Hybrid AI Systems Grounded on Just-in-time Qualitative Spatio-Temporal Reasoning

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Outline

Personal Details

- Birthplace: Wickede, Germany
- Nationality: Hellenic
- Languages: Greek $\succ$ English $\succ$ German $\succ$ Spanish $\succ$ French
- Research fellow (Wissenschaftlicher Mitarbeiter) with 5h/week teaching load at Otto-Friedrich-University Bamberg (Germany)

Education

- Ph.D. in Computer Science in 2017 from Université d'Artois (France); brief stay in University of Technology Sydney (Australia)

UNIVERSITÉ D'ARTOIS

- M.Sc. in Advanced Information Systems and B.Sc. in Computer Science in 2012 and 2009 respectively from the National and Kapodistrian University of Athens (Greece)

HELLENIC REPUBLIC
National and Kapodistrian
University of Athens

Hybrid AI: An Overview

Part I

Neuro-Symbolic AI

Neural-symbolic AI seeks to bring together robust learning in neural networks with reasoning and explainability via symbolic representations for network models

A. d'Avila Garcez and L. C. Lamb[1]

[1] A. d'Avila Garcez and L. C. Lamb: *Neurosymbolic AI: The 3rd Wave*. (2020) `https://arxiv.org/abs/2012.05876`

Neuro-Symbolic AI Architectures

- Neural architectures for logical reasoning[2]
- Logical specification of neural networks[3]
- *Architectures integrating learning and reasoning*[4]
    - ***Our main focus here!***

[2] E.g., W. W. Cohen et al.: *TensorLog: A Probabilistic Database Implemented Using Deep-Learning Infrastructure*. In: J. Artif. Intell. Res. 67 (2020)

[3] E.g., G. Sourek et al.: *Lifted Relational Neural Networks: Efficient Learning of Latent Relational Structures*. In: J. Artif. Intell. Res. 62 (2018)

[4] E.g., R. Manhaeve et al.: *Neural probabilistic logic programming in DeepProbLog*. In: Artif. Intell. 298 (2021)

Neuro-Symbolic AI Overview

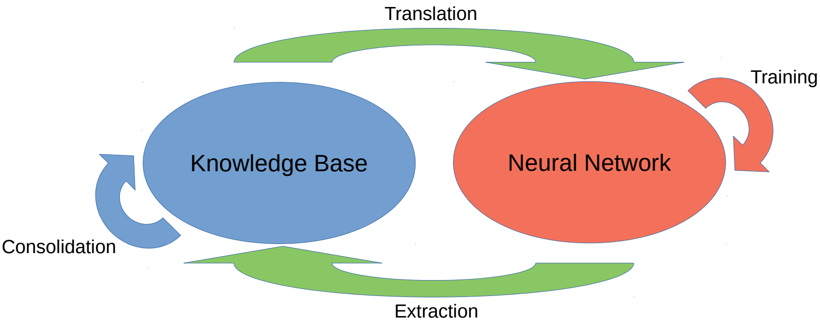


Figure: Cyclical interaction in Neuro-Symbolic AI; a symbolic system feeds symbolic (partial) knowledge to a neural network system, which can be trained on raw data, and knowledge acquired through machine learning can then be extracted back to the symbolic system, and made available for further processing in symbolic form[5]

[5] S. Bader and P. Hitzler: *Dimensions of Neural-symbolic Integration - A Structured Survey*. In: We Will Show Them! Essays in Honour of Dov Gabbay (1). 2005

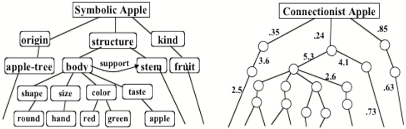
Neuro-Symbolic AI Components

Symbolic AI module

- A knowledge base (KB), which stores facts and rules
- A symbolic model, viz., the KB's logic (e.g., modal logic, first-order logic, deductive reasoning, and so on)

Machine learning module

- Any kind of neural network architecture or other connectionist model[6]



- Raw data

[6] M. Minsky: *Logical Versus Analogical or Symbolic Versus Connectionist or Neat Versus Scruffy*. In: AI Mag. 12 (1991)

Alternative Terms for Neuro-Symbolic AI

- Data-driven vs knowledge-driven
- Subsymbolic vs symbolic
- Learners vs solvers
- Thinking fast vs thinking slow (Daniel Kahneman)
- Statistical learning vs symbolic reasoning
- Perception vs logical reasoning
- Connectionism vs computationalism
- Scruffy vs neat

Why Neuro-Symbolic AI?

- High explainability and high accuracy performance
  - Explainability stems from Symbolic AI
  - Accuracy[7] stems from ML model
- Mimics human problem-solving
  - Perception, mostly accurate and fast, can be seen as a data-driven process
  - Reasoning, mostly complex and slow, can be realized by logical reasoning
- Hot research topic and major AI challenge[8]

[7] ML models can be designed and trained with relatively much less effort compared to their accuracy performance

[8] https://ai100.stanford.edu/2021-report/gathering-strength-gathering-storms-one-hundred-year-study-artificial-intelligence

Ok, but Why Not End-to-end Learning?

Representation learning only includes statistical information—it does not capture perturbations (interventions), reasoning, planning

*ML models should be tied to assumptions that align with **physics** and **human cognition** to allow for generalization*

Modular approach: decompose knowledge into independent and recomposable pieces

B. Schölkopf et al.[9]

[9] B. Schölkopf et al.: *Towards Causal Representation Learning*. (2021) `https://arxiv.org/abs/2102.11107`

ML Caveats: Statistics and Causality (1/4)

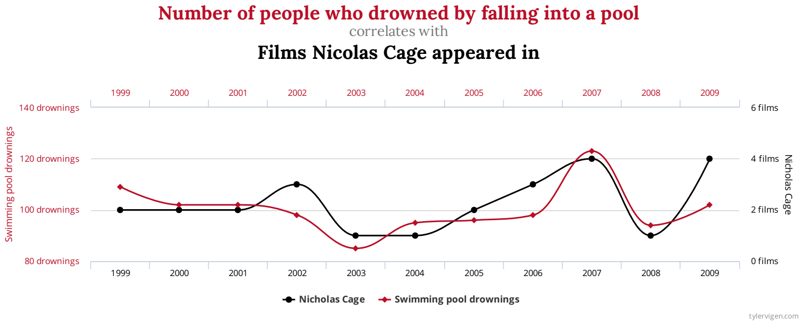


Figure: Nicolas Cage causing deaths?[10]

[10] http://www.tylervigen.com/spurious-correlations

ML Caveats: Perturbations/Interventions (2/4)

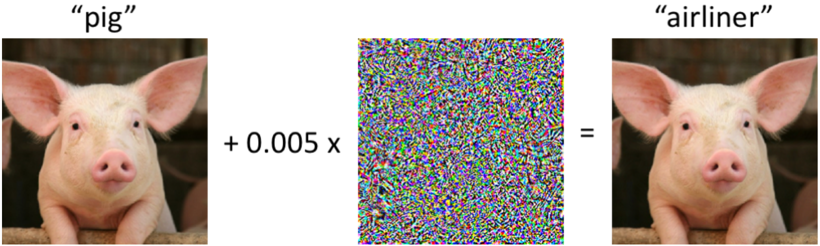


Figure: An adversarial example[11]

- Relation to causality: conditional probabilities cannot reliably predict the outcome of an intervention
  - “Seeing people with open umbrellas suggests that it is raining” $\rightarrow$ “Closing umbrellas does not stop the rain”

[11] https://gradientscience.org/intro_adversarial/

ML Caveats: Counterfactuals (3/4)

- Counterfactual problems involve:
  - reasoning about why things happened;
  - imagining the consequences of different actions in hindsight;
  - and determining which actions would have achieved a desired outcome
- "Would a given patient have suffered heart failure if they had started exercising a year earlier?"

ML Caveats: Data Diversity (4/4)

- Data diversity is an untestable condition a priori

Figure: Thanks to machine learning models the robot apocalypse was short lived[12]

[12] https://www.smbc-comics.com/comic/rise-of-the-machines

Ok, but Why Not Just Symbolic AI Then?

- Knowledge acquisition bottleneck
  - Never-ending need for carefully crafted rules
  - Too much data vs too few domain experts to classify and structure it
  - Semantic alignment issues
- Symbols can be largely used when the input is definite and falls under certainty

Neuro-Symbolic AI Sum-up So Far

- Better than standalone Machine Learning or Symbolic AI
- Statistics (correlations) + logic $\approx$ causality
- Raises many open questions / opportunities for research
- Resembles human reasoning, with respect to some rationale
- Still far away from dealing with "insight problems"[13]

[13] https://thereader.mitpress.mit.edu/ai-insight-problems-quirks-human-intelligence/

Hybrid AI with a Spatio-Temporal Flavor

Part II

Flavors of Logic

We recall the previous quote

> *ML models should be tied to assumptions that align with **physics** and **human cognition** to allow for generalization*
>
> *B. Schölkopf et al.*[14]

[14] B. Schölkopf et al.: *Towards Causal Representation Learning*. (2021) https://arxiv.org/abs/2102.11107

Two Logical Rules: Which is Better? Why?

- "if I accelerate faster than the vehicle directly in front of me, then I will overtake it"

- "if I accelerate faster than the vehicle directly in front of me, then I will crush it"

Injecting Causality via Spatio-Temporal Calculi

- Qualitative Spatial & Temporal Reasoning (QSTR) is a major field of study in KR, and Symbolic AI in general[15]
- QSTR abstracts from numerical quantities of space and time by using natural descriptions instead (e.g., *precedes*, *contains*, *is left of*), grounded on ***physics*** and ***human cognition***

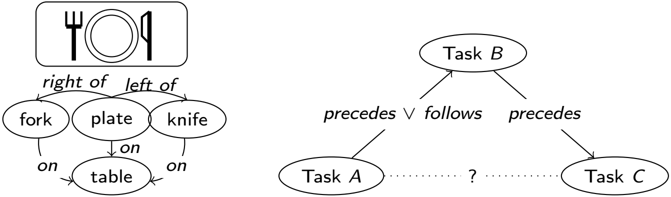


Figure: Left: Qualitative abstraction of a spatial configuration, Right: Temporal constraint network of 3 variables (tasks); ? denotes complete uncertainty

[15] G. Ligozat.: *Qualitative Spatial and Temporal Reasoning*. ISTE Series. Wiley, 2011

Example Calculus: The RCC8 Constraint Language

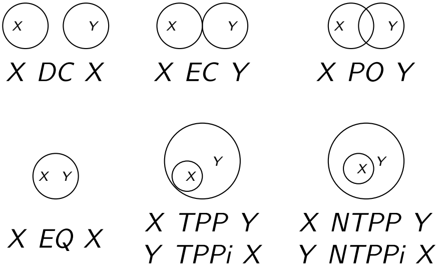


Figure: The base relations of RCC8; $\cdot i$ denotes the inverse of $\cdot$

An abundance of calculi exist for many types of spatial and temporal information (e.g., trajectories, occlusion, intervals)[16]

[16] F. Dylla et al.: *A Survey of Qualitative Spatial and Temporal Calculi: Algebraic and Computational Properties*. In: ACM Comput. Surv. 50 (2017)

Applications: Geospatial Semantic Segmentation

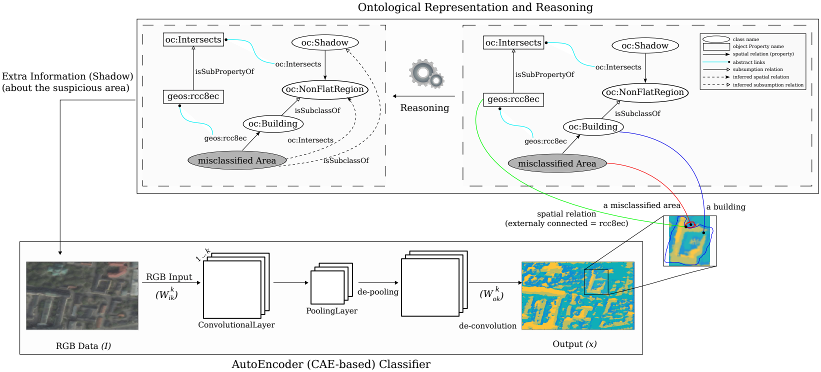


Figure: A semantic referee reasons about the mistakes made by the classifier based on ontological concepts and provides additional information back to the classifier that prevents the classifier from making the same misclassifications[17]

[17] M. Alirezaie et al.: *Semantic referee: A neural-symbolic framework for enhancing geospatial semantic segmentation*. In: Semantic Web 10 (2019)

Applications: Medicine / Image Processing

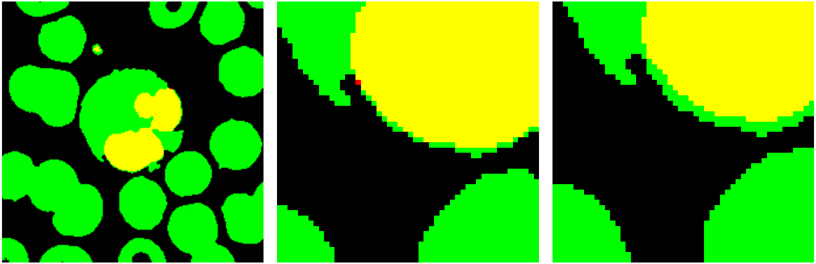


Figure: Left: segmented cell bodies (green), lobulated cell nuclei (yellow and red) and background (black), Middle: segmented cell nucleus extending outside border of host cell (red pixels), Right: the result of applying a morphological erosion operator; in this case the original *partially overlaps* relation changes to *proper part*[18]

[18] M. Sioutis et al.: *Ordering Spatio-Temporal Sequences to Meet Transition Constraints: Complexity and Framework*. In: AIAI. 2015

Applications: Region Approximation / Emergency Response

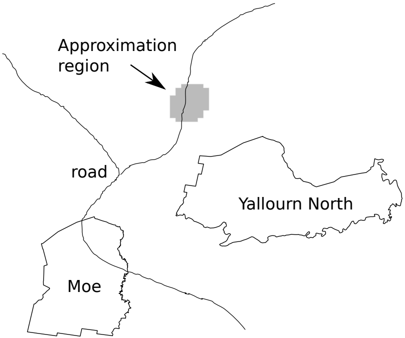


Figure: Illustration of locating a region by natural language descriptions, e.g., "Bushfire burning about 5km northwest of Yallourn North" and "I saw fire about 10km northeast from Moe", with the help of a region approximation method[19]

[19] Ongoing work with Southwest Jiaotong University (China) (submitted to a journal)

Applications: Drone Monitoring

Figure: "Never fly over an urban area for more than 3 minutes": $\forall r \in$ UrbanRegion, $\Box(PO \vee TPP \vee NTPP(\text{Drone}, r) \rightarrow \Diamond_{[\mathbf{0},\mathbf{180}s]} DC(\text{Drone}, r))$[20]

[20] F. Heintz and D. de Leng: *Spatio-Temporal Stream Reasoning with Incomplete Spatial Information*. In: ECAI. 2014

A Case of Robustness in AI

- We want to have some measure of the quality of a spatial or temporal configuration, viz., *scenario*.[21]
- We focus on scenarios that can withstand perturbations, i.e., that limit as much as possible the need for successive repairs.

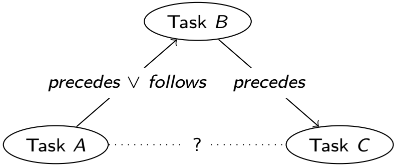


Figure: Tasks scheduled in a factory; as there might be unpredictable incidents concerning resource availability (e.g., power outage), how should the factory schedule production so that it may be least disturbed?

[21] M. Sioutis et al.: *On Robustness in Qualitative Constraint Networks*. In: IJCAI. 2020

Robust Scenario

Definition

Given a network $\mathcal{N}$, a scenario $\mathcal{S}$ of $\mathcal{N}$ is robust iff:

$$\mathcal{S} \in \underset{\mathcal{S}' \in [[\mathcal{N}]]}{\arg\max}\, \mathsf{similarity}(\mathcal{S}', [[\mathcal{N}]])$$

where

$$\mathsf{similarity}(\mathcal{N}, \mathfrak{M}) = \frac{\sum_{\mathcal{N}' \in \mathfrak{M}} \#\mathsf{sameConstraints}(\mathcal{N}, \mathcal{N}')/|\mathcal{N}'|}{|\mathfrak{M}|}$$

Intuitively, a robust scenario of a network $\mathcal{N}$ has the largest number of common constraints on average with each scenario of $\mathcal{N}$, i.e., with each satisfiable atomic network in $[[\mathcal{N}]]$.

Revisiting the Task Scheduling Example

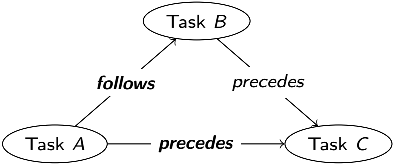


Figure: Tasks scheduled in a factory, revisited

- Choosing *follows* over *precedes* between Tasks A and B, maintains the whole range of possibilities between Tasks A and C.
- Choosing *precedes* over any other relation between Tasks A and C, can resist the change of *follows* switching back to *precedes* between Tasks A and B.

Evaluation: Perturbation Tolerance Comparison

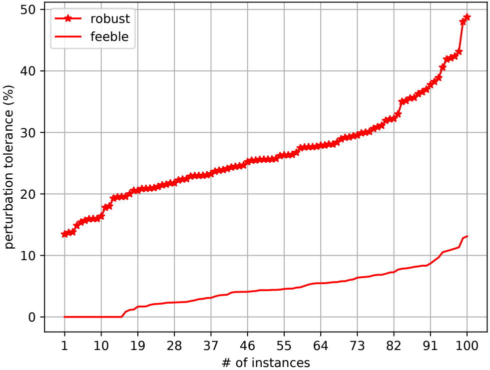


Figure: Perturbation tolerance comparison with job-shop dataset

Extending Framework with Probabilities

Definition

Given a scenario $\mathcal{N}$ and the probabilities $p_{ij}(\mathcal{N}[v_i, v_j])$ of relations $\mathcal{N}[v_i, v_j]$ in $\mathcal{N}$, the *robustness measure* of $\mathcal{N}$ is defined to be:

$$\text{robustness}(\mathcal{N}) = \frac{\sum_{v_i, v_j \in V} p_{ij}(\mathcal{N}[v_i, v_j])}{|\mathcal{N}|}.$$

Here, instead of considering the choices between *precedes* $\vee$ *follows* as equally likely, we can achieve more detailed notions of robustness.[22]

[22] M. Sioutis and Hua Meng: *Towards Robust Qualitative Spatio-Temporal Reasoning for Hybrid AI Systems*. In: IEEE ISKE. 2021

Enabling Abductive Learning

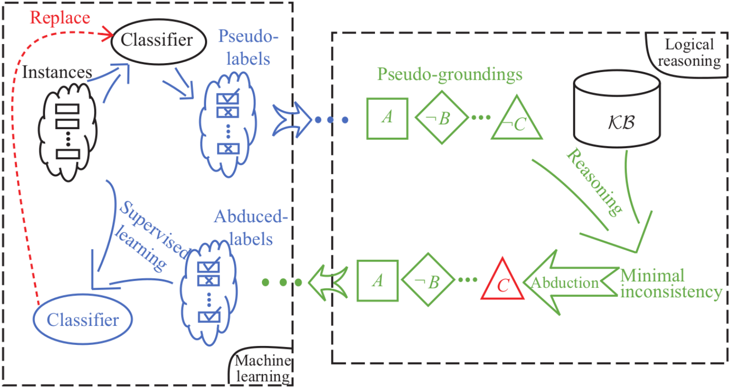


Figure: Abductive Learning framework[23]

[23] Z.-H. Zhou: *Abductive learning: towards bridging machine learning and logical reasoning*. In: Sci. China Inf. Sci. (2019)

Enabling Abductive Learning: Underlying Challenges (1/2)

- Adaptive and dynamic algorithms for runtime verification of neural network-based components
- Parsimonious local consistencies (e.g., restricted to neighbourhood[24])
- Dynamic algorithms for repair (revision), inconsistency minimization

[24] M. Sioutis et al.: *On neighbourhood singleton-style consistencies for qualitative spatial and temporal reasoning*. In: Inf. Comput. (2020)

Enabling Abductive Learning: Underlying Challenges (2/2)

- Relation-aware and/or lazy tree decompositions
- Backbone-based decoupling and backdoor-based search space splitting approaches[25] (reasoning shortcuts)
- Exploitation of AI hardware (e.g., GPUs)

[25] M. Sioutis and T. Janhunen. *Towards Leveraging Backdoors in Qualitative Constraint Networks*. In: KI. Short paper. 2019

Hybrid AI Systems Grounded on QSTR (1/4)

Neuro-symbolic AI

- Verification and explanation of ML-based decisions (interpretability)
- Abductive Learning (logical abduction + consistency optimization):[26]

$$X^{(90\%\text{ yolk})}\ _{\text{is } \textit{contained in}}{}^{(40\%\text{ true})}\ _{\text{or } \textit{overlaps}}{}^{(60\%\text{ true})}\ Y^{(95\%\text{ egg})}.$$

[26] M. Sioutis and D. Wolter: *Qualitative Spatial and Temporal Reasoning: Current Status and Future Challenges*. In: IJCAI. Survey paper. 2021

Hybrid AI Systems Grounded on QSTR (2/4)

AI Planning

- Utilizing dynamic spatio-temporal representations of an environment
- Applications of spatio-temporal models in motion planning and control under complex spatio-temporal tasks

$$\big(\text{Train } X \ \{\textit{uses}\} \ \big(\text{Track } A \oplus \text{Track } B\big)\big) \wedge \big(\text{Train } Y \ \{\textit{uses}\} \ \text{Track } B\big) \wedge$$

$$\big(\text{departInt(Train } X) \ \{\textit{precedes}\ _{10\%}, \textit{meets}\ _{30\%}, \textit{overlaps}\ _{60\%}\big\} \ \text{departInt(Train } Y)\big)$$

$$\Box\big(\neg\text{blocked(Track } A) \wedge \neg\text{blocked(Track } B)\big)$$

$$\text{Update: } \big(\Diamond\text{blocked(Track } A)\big)\ _{90\%}$$

Hybrid AI Systems Grounded on QSTR (3/4)

Hierarchical portfolio of solvers

- QSTR information can be encoded/tackled in different ways (aside from native QSTR approaches), e.g.,:
  - as SAT or even traditional CSP instances[27];
  - and as Answer Set Programming (ASP) instances too[28,29]
- Automate choice/combination of tools for a given task

[27] M. Westphal and S. Wölfl.: *Qualitative CSP, Finite CSP, and SAT: Comparing Methods for Qualitative Constraint-based Reasoning*. In: IJCAI. 2009

[28] G. Baryannis et al.: *A Generalised Approach for Encoding and Reasoning with Qualitative Theories in Answer Set Programming*. In: Theory Pract. Log. Program. 20 (2020)

[29] T. Janhunen and M. Sioutis.: *Allen's Interval Algebra Makes the Difference*. In: DECLARE. 2019

Hybrid AI Systems Grounded on QSTR (4/4)

Data mining

- Removal of redundancy from spatio-temporal KBs
- Pattern discovery / identification at run-time
- Facilitation of spatio-temporal pattern recognition algorithms

Final Remarks

- QSTR, within Neuro-Symbolic AI especially, is a research area relevant for many AI application domains (e.g., in defence or medicine)
- It extends from Theoretical Computer Science to Practical Applications, and vice versa
- Important to consider modular architectures for AI that are grounded on ***physics*** and ***human cognition***

Thank you for your interest and attention!

`http://msioutis.gitlab.io`

The purpose of abstraction is not to be vague, but to create a new semantic level in which one can be absolutely precise

Dijkstra

(Inter)national Research Experience and Collaborations

Research experience

- Postdocs: Aalto University (Finland), Örebro University (Sweden), University Institute of Technology of Lens (France)

Collaborations (aside from host universities)

- Prof. Manuel Bodirsky (TU Dresden, Germany)
  Algorithms/Complexity
- Dr. Marjan Alirezaie (Örebro University, Sweden)
  Neuro-Symbolic AI
- Dr. Zhiguo Long (Southwest Jiaotong University, China)
  QSTR/ML
- Prof. Tomi Janhunen (Tampere University, Finland)
  Answer Set Programming

Contributions in Other CS/AI Topics

I collaborated with Researchers in the context of:

- Graph Compression (ECIR '14, CIKM '14)
- Modal Logics (GCAI '15)
- Simple Temporal Networks (ECAI '16)
- Social Network Analysis (SocInf@IJCAI '16)
- Agents (AAMAS '18)
- Classical Constraint Programming (COMPJ'18)
- Neuro-symbolic Learning and Reasoning (SWJ'19)
- Answer Set Programming (DECLARE/INAP'19)
- Machine Learning (IEEE Access'20)
- Satisfiability Modulo Theories (CP'18)