearn/](https://github.com/comfortlearn/)
2. The overall structure of this ABM using a gym environment is

```
# main file
import ...

###
# load zone(s) energy model or historical data from config files
###

# instantiate actual environment
env = ComfortLearn(**env_params)
observations_spaces, actions_spaces = env.get_state_action_spaces()

###
# load agent stuff, as of now it's a big TODO though
###

# start simulation
state = env.reset()
done = False

actions = agent.select_action(state)

while not done:
    next_state, reward, done = env.step(actions)
    action_next = agent.select_action(next_state)
    action = action_next
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```

```
# comfortlearn file

import ...

class ComfortLearn(gym.Env):
    def __init__(args):
        # load states and actions for each zone

        # create occupants objects and load their data, this will be ABM!

        # create zone objects and load their data

    def step(self, actions):
        # where the magic happens! How does the environment changes at every time step?
        # right now, the environment just evolves based on historical data, meaning we just read
        # the next row in the dataframe

        return states, reward, done

    def reset(self):
        # let's take it from the top, shall we?
        # we restart values and conditions to the very beginning

    # auxiliary, getters, and setters functions are also used
```

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Hands on (again!)!

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3. So, let's run:

```
python main.py configs/baseline_tolerance_week.yaml
```



OpenAI gyms are very versatile and a good (and promising!) option for agent-based with or without RL!



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(and also Vim and working in the terminal is extremely cool)