EEML

Eastern European Machine Learning summer school

PROJECT PITCHES

Projects: Motivation

(1) Improve interaction among participants

(2) Build collaborations and support network (social aspect of research)

(3) Allow you to show your expertise and knowledge

Projects: Concept

- **Self-organize** into teams of at least 4 (representing at least 2 different institutions, highly recommended to be in different countries)

- Each team needs to brainstorm on a project (doable in ~14 days) -- suggestions available

- Pitch the plan (due EOD Wed 14th July) for approval

- Present the plan (Thursday 15th) during Challenge Presentations

- (Optional) Commit (as a team) to work on it, and provide a short write-up of the outcome by 29th July

Projects: High-level suggestions

- Exploring recently proposed benchmarks (e.g. LiRO, KLEJ, ContinualWorld, etc.)
- Design / collect data for evaluating certain aspects of a system
- Test a very concise and specific hypothesis (e.g. suggestions or hypotheses discussed during lectures)
- Add your own project ideas

We encourage projects with an explicit social good aim and diverse teams (e.g. expertise, location, gender, etc.).
Evaluation will take into account difficulty of the project, execution of the plan, clarity of the presentation.

Join #projects slack channel for more details and clarifications

Team name ABC: Project title XYZ

Members	Affiliations

Description of the topic / project

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Team name ABC: Project title XYZ

Details of the topic / project (cont.)

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T1: Improving Agent Behavior via Causal States

Members	Affiliations
Ilija Stanojković	1plusX
Fabian Otto	University of Tübingen, Bosch Center for Artificial Intelligence
Lovro Vrček	University Zagreb
Maximilian Thiessen	TU Wien
Nirav Diwan	IIITD
Roberto R. M. Rivero	LSE
Matej Zečević	TU Darmstadt

Combining Reinforcement Learning with Causality and Graph-based Models

Please consider our overview on the next slide.

Improving Agent Behavior via Causal States

Combining Reinforcement Learning with Causality and Graph-based Models

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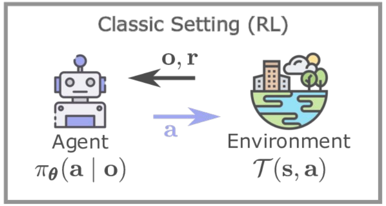
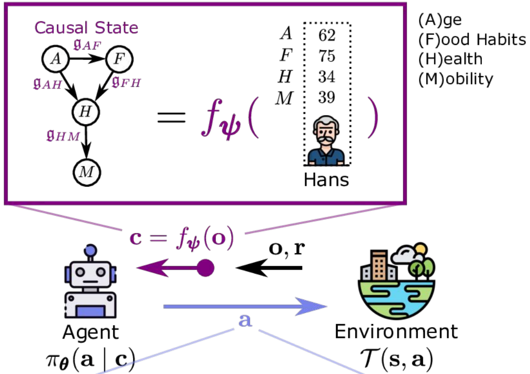


Example Task:
Assistance Robot



Action now might be a new, more *healthy Diet-plan* because the agent knows a *good Nutrition benefits Health.*

$$F \rightarrow H \wedge \mathfrak{g}_{FH} > 0$$

f_ψ will be GNN $f_\psi(\mathbf{O}, \mathbf{A})$

Inductive bias on graphs, ideal for Causal Structure.

Resulting embeddings will contain information on actual form of relations (e.g. strength) opposed to only existence and directedness.

T2

ML through a looking glass: Explainability in Deep Learning

Members	Affiliations
Mathys Grapotte	Sanofi,Chilly-Mazzarin IGMM- CNRS Montpellier, France
Cristian Militaru	Technical University of Cluj-Napoca, Romania
Divij Pawar	Mumbai University, Mumbai, India
Rosa Paccotacya Yanque	University of Campinas, Brazil
Maria Nicolae	Politehnica University of Bucharest
Đurđica Vukić	University of Rijeka, Croatia
Péter Kovács	Budapest University of Technology, Hungary
Anas Zafar	National University of Computer and Emerging Sciences, Pakistan
József Konczer	Wolfram Research
Sudhanshu Mishra	Indian Institute of Technology Kanpur
Weld Lucas Cunha	University of Campinas, Brazil

Goal: a tutorial touching upon plenty of algorithms proposed for explaining machine learning models.

Details on next slide

ML through a looking glass: Explainability in Deep Learning

- Goal of project: collecting plenty of methods for explaining machine learning models in a tutorial format (explaining theory + code)
- Planned structure:
  - intro with motivation (maybe incorporating expertise from Rosa and Mathys)
  - methods with theory & code in a modular manner, may including consensus on them if applicable
  - "horizons" section: promising methods we didn't include, interesting related papers or similar

Hopefully, our project will get newbies/intermediate people think about the problem of explainability and get them familiar with some elaborated methods. [Btw. learning about them is also a goal for the team]

T3 : Uncertainty Guided Pseudo Labels Selection for UDA

Members	Affiliations
M. Akhtar Munir	Information Technology University of Punjab, Pakistan
Dániel Horváth	Institute for Computer Science and Control, Budapest, Hungary Eötvös Loránd University, Budapest, Hungary
Sree Harsha Nelaturu	University of Florida, Gainesville, USA
Jalal Al-afandi	Pázmány Péter Catholic University Faculty of Information Technology and Bionics

Uncertainty Guided Pseudo Labels Selection For Unsupervised Domain Adaptation (UDA)

T3: Uncertainty Guided Pseudo Labels Selection for UDA

T4: EENLP - mapping NLP state for EE languages

Members	Affiliations
Aleksey Tikhonov	Yandex, Berlin
Alex Malkhasov	Financial University under the Government of the Russian Federation
Andrey Manoshin	Mephi/Greenatom (Russia)
George Dima	University Politehnica of Bucharest
Réka Cserháti	University of Szeged (Hungary)
Md.Sadek Hossain Asif	Notre Dame College, Dhaka
Matt Sárdi	Mozaik Education (Hungary)

Goals:

- to make a broad meta index of existing natural language processing benchmarks for Eastern European languages;
- to make another meta index of existing pre-trained models for Eastern European languages;
- to conduct an evaluation study of such models on collected benchmarks (including cross-lingual transfer learning).

Motivation:

- The current state of NLP across Eastern Europe seems to be a little bit uneven and disjointed.
- We believe the results of this project could be small but valuable block for building the generalized NLP field of Eastern Europe.

T4: EENLP - mapping NLP state for EE languages

Stage 0: define/enumerate EE languages (20+)

Stage 1: search for benchmarks and datasets (focus on semantic and NLU)
Resulting artifact: a published meta index of datasets

Stage 2: search for pre-trained models (Transformers, ELMo, ULMFiT, ...)
Resulting artifact: a published meta index of existing models across languages

Stage 3: cross-evaluation
Resulting artifact: a published report with the results of the evaluation and possible future work directions

T5: Self-supervised representation learning for sample efficient RL

Members	Affiliations
Sushil Thapa	New Mexico Tech | lanl.gov, USA
Martin Balla	Queen Mary University of London, UK
Benjamin Hahn	Advertima, Zurich Switzerland | ETH Zurich, Imperial College London
Quan Duong	University of Helsinki, Finland
Mahan Tourkaman	KTH Royal Inst. of Technology, Sweden

Background:

- Self-supervised learning has been successful in the field of NLP and Vision by learning rich representations through self-supervised pre-training (like simCLR,MoCo) and applying them to downstream tasks.
- Deep RL is challenging as the agent has to learn a good representation and a policy at the same time from high dimensional space, especially when rewards are sparse and delayed

Motivation:

- Utilize self-SL techniques and Human priors to improve sample efficiency in RL
- Create an agent for the MineRL 2021 Diamond Competition

Keywords: Reinforcement learning, Self supervised learning, Imitation learning, Exploration

T5: Self-supervised representation learning for sample efficient RL

Problem: MineRL[1] Diamond Competition (NeurIPS 2021)

- Human demonstration (60 million frames)
- Sparse rewards
- Only 8 million interactions allowed with MineCraft

Approach: Approaches like CURL[2] improves data-efficiency by extracting high-level features from raw pixels using contrastive learning and performs off-policy control on top of the extracted features.

Proposed Extensions:

- Data augmentation[3][4]
- Imitation learning
- Exploration

T6: Continual Learning in Continual World

Members	Affiliations
Endre Borza	Hungarian Academy of Sciences
Luca Viano	EPFL
Ghada Sokar	Eindhoven university of technology
Chen-Yu Yen	NYU
Abhiroop Bhattacharya	ETS
Cassandra Engstrom	CUNY The Graduate Center

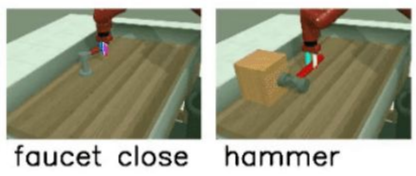
Continual World is a benchmark consisting of diverse robotic tasks, with the aim of encouraging the in-depth study of continual learning and reinforcement learning.

Reproducing and investigating one property of a tested algorithm from the 7 tested in the original paper.

first exploring what properties are straightforward to investigate, and are suitable for hypothesis testing.

Key insights from the Continual World paper:

- A-GEM not working
- PackNet being unstable
- PackNet beating everything after clipping
- 5/7 achieving negative forward transfer



T6: Continual Learning in Continual World

Details of the topic / project (cont.)

Analyse PackNet and A-GEM based on the following properties:

- Forward transfer
- Forgetting
- Backward transfer

Challenges:

- The benchmark depends on a proprietary software, which is not free
- Difficult to analyse the learning dynamics of the model
- None of the methods show any instance of backward transfer
- Limited time and compute

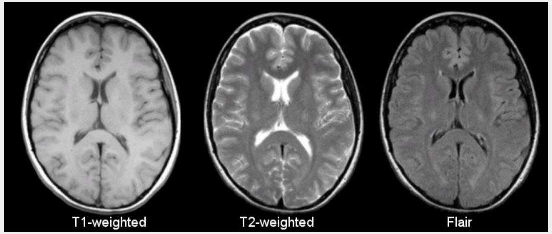
T7: MediSinGAN

Members	Affiliations
Anagha Zachariah	VIT,India
Ekaterina Nepovinnykh	LUT, Finland
Phuc Nguyen	University of Cincinnati, US
Md.Sadek Hossain Asif	Notre Dame College, Dhaka, Bangladesh
Madhu mithra K K	IIT Madras, India
Rajkumar Vaghashiya	PDEU, India
Samarghitan Flaviu	Neurolabs, Romania
Amrit Kumar Jethi	IIT-Madras, India
Margarete Kattau (Adviser)	The Institute of Cancer Research London and The Royal Marsden NHS Foundation Trust, London

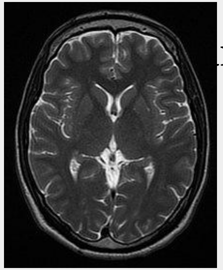
- Typically, AI-assisted medical imaging approaches demand large amounts of data, which is usually difficult to collect
- However, SinGAN presents the ability to generate sample images using a single training image
- In medical domain, we aim to use SinGAN for the following:
  - MRI cross-modality image-to-image translation
  - Synthetic medical data generation
  - Medical Image segmentation
- Tech stack: Jax, Colab, Flax

T7: MediSinGAN

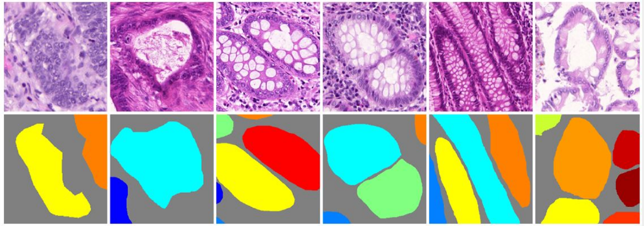
- MRI cross-modality image-to-image translation
  - collecting multiple scans from each subject is not
    - Use-case: generate T2 images from T1 images



- Synthetic medical data generation
  - Obtaining real medical data is costly and there is an positive and negative samples
    - Use-case: MRI tumour data generation



- Medical Image segmentation
  - Using an inverse paint-to-image approach
    - Use-cases: Histopathology, Retinal Analysis, ,



*We plan to continue our work after the school.