





Francesco De Lellis

Nonlinear and distributed control strategies based on reinforcement learning for complex and multi-agent systems

Tutor: prof. Mario di Bernardo co-Tutor: prof. Giovanni Russo

Cycle: XXXV

Year: 2021



My background

- MSc degree in Control Engineering
- Member of the research group on "Sincronizzazione e Controllo di Reti e Processi" (SINCRO)
- PhD start date: 01/11/2019
- Scholarship: University of Naples Federico II ITEE grant
- Ongoing collaborations:
 - Prof. Giovanni Russo from University of Salerno
 - Prof. Mirco Musolesi from University College London



Research field of interest

- Reinforcement learning (RL) offers powerful algorithms to search for optimal controllers of systems with nonlinear, possibly stochastic dynamics that are unknown or highly uncertain
- State of the art RL encounters different limitations when applied to develop Control Strategies for dynamical systems:
 - Data efficiency
 - High-dimensional continuous state and action spaces
 - Training off-line: Safety
- For these reasons I am putting effort into adapting existing Reinforcement Learning strategies specifically for control application by:
 - Leveraging partial/incorrect modeling
 - Driving the learning process with partially faulty control laws



Summary of study activities

- The study activities have been focused on testing the Control Tutored Reinforcement Learning strategy developed during the studies
- Ad hoc PhD courses / schools:
 - Reinforcement Learning Virtual School
 - FMG Data-Driven Control Summer School
 - IELTS Course organized by CLA
 - Strategic Orientation for STEM research and writing
- Conferences / events attended:
 - European Control Conference 2021 (ECC21)
 - SIAM Conference on Applications of Dynamical Systems (DS21)
 - IEEE International Workshop on Cellular Nanoscale Networks and their Applications (CNNA21)



Research activity(1)

• The **research idea**:



- Determine under which condition it is useful to bring control laws into RL algorithms
- Determine what kind of advantages these strategies can have in the control of dynamical system



- Defining the key features of the RL part and the Control part
- Apply the strategy on a unified framework (e.g.OpenAl gym)
- Compare the results with the existing solution in literature



Research activity(2)

• The **developments**:

- Formalization of the Control Tutor Reinforcement Learning
- The CTQL strategy
- Deep CTQL
- The **expected results**:
 - Shorter learning times
 - Increased robustness of the final control solution
 - Less dependency on the hyperparameter tuning





activity and future research

• The validation:



- Validation of novel strategies have to be done on a unified framework like the OpenAI gym
- The benchmarking has to be done with the use of specific metrics







Products

[P1]	Francesco De Lellis, Giovanni Russo, and Mario di Bernardo. "Tutoring					
	Reinforcement Learning via Feedback Control", European Control					
	Conference (ECC), 2021					
[P2]	Francesco De Lellis, Fabrizia Auletta, Giovanni Russo, Pietro De Lellis and					
	Mario di Bernardo. "					
	An Application of Control-Tutored Reinforcement Learning to the Herding					
	Problem", IEEE International Workshop on Cellular Nanoscale Networks and					
	their Applications (CNNA), 2021					
[P3]	Marco Coraggio, Shihao Xie, Francesco De Lellis, Giovanni Russo, Mario di					
	Bernardo. "Intermittent non-pharmaceutical strategies to mitigate the					
	COVID-19 epidemic in a network model of Italy via constrained optimization					
	", Accepted by Conference of Decision and Control (CDC), 2021					



Next years

• First year credits:

	Courses	Seminars	Research	Tutorship	Total
Bimonth 1	0	3.2	8	0.24	11.44
Bimonth 2	3.6	2.8	8	0.24	14.64
Bimonth 3	0	5.4	5	0.16	10.56
Bimonth 4	5	3.8	6	0.32	15.12
Bimonth 5	0	1.6	6	0.28	7.88
Bimonth 6	4	2.4	8	0.1	14.5
Total	12.6	19.2	41	1.34	74.14
Expected	10 - 20	5 - 10	30 - 45	0-1.6	45 – 96.6

Didactic support for the course Dinamica e Controllo Non Lineare

• Expected credits:

	Courses	Seminars	Research	Tutorship	Total
Year 1	10.6	6.8	41.6	1.6	61
Year 2	12.6	19.2	41	1.34	74.14
Year 3	6.8	0	60	1.6	68.6

