EEML

@EEMLcommunity

More than a summer school

Empower the ML community in Eastern Europe by bringing there (even virtually) people from everywhere in the world.

Our values:

- **Excellence**
- **Diversity**
- **Inclusion**

More than a summer school

Empower the ML community in Eastern Europe by bringing there (even virtually) people from everywhere in the world.

Personal project of the organisers.

Organised on a volunteering basis, with support from sponsors, non-profit.

Impact from previous editions

Through contacts made at the school:

- Some participants found phd positions
- Some participants found visiting researcher positions
- Some participants started collaborating after the school, leading to papers or longer term collaborations between labs
- The github tutorials were used for other workshops
- We’re organising different events in collaboration with school participants: e.g. workshop in Lviv, Timișoara

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Repatriot

+ Thank you, Aleksandra, for the beautifully customised online town rooms!
+ Thank you, Maciej, for the great collection of Polish classical music!

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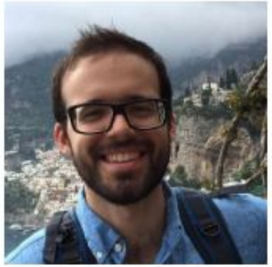

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Best practices in ML research panel

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Acknowledgements

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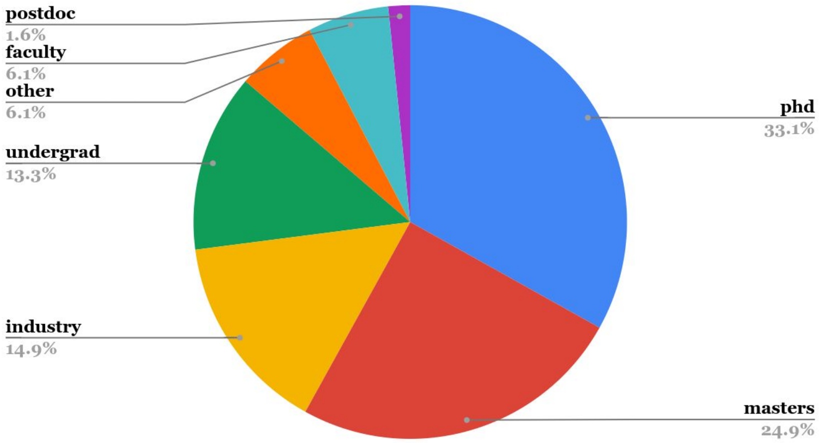
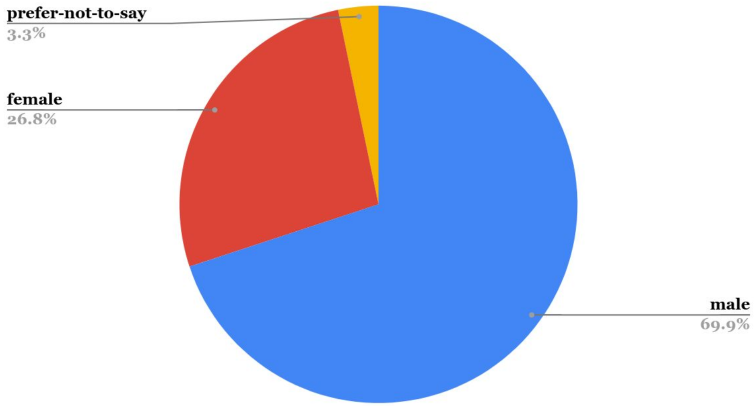
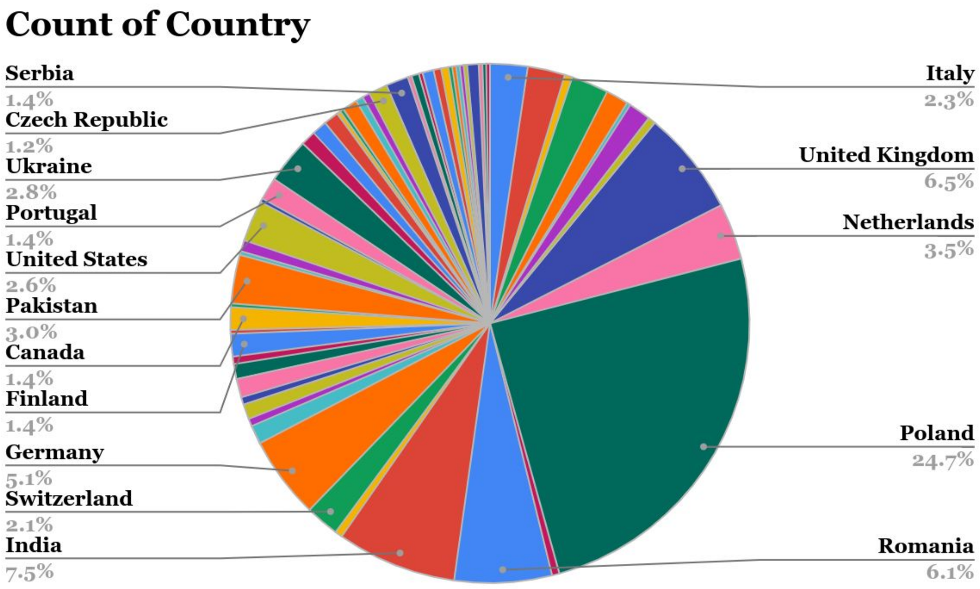
Gather

Phillip, Kumail, Cyrus

Participants







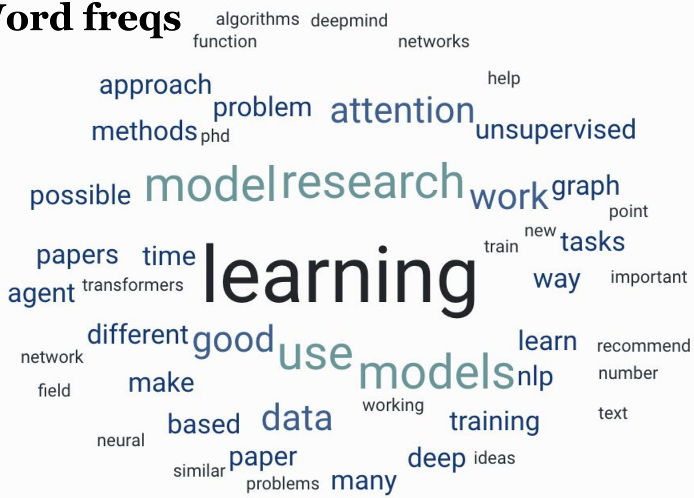
430 participants from selection, representing 60 countries

Activity during EEML2020

Active participants	492
Joined participants	4491
Engagement score	4087

Questions	872
Likes / dislikes	3050 / 0
Anonymous rate	50%

Word freqs



Most active participants

	Participant	Questions	Likes
A	Alessio Brini	39	116
S	Shriraj Sawant	25	84
G	Giorgio	16	71
R	Roberto-Rafael Maura-Rivero	8	58
C	Cugur	4	54

What’s next?

- School platform through portal will stay up for 1 more week.
- (Most of) the school sessions will be publicly available on youtube in ~10 days.
- EEML rocket chat will stay up until August 1. Download discussions to keep references, contacts, materials.
- e-Certificate of attendance - delivered next week by email.
- Feedback form on the school - next week. Please fill it in!
- If you want to apply for next year’s edition (in person/virtual), please do!
- If you enjoyed the school, tell your friends / colleagues about it!

DOs and DONs when applying

Statement of research interests

2-page abstract (research, reproduction, review)

Read the instructions on the Application page!

DOs and DONs when applying

Statement of research interests:

Don't:

"I am interested in Deep Learning."

Do:

Write 1-2-3 paragraphs on what ML project you've worked on and your background. Why do you want/need to attend this school?

Check the speakers for that edition and say why you want to see/meet them (your research interests should relate to a subset of the speakers).

DOs and DONs when applying

2 page abstract

DON'T

Don't submit full papers

Don't submit school reports

Don't submit a CV instead of abstract

Augmented Analytics on Customer Intelligence Framework: A Case Study on Customer Retention

Abstract

Nowadays, visual-based data discovery methods have dominated the conventional BI industry over the last ten (10) years. Visual-based data discovery capabilities have become the defining features of modern analytics and BI applications. Such easy-to-use tools allow users to easily compile data, visually test theories and find new insights into data. They have changed how business users explore data in comparison to the IT-centric, semantic-layer-based approach of typical BI applications. Visual-based data discovery features - now standard features of modern analytics and BI platforms - are easy to use, as users analyze data by creating visual queries to test hypotheses. However, when data sizes and the number of variables are huge, it is not possible for users to explore every possible trend and combination, let alone decide if the result are the most significant, relevant and actionable (Gartner, 2019). Augmented analytics is a next-generation data and analytics paradigm that uses machine learning to automate data preparation, insight discovery and insight sharing for a broad range of business users, operational workers and citizen data scientists. This research study, therefore, has an interest to propose CI framework by integrating augmented analytics.

DO

Learning a Robust Society of Tracking Parts using Co-occurrence Constraints

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Abstract

Object tracking is an essential problem in computer vision that has been researched for several decades. One of the main challenges in tracking is to adapt to object appearance changes over time, in order to avoid drifting to background clutter. We address this challenge by proposing a deep neural network architecture composed of different parts, which functions as a society of tracking parts. The parts work in conjunction according to a certain policy and learn from each other in a robust manner, using co-occurrence constraints that ensure robust inference and learning. From a structural point of view, our network is composed of two main pathways. One pathway is more conservative and monitors a large set of simple tracker parts learned as linear filters over deep feature activation maps with a single closed-form formulation. The second pathway is more progressive as it is learned completely online and thus it is able to better model object appearance changes. As shown in the experimental section, our approach achieves state of the art performance on the challenging VOT17 benchmark, outperforming the existing published methods both on the general EAO metric as well as in the number of fails by a significant margin.

1 Introduction

Visual tracking is about being able to adapt the current knowledge about an object model to changes that take place continuously in the stream of video. It is also about being stable and robust against background noise during frame by frame inference. A tracking model composed of many parts, with different degrees of complexity, could use the co-occurrences of their responses in order to monitor over time, which parts are reliable and which are not.

Our main contributions: 1) Our first contribution is the design of a tracker as a dual-pathway network, with FilterParts and ConvNetPart pathways working in complementary ways within a robust society of tracking parts. FilterParts is more robust to background noise and uses many different and relatively simple trackers learned on top of deep feature activation maps. ConvNetPart is better capable to learn object appearance and adapt to its changes. It employs a deep convolutional network that is learned end to end during tracking using unsupervised high confidence frames for ground-truth. 2) Our second contribution is that every decision made for learning and inference of the tracker is based on robust co-occurrence constraints. Through co-occurrences over time we learn which FilterParts classifiers are reliable or not. Thus we can change their roles and add new ones. Also, through co-occurrences between the vote maps of the two pathways, we decide which frames to choose for training the ConvNetPart path along the way. Last but not least, through co-occurrences we decide the next object center by creating a combined vote map from all reliable parts. 3) Our third contribution addresses a theoretical point. We show that the efficient closed-form formulation for learning object parts simultaneously in a one sample vs. all fashion is equivalent to the more traditional, but less efficient, balanced one vs. all formulation.

2 Architecture

At the structural level, the Society of Tracking Parts (STP) has two pathways: FilterParts and ConvNetPart pathways (Figure 1). The first pathway is formed of smaller object parts that are classifiers represented by linear classifiers over activation maps, from a pre-learned convolutional net. The ConvNetPart pathway is a deep convolutional net, with the same structure as the first pathway up to a given depth.

3 Experiments

For computing the final Expected Average Overlap (EAO) evaluation score, VOT setup is re-initializing the tracker when it completely misses the target. In Table 1 we present the results after running our tracker through the VOT toolkit. Our STP outperforms the current state of the art methods on VOT17 [1], and is in the top three on VOT16 [2]. Note that we used the exact same set of parameters on all videos from both VOT17 and VOT16. What distinguishes our tracker the most from the rest is the much lower failure rate (0.76 vs. second best 1.13, on VOT17). We think this is due to the robustness gained by the use of co-occurrence constraints in all aspects of learning and inference, and the dual-pathway structure, with each pathway having complementary advantages.

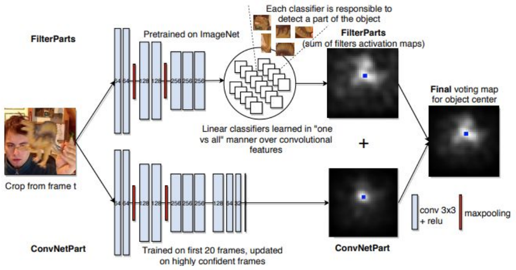

Figure 1: STP overview: The tracker functions as a society of parts. It combines the vote for center maps from all parts over two main pathways, FilterParts and ConvNetPart. The two pathways are learned differently. The FilterParts classifiers once learned are fixed individually but adapt as a group. The ConvNetPart is trained end-to-end with back-propagation over unsupervised tracker outputs from previous highly confident frames (HCFs).

Dataset / Tracker	VOT17 [1]			VOT16 [2]		
	EAO	Failure rate	Accuracy	EAO	Failure rate	Accuracy
STP (ours)	0.309	0.765	0.44	0.361	0.47	0.48
CFWCR [3]	0.303	1.2	0.48	0.39	0.81	0.58
ECO [4]	0.28	1.13	0.48	0.374	0.72	0.54
CCOT [5]	0.267	1.31	0.49	0.331	0.85	0.52
Staple [6]	0.169	2.5	0.53	0.295	1.35	0.54
ASMS [7]	0.169	2.23	0.494	0.212	1.925	0.503
CCCT [8]	-	-	-	0.223	1.83	0.442
EBT [9]	-	-	-	0.291	0.9	0.44
CSRDCF [10]	0.256	1.368	0.491	-	-	-
MCPF [11]	0.248	1.548	0.510	-	-	-
ANT [12]	0.168	2.16	0.464	-	-	-

Table 1: Top published trackers in terms of expected average overlap (EAO), Robustness (Failure rate) and Accuracy, on VOT17 [1] and VOT16 [2] benchmarks. Our failure rate is the best by large margins on both datasets (42% and 67%). Our overlap score is lower as we did not explicitly learn object shape or mask, but focus instead on its center.

4 Conclusions

We have proposed a deep neural network system for object tracking that functions as a society of tracking parts. Our tracker has two main deep pathways, one that is less flexible but more robust, and the second that is less robust but more capable of adapting to complex changes in object appearance. Each part uses co-occurrences constraints in order to keep its robustness high over time, while allowing some degree of adaptability. The two pathways are also combined in a robust manner, by joining their vote maps and picking the locations where their votes co-occurred the most. From a technical point of view, the novelty aspects of our system include the way the classifiers in the FilterParts pathway are learned and ascribed different roles, depending on their degree of reliability. These roles relate the idea of a society, where some parts are candidates that are being monitored, others are reliable voters, where those who proved their reliability long enough become gold members. Another novelty aspect which brings an important value in practice, is the way we train the ConvNetPart on high confidence frames only, by selecting for training only those frames where the two different and complementary pathways, agree. We also provide a novel theoretical result, to the best of our knowledge, we proves that the efficient one sample vs. all strategy employed for learning the classifiers in the FilterParts path, is stable and gives basically the same result as in the balanced case. In experiments we provide solid validation of our design choices and show state of the art performance on VOT17 and top three on VOT16, while staying on top on both in terms of failure rate, by a significant margin.

\+ Page for references

DO

Recurrent Space-time Graphs for Video Understanding

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[1]Bitdefender, Romania [2]Institute of Mathematics of the Romanian Academy
[3]University "Politehnica" of Bucharest

1. Introduction

Visual learning in the space-time domain remains a very challenging problem in artificial intelligence. We propose a neural graph model, recurrent in space and time, suitable for capturing both the appearance and the complex interactions of different entities and objects within the changing world scene. Our model passes messages iteratively in two complementary ways: spatially inside a single time step and temporally across the video. We demonstrate, through extensive experiments, a competitive performance over strong baselines on the tasks of recognizing complex patterns of movement in video and activity recognition on the Kinetics dataset.

Our graph model is related to some previous graph models such as [3, 4, 1, 5], but those models are developed for tasks unrelated to video. From the video understanding literature we compared our model to [6] and [2].

2. Graph model

2.1. Graph creation

We create a graph with N nodes and use it to process a feature volume $F \in \mathbb{R}^{T\times H\times W\times C}$. Features from each time step F^t are re-sized into multiple grids, each corresponding to a different scale. Each cell would be used as input to a node. Two nodes are connected if they are neighbours in the same grid or if their regions of interest at different scales intersect.

2.2. Space Processing Stage

Spatial interactions are established by exchanging messages between the nodes. The process involves 3 steps: **send** messages between all connected nodes, **gather** information from the received messages at each node and **update** internal node representation.

Message sending function. For every connected pair of nodes (i, j), the function $f_{send}(\mathbf{v}_j, \mathbf{v}_i)$ models pairwise interaction between the two, implementing as a multilayer perceptron (MLP) with 2 layers applied on the concatenation of the two node features.

Gather function. Each node receives a message from each of its neighbours and aggregates them using the f_{gather} function. We weight each message according to its importance, by learning an attention mechanism

$$f_{gather}(\mathbf{v}_i) = \sum_{j\in\mathcal{N}(i)} \alpha(\mathbf{v}_j, \mathbf{v}_i) f_{send}(\mathbf{v}_j, \mathbf{v}_i) \in \mathbb{R}^D. \quad (1)$$

The weighting function α could be computed in multiple ways: by projecting the concatenated representations of the two nodes or by computing the dot product between them, as a measure of similarity between 2 entities.

Update function. We want each node to be capable of taking into consideration global information, while also maintaining a local identity. Thus we update the representation of each node with the information gathered from its neighbours, using function f_{update} modeled as an MLP.

$$f_{space}(\mathbf{v}_j) = \mathrm{MLP}_u([\mathbf{v}_i | f_{gather}(\mathbf{v}_i)]) \in \mathbb{R}^D. \quad (2)$$

In general, the parameters of the MLP could be shared among all nodes at all scales or we can use different sets of parameters for different scales.

2.3. Time Processing Stage

This stage follows the space processing steps, thus each node has been updated, incorporating information from its spatial neighbours into a node space representation $\mathbf{v}_{i,space} = f_{update}(\mathbf{v}_i)$.

Each node updates its state in time by aggregating the spatial representation with its time representation from the previous step using a recurrent function such as LSTM or vanilla RNN.

$$\mathbf{v}^t_{i,time} = f_{time}(\mathbf{v}_{i,space}\mathbf{v}^{t-1}_{i,time}). \quad (3)$$

The global representation of the graph is obtained using $f_{aggregate}$, computed as a sum over all nodes features, and passed through a final classifier.

Discussion on the graph model and architecture. We adapt our model to gains different capabilities. For capturing complex interactions between long-distance neighbours, the model could have multiple space processing blocks. We want each interactions between nodes in space to have access to historic information, thus we interleave Space and Time processing stages.

[*]Equal contribution.

3. Experiments

We perform experiments on 2 different video classification tasks that involve complex object interactions. We create a synthetic dataset by moving digits (3 or 5) randomly such that two of the digits (that gives the class of the video), which could be far apart, follow the same moving pattern.

This dataset is useful because we can control the movement patterns and their level of complexity and thus we can better understand the role of each component in our system. We use this dataset to perform ablation studies and compare to different powerful baselines from the literature.

In the second set of experiments we test our model on the very large and challenging Kinetics dataset [2] for activity recognition in real world videos.

3.1. Baselines

We compared to three strong baseline models that are often used to process videos. For all tested models we used a convolutional network as a backbone for a larger model. It is a small CNN with 3 layers, pre-trained to classify a digit in a frame of the video.

The baselines used are: **Mean + LSTM** that does average pooing on the backbone conv features of each frame and aggregate temporal information using an LSTM; **ConvNet + LSTM** that replace the average pooing with 3 more conv layers; **I3D** and **Non-Local** smaller versions of 3D conv models of [2] and [6];

In Table 1 we present results, on both 3Digits and 5Digits datasets, which show that RSTG significantly outperform baselines.

3.2. Ablation study: need for space-time

We claim that solving the moving digits task requires a model capable of capturing pairwise interactions both in space and time. RSTG is able to accomplish that, through spatial connections between nodes and the temporal updates of their state. In order to prove the benefits of each element, we perform experiments that shows the contributions brought by each one and present them in Table 1.

Space-Only RSTG. We create this model in order to prove the necessity of having a powerful time modeling by replacing the recurrence from the Temporal Stage with an average pool across time dimension, applied for each node.

Time-Only RSTG. This model performs just the Time Processing Stage, without any spatial message-passing between nodes.

Homogeneous Space-time RSTG. This model allows the graph to interact both spatially and temporally, but using the same function with same parameters for both stages.

Table 1. Results on the Moving 3Digits and 5Digits datasets compared to strong baselines from the literature and ablation study

Model	3 Digits	5 Digits
Mean + LSTM	77.0	-
Conv + LSTM	95.0	39.7
I3D	-	90.6
Non-Local	-	93.5
RSTG: Space-Only	61.3	-
RSTG: Time-Only	89.7	-
RSTG: Homogenous	95.7	58.3
RSTG: 1-temp-stage	97.0	74.1
RSTG: all-temp-stages	**98.9**	**97.2**

Table 2. Results on the Kinetics-400 dataset. We show how our model could improve the state-of-the-art model I3D [2].

Model	Kinetics 400 valid
I3D	72.26
RSTG	72.50

Heterogeneous Space-time RSTG. This is our full model with different spatial and temporal processing. In **1-temp RSTG** model, for each time step, we performed 3 successive spatial iteration, followed by a single final temporal update. In **all-temp RSTG** model we alternate between the Time-Processing stages and Space-Processing stages. We use one Time-Processing stage before each spatial one, and a last time stage to obtain the final nodes representation.

3.3. Activity recognition in real world videos

To study how the RSTG model performs on real videos, we experiment on Kinetics-400 dataset [2]. To test our RTSG model on Kinetics dataset we used as a backbone feature-extractor the I3D model [2]. Our model receives the feature volume, creates the graph nodes and process them into a final feature vector v_{graph} that is added to v_{i3d} to make the final prediction.

From the features volume we extracted, by mean-pooling, slices of 4, 8 and 16 time steps. We applied RSTG on each one and average their outputs, obtaining results in Table 2.

4. Conclusion

In this paper we introduce the Recurrent Space-time Graph (RSTG) model, which is specifically designed to learn in both space and time for efficient video understanding. In extensive experiments on 2 challenging problems, including activity recognition on Kinetics dataset, our proposed model demonstrated competitive performance when compared to state of the art methods and powerful baselines. In future work we plan to explore the capabilities of RTSG on other spatio-temporal learning datasets and tasks.

\+ Page for references

EEML2020 Awards

Certificate of participation

CERTIFICATE OF PARTICIPATION

EEML CERTIFIES THAT

ALEKSANDRA NOWAK

has attended the virtual sessions of
EEML2020 summer school.

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EEML2020 PROGRAM INCLUDED THE FOLLOWING ACTIVITIES:

- 14 hours of lectures
- 7 hours of tutorials (coding sessions)
- 4 hours of poster presentations
- 9 hours of panel discussions
- 11 hours of group project discussions (optional)
- 1 hour of mentorship session (optional)

EEML2020 Awards

Best posters & Best unconference proposal

EEML2020 Awards

Best posters & Best unconference proposal

Awards: ticket for EEML2021 (no selection, no fees)!

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Best posters

Reinforcement Learning

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Reinforcement learning based brain-computer interface

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Finding transferable sub-policies using meta-learning

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Deep Learning

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Few shot learning by features adaptation with Graph Neural Networks

ARMAND NICOLICIOIU

ANDREI NICOLICIOIU

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Representing Point Clouds with Generative Conditional Invertible Flow Networks

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TOMASZ TRZCIŃSKI JAN CHOROWSKI

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Emerging Representations for Counting in a Neural Network Agent Interacting with a Multimodal Environment

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Applications

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Translating Visual Art into Music

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Comparative Analysis of Music Emotion Recognition using Deep Neural Networks

GLORIA-RUXANDRA MACIUCA

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BERT for Romanian Language Understanding

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Review & Reproduction

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BEST POSTER AWARD

Implementation of Contrastive Predictive Coding

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Reproduction of DPOD: 6D pose detector and refiner

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Proximal Policy Optimization paper review

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EEML2020 Awards

Best unconference proposal

EEML2020 SUMMER SCHOOL

EEML

BEST UNCONFERENCE PROPOSAL

3-2-1D Band: 3D historic landmark reconstruction

DAMIAN PĘSZOR
BIHAO WANG
TEHREEM FATIMA
MARCIN PRZEWIĘŹLIKOWSKI
CAIUS-IOAN DEBUCEAN
JAVED AHMAD
JELENA TRISOVIC
LU YAN

Doina Precup
Razvan Pascanu
Viorica Patraucean
Jacek Tabor
Wojciech Czarnecki

EEML2020 SUMMER SCHOOL

EEML

BEST UNCONFERENCE PROPOSAL

Hate-Busters: Hate speech detection in under-resourced languages

MRINAL ANAND ANGELINA AQUINO TAMÁS FICSOR CRISTIAN POPA

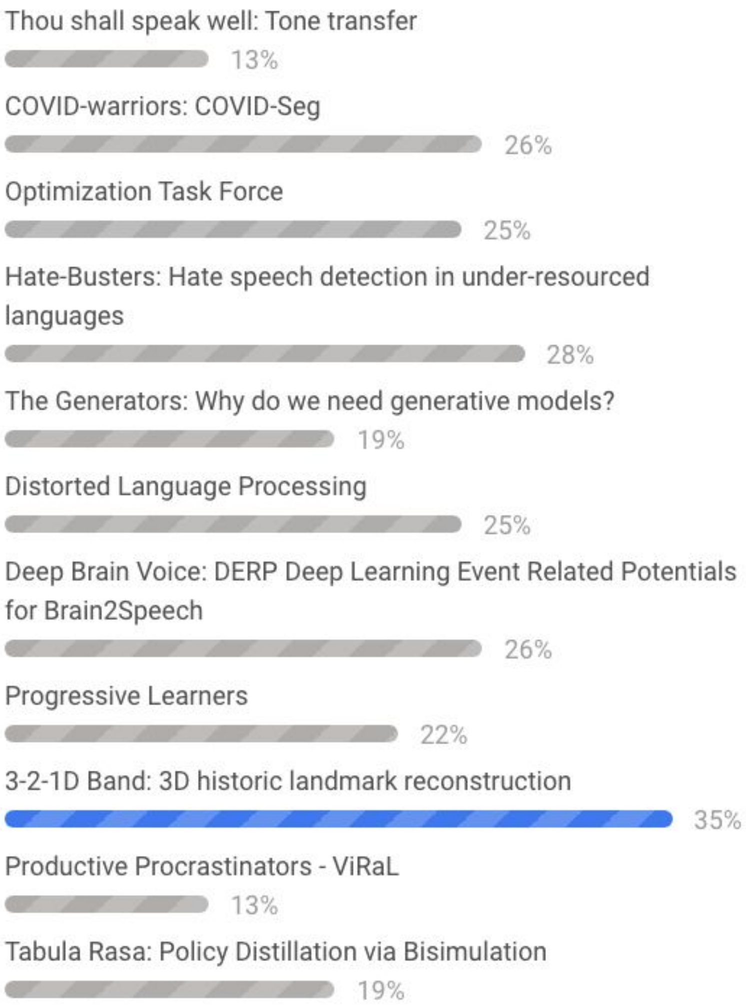
HASSANE KISSANE DOMINIK KRZEMIŃSKI SZYMON OLEWNICZAK ADE ROMADHONY

MYKOLA PETRYCHKO PRITHVIRAJ PRAMANIK SURANGIKA RANATHUNGA

Doina Precup Razvan Pascanu Viorica Patraucean

Jacek Tabor Wojciech Czarnecki

Vote for best unconference proposal



Q&A with the organisers