ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

POLITECNICO
MILANO 1863

Handling Non-Stationary Experts in Inverse Reinforcement Learning: A Water System Control Case Study

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M. Giuliani M. Restelli

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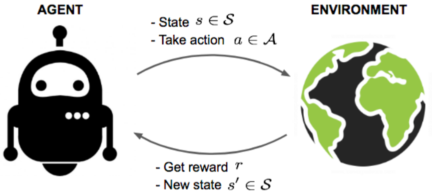
M2L Summer School

Motivations and Goal

- **RL**: Maximize sum of rewards



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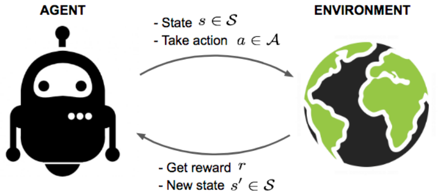

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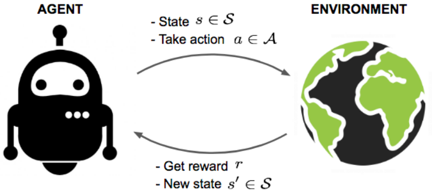

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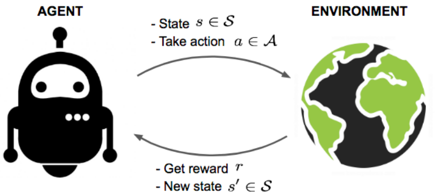

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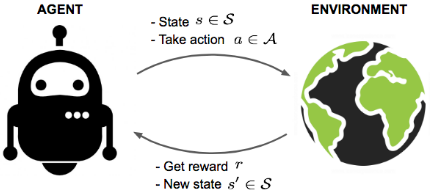

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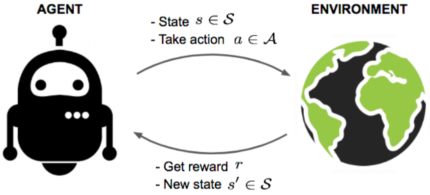

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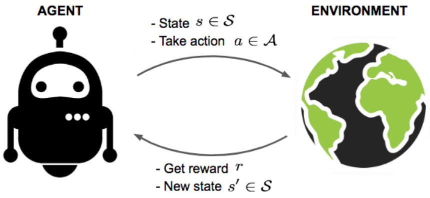

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- Parametrized policy $\pi_{\boldsymbol{\theta}}$:

$$J_\pi(\boldsymbol{\theta}, \boldsymbol{\omega}) = \mathop{\mathbb{E}}_{\substack{s_0 \sim \mu \\ a_t \sim \pi_{\boldsymbol{\theta}}}} \left[\sum_{t=0}^{+\infty} \gamma^i R_{\boldsymbol{\omega}}(s_t, a_t) \right] = \boldsymbol{\omega}^T \boldsymbol{\psi}(\boldsymbol{\theta})$$

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  - $\rightarrow$ account for the uncertainty in the Jacobian estimation
  - $\rightarrow$ allows computing likelihood of D given $\boldsymbol{\omega}$, $p(D|\boldsymbol{\omega})$

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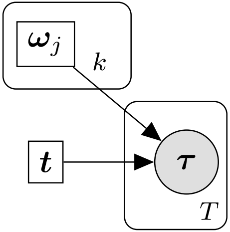

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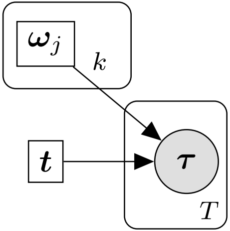

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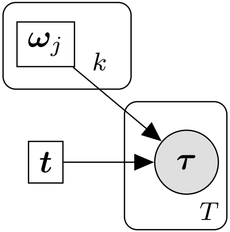

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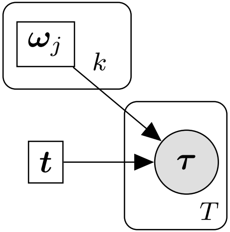

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- Find rewards $\mathbf{R} = (R_{\boldsymbol{\omega}_1}, \dots, R_{\boldsymbol{\omega}_k})$

Non Stationary-Σ-GIRL

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NS-Σ-GIRL (adaptation of *Opt* (Truong et al., 2020))

1. Define Likelihood of $\boldsymbol{\tau}$ under solution $\Omega = (\boldsymbol{\omega}_1, \dots, \boldsymbol{\omega}_k, t_1, \dots, t_{k-1})$

$$\mathcal{L}(\Omega|\boldsymbol{\tau}) = p(\boldsymbol{\tau}|\Omega) = \prod_{i=1}^{T} \sum_{j=1}^{k} p(\tau_i|\boldsymbol{\omega}_j) \mathbb{1}_{\{i \in I_j\}}$$

2. For each $1 \leqslant u < v \leqslant T$ solve:

$$\min_{\substack{\boldsymbol{\omega}_{uv} \in \mathbb{R}^q_{\geqslant 0} \\ \|\boldsymbol{\omega}_{uv}\|_1 = 1}} (v-u) \sum_{i=u}^{v-1} \left\| \widehat{\nabla}_{\boldsymbol{\theta}} \psi_i(\boldsymbol{\theta}) \boldsymbol{\omega}_{uv} \right\|^2_{[(\boldsymbol{\omega}_{uv} \otimes \mathbf{I}_d) \boldsymbol{\Sigma}_i (\boldsymbol{\omega}_{uv} \otimes \mathbf{I}_d)^T]^{-1}} .$$

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- Data are daily and were provided by Consorzio dell'Adda (`www.addaconsorzio.it`)

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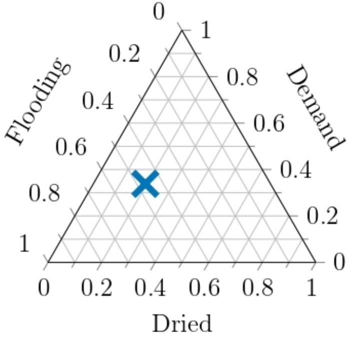
- *Drought risk* (ϕ^L): penalize large releases with low lake levels

Single Reward Setting



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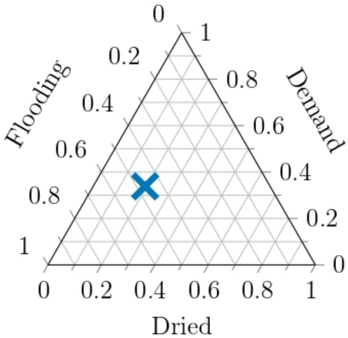

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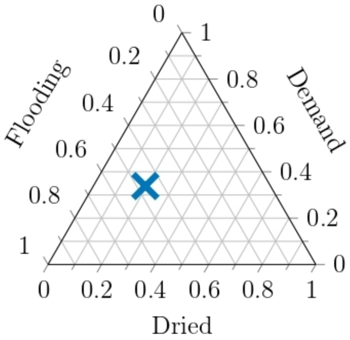

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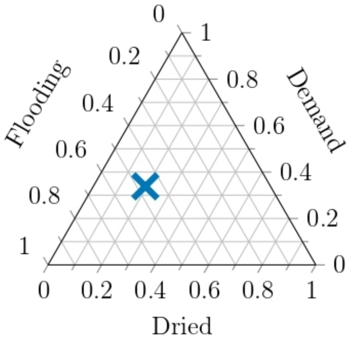

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Recent Flooding (Como, 2020)

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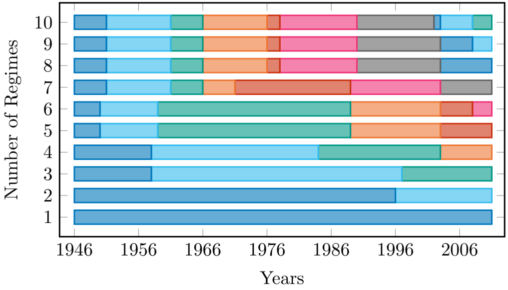

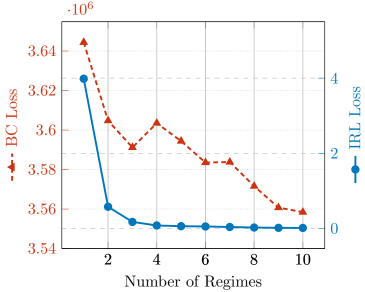

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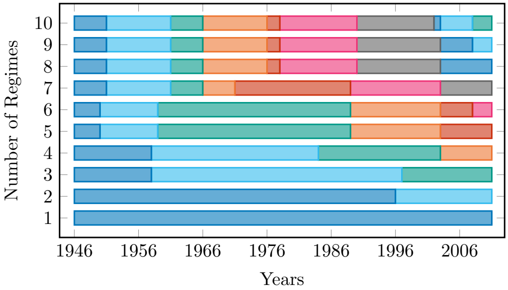

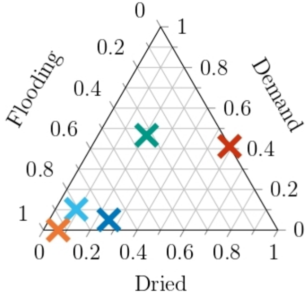

Conclusions

- Extended Σ-GIRL to the non-stationary setting
- Carefully designed reward features that explain the expert behaviour
- Indentified several hystorical regimes of interest

Thank You for Your Attention!

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