Loads of people and a bit of COVID

infection reduction in critical infrastructures

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TOR VERGATA UNIVERSITY OF ROME

School of Engineering

Roadmap

1. Infection risk
2. Crowd modeling
3. Crowd control

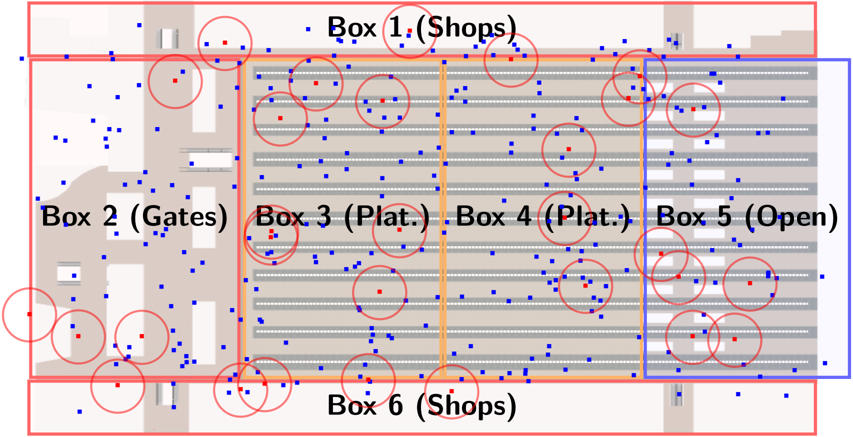

Figure 1: *Mixed box* model - Termini station

Geometric setup

Figure 2: Room setup.

- **black walls**: insulated walls
- **blue walls**: ventilated walls
- **red circles**: Infectious agents
- **green circles**: Susceptible agents

Model Characteristics

Infectious parameters

The infectious model depends on [1]:

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- **Dose of quanta received:** D_q in a period of time
- **Inhalation Rate:** IR

Model Characteristics

Infectious parameters

The infectious model depends on:

- **Volume of the personal area:** V

Model Characteristics

Infectious parameters

The infectious model depends on:

- **Volume of the personal area:** V
- **Distance between subjects:** d

Mathematical model

Model equations

Time dependence:

$$n(t) = n_0 e^{-IVRR \cdot t} + \frac{ER_q \cdot I \cdot V}{IVRR}(1 - e^{-IVRR \cdot t}) \tag{1}$$

Mathematical model

Model equations

Time dependence:

$$n(t) = n_0 e^{-IVRR \cdot t} + \frac{ER_q \cdot I \cdot V}{IVRR}(1 - e^{-IVRR \cdot t}) \tag{1}$$

Steady-State concentration:

$$n_\infty = \lim_{t \to \infty} n(t) = \frac{ER_q \cdot I \cdot V}{IVRR} \tag{2}$$

Mixed box - recap

Time-scale assumption

It is assumed that the latent period of the disease is longer than the time scale of the model, and the droplets are instantaneously and evenly distributed in the box.

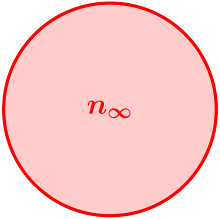

Figure 3: Mixed box approximation. Uniform quanta concentration at the steady-state condition

Risk calculation

Dose of quanta received

$$D_q = IR \int_0^T n(t)dt = IR \cdot n_\infty \cdot T, \tag{3}$$

Infection risk

$$r \propto 1 - e^{-D_q} \tag{4}$$

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Mixed Box modeling

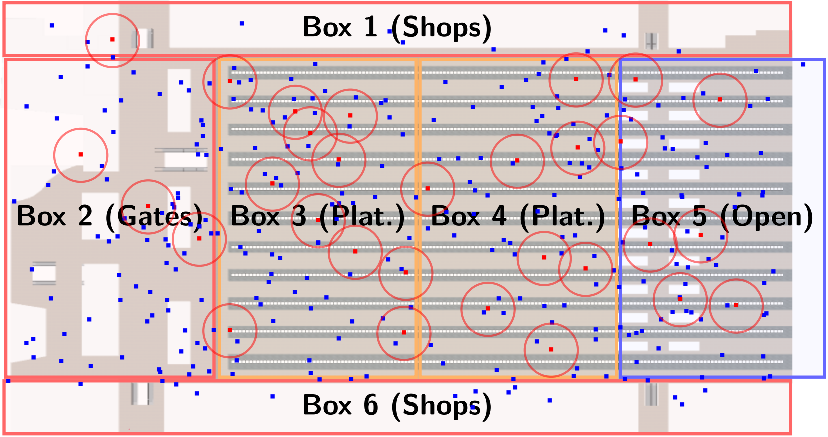

Figure 4: *Mixed box* model - Termini station

Task modeling

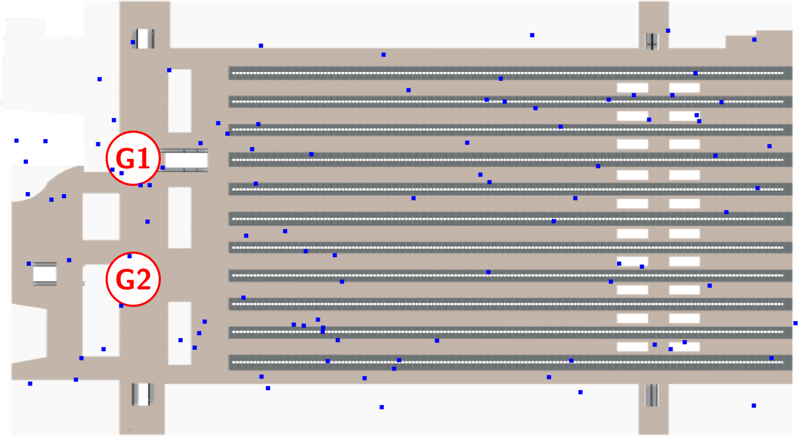

Figure 5: Potential goal description - Termini station

Crowd modeling

Modeling approaches [3]

- Microscopic model
- Macroscopic model

Crowd modeling

Modeling approaches [3]

- Microscopic model (Low level social interaction)
- Macroscopic model (Train schedule, Ventilation, Gate openings)

Social Force Model

General Idea

Model the interactions between agents accordingly to Newton's Law.

Kinds of force

Agents i, j, Environment w:

- **Self motivation:** F_0
- **Agents interaction:** $F_{ij} = -k_p \cdot d_{ij}$
- **Environment interaction:** $F_{iw} = -k_w \cdot d_{iw}$

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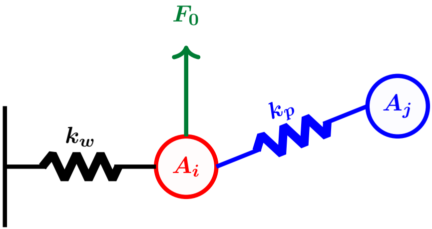

Figure 6: Social Force Model

Extended Social Force Model

General Idea

Starting from the standard SFM, add group affiliation dynamics.

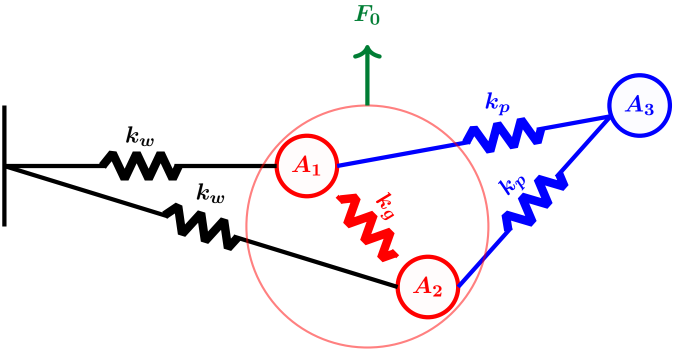

Figure 7: Extended Social Force Model

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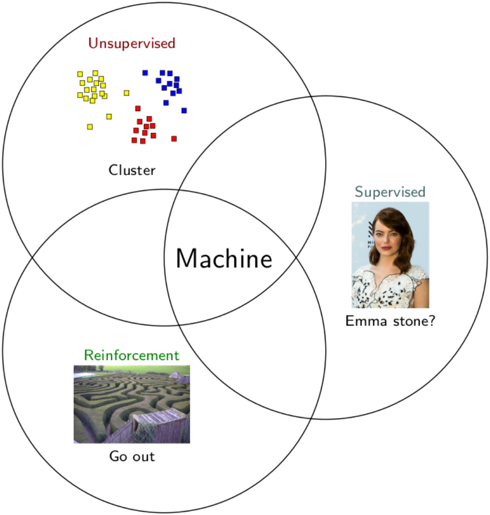

Figure 8: Machine Learning overview

Reinforcement Learning

General idea

Modification of the Agent's actions based on the interactions with the Environment.

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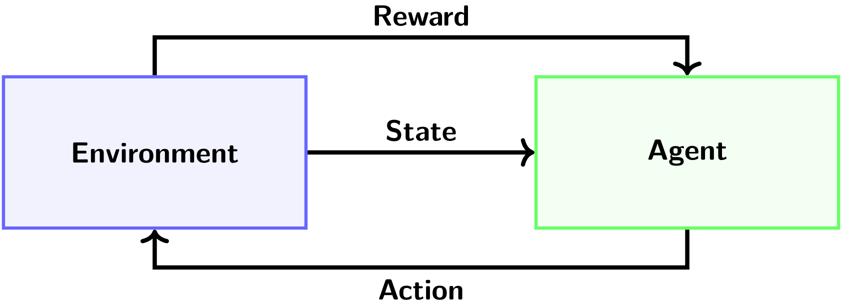


Figure 9: General RL framework scheme.

RL ingredients

Key concepts [2]

- State x: Agent state
- Action a: in a set $\mathcal{A}$
- Policy $\boldsymbol{\pi}$: rule used to take $a = \boldsymbol{\pi}(x)$
- Value function $\boldsymbol{v}_{\pi}$: state goodness estimation w.r.t $\boldsymbol{\pi}$
- Model: Agent's belief of the Environment

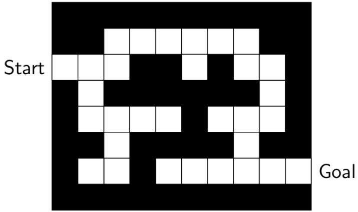
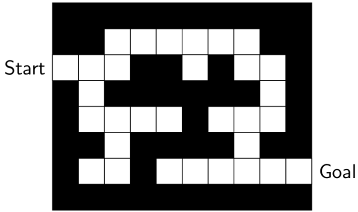


Figure 10: Maze escape example



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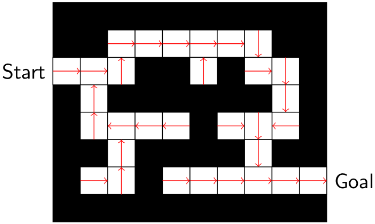

Figure 11: Maze escape solution

- State: location x_t
- Actions: $\mathcal{A} =$ N,E,S,W
- Reward: $R_t = -1$

From an initial policy $\boldsymbol{\pi}$

$$\boldsymbol{v}_\pi \rightarrow \boldsymbol{v}_{\pi^\star}$$

Framework setup

Environment - Termini station

- Agent movements
- Train arrivals

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Agent

- State: number of people, position, time, and individual risk r_i
- Reward: average infection risk r

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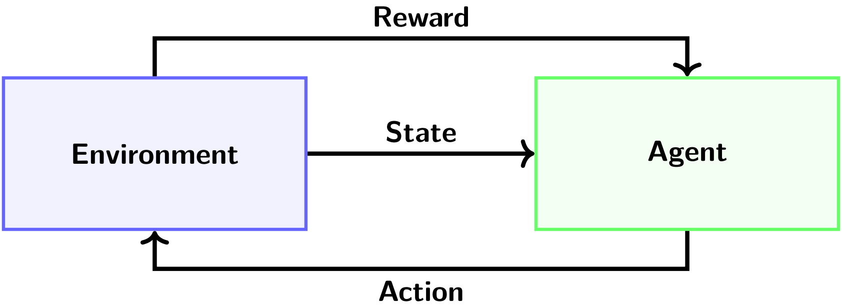
Action

- Train scheduling
- Ventilation
- Gate openings

Algorithm result



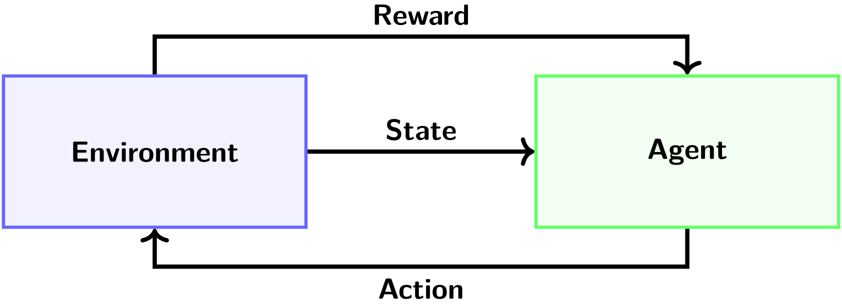
Behavioral policy

The RL algorithm will return an optimal behavioral policy ($\boldsymbol{\pi}^\star$), namely an optimal set of actions maximizing the Reward:

$$\lim_{N \to \infty} \boldsymbol{\pi} = \boldsymbol{\pi}^\star, \tag{5}$$

being N the number of simulations/experiments.

Algorithm result



To recap

1. **There's a lot of COVID**: environment and infection risk modeling
2. **There are lots of people**: agents interactions (SFM)
3. **Can we pull it off?** Reinforcement Learning approach

Thanks for your attention

Time for *Q&A!*

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[3] Qingqing Wang et al. "Improved multi-agent reinforcement learning for path planning-based crowd simulation". In: *IEEE Access* 7 (2019), pp. 73841–73855.