



European Lighthouse of AI for Sustainability

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Funded by
the European Union



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Funded by
the European Union

Theme Development Workshop on Sustainability & AI

Theme Development Workshops (TDWs)

7 March, 2025

Bucharest, Romania

www.elias-ai.eu





Funded by
the European Union

TDW on Sustainability & AI

Agenda

09:00 – 09:10 | Welcome & Introductions

- Opening remarks
- Introduction to the workshop's theme: AI and Sustainability
- Overview of the sessions and objectives

Nicu Sebe (UNITN), Filareti Tsalakanidou (CERTH)

09:10 – 09:30 | Session 1: Regulatory and Ethical Aspects

Keynote:

- Marko Milosavljevic (University of Ljubljana, Slovenia)

Q&A and Discussion: 5 mins

09:30 – 10:10 | Session 2: AI for a Sustainable Planet

Keynotes:

- Saso Dzeroski (Jozef Stefan Institute, Slovenia)
- Marius Leordeanu (National University of Science and Technology POLITEHNICA Bucharest, Romania)

Q&A and Discussion: 10 mins

10:10 – 10:50 | Session 3: AI for a Sustainable Society

Keynotes:

- Nicolò Cesa-Bianchi (University of Milan, Italy)
- Ioana Manolescu (INRIA, France)

Q&A and Discussion: 10 mins

10:50 – 11:10 | Break

11:10 – 11:30 | Session 4: Trustworthy AI for Individuals

Keynotes:

- Lorenzo Baraldi (University of Modena and Reggio Emilia, Italy)
- Nicu Sebe (University of Trento, Italy)

Q&A and Discussion: 10 mins

11:30 – 11:50 | Session 5: Fostering the Next Generation of AI Talents

Keynote:

- Charlotte Delage (Institute Polytechnique of Paris, France)

Q&A and Discussion: 5 mins

11:50 – 12:30 | Session 6: Entrepreneurship and Tech Transfer

Keynotes:

- Nina Peters (University of Tübingen, Germany)
- Isabelle Siegrist (ETH Zurich, Switzerland)

Q&A and Discussion: 10 mins

12:30 – 12:45 | Conclusion & Wrap-up

- Summary of key takeaways
- Final remarks and next steps

Nicu Sebe (UNITN), Filareti Tsalakanidou (CERTH)



Multi-view Self-supervised Consensus for Sustainable AI

Marius Leordeanu

University POLITEHNICA of Bucharest

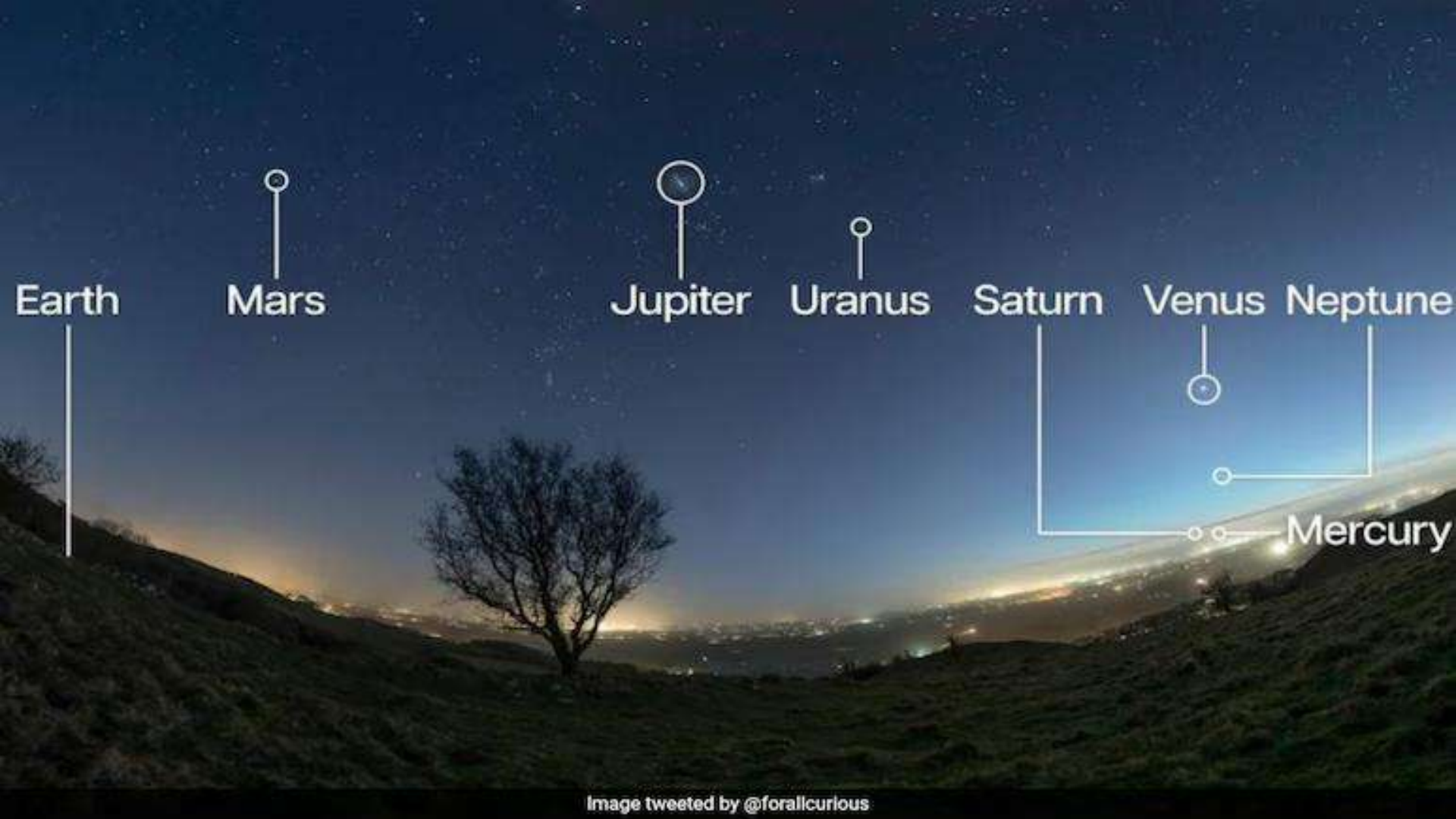
1st Theme Development Workshop on Sustainability & AI

The Planets have aligned for the Romanian Artificial Intelligence

On February 28th 2025, the Government and Consortium of Universities and Companies, have aligned to sign the start of the **Romanian AI HUB**

... along with the rare alignment of Mars, Jupiter, Uranus, Saturn, Venus, Neptune and Mercury.





Earth

Mars

Jupiter

Uranus

Saturn

Venus

Neptune

Mercury

HRIA

Romanian Hub for Artificial Intelligence



Co-funded by
the European Union



HRIA Consortium – 15 partners

Leader – National University of Science and Technology POLITEHNICA București



Technical University of Cluj-Napoca



IT Center for Science and Technology SRL



West University of Timișoara



Greensoft SRL



Technical University “Gheorghe Asachi” of Iași



Neural Grader SRL



University Politehnica of Timișoara



Safetech Innovations SA



University of Bucharest



SoftTehnica SRL



University “Babeș Bolyai” of Cluj-Napoca



Technology Systems and Services International SRL



Beia Consult International SRL



Terrasigna SRL



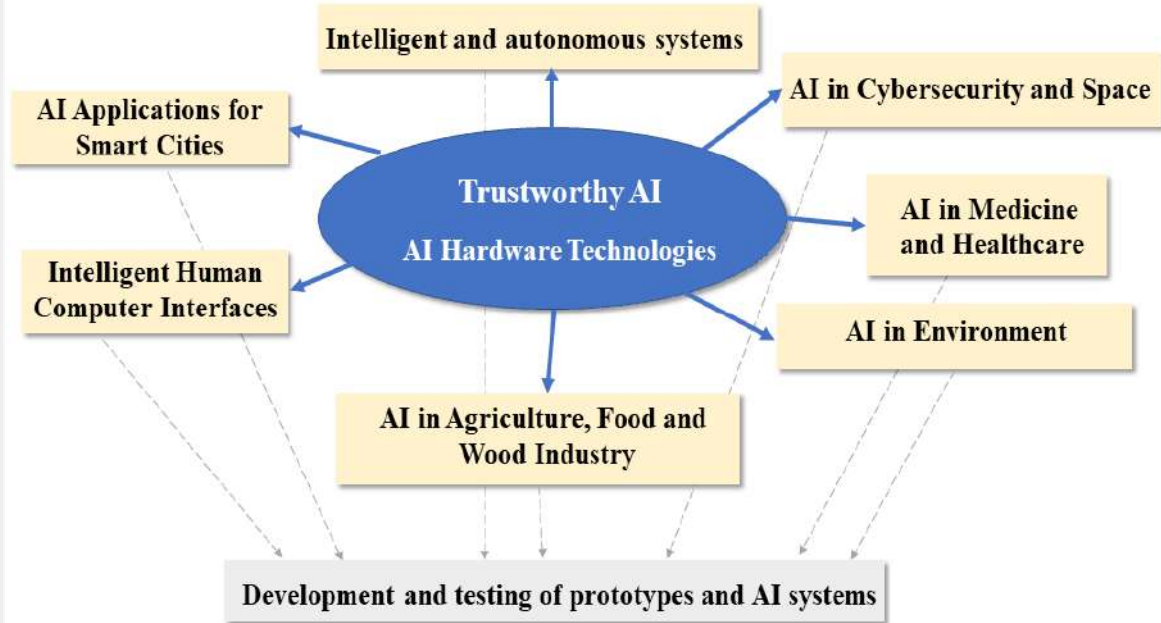
Project in the framework “Smart Growth, Digitalization and Financial Instruments Program” (PoCIDIF)

Duration: 5 years (2025-2029)

Non-reimbursable budget: 65 Million Euro

Main research topics

- Trustworthy AI
- AI Hardware Technologies
- Intelligent and Autonomous Systems
- Intelligent Human Computer Interfaces
- AI in Medicine and Healthcare
- AI in Cybersecurity and Space
- AI Applications for Smart Cities
- AI in Environment
- Development and testing of AI prototypes and systems





ENFIELD: European Lighthouse to Manifest Trustworthy and Green AI

HORIZON-CL4-2022-HUMAN-02-02

Vision and mission: Create a unique European Centre of Excellence that excels in fundamental research in the pillars of **Adaptive, Green, Human-Centric, and Trustworthy AI** and will further advance the research within applications of **healthcare, energy, manufacturing and space**

Project Concept

Thematic Areas



GREEN AI (SINTEF)



ADAPTIVE AI (IMT)



HUMAN-CENTRIC AI (TUE)



TRUSTWORTHY AI (NTNU)

Available Resources

- Research Labs
- Data
- Infrastructure
- DIHIWARE Platform

Strategic Initiatives

- Policy Initiatives
- Networks and Alliances
- (Inter-) National R&I Projects

Innovation Paradigm

- DIHs and Incubators
- Industry Collaborations
- Open Cascading Calls: TES & TIS

Application Domains



ENERGY
(INESC)



HEALTHCARE
(ICCS)



MANUFACTURING
(POLIMI)



SPACE
(ECOE)

Consortium

30 partners from 19 European countries

Common Research Vision and Roadmap

Safety and Security Risks Assessment Framework Regulations

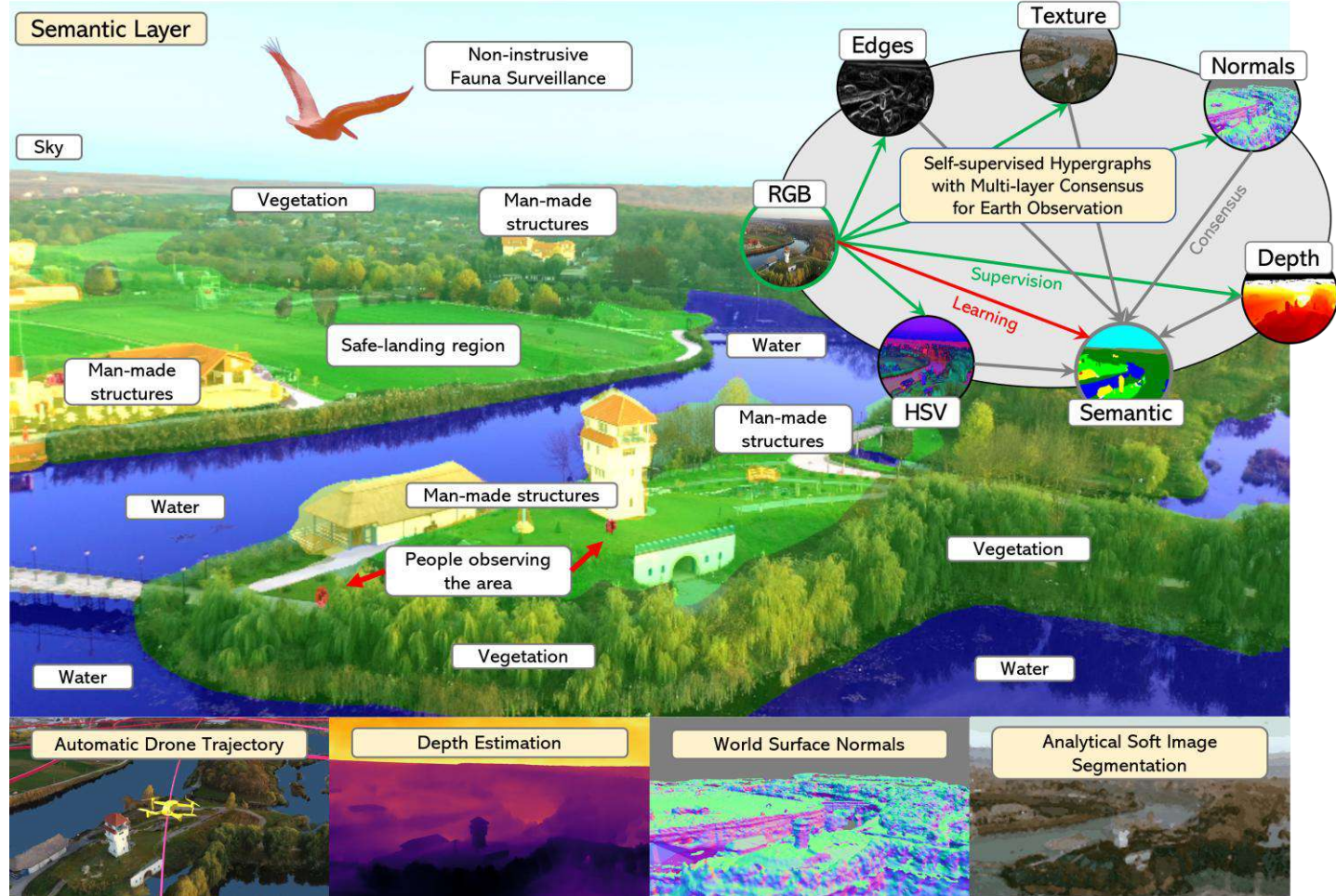
Standards and Certification

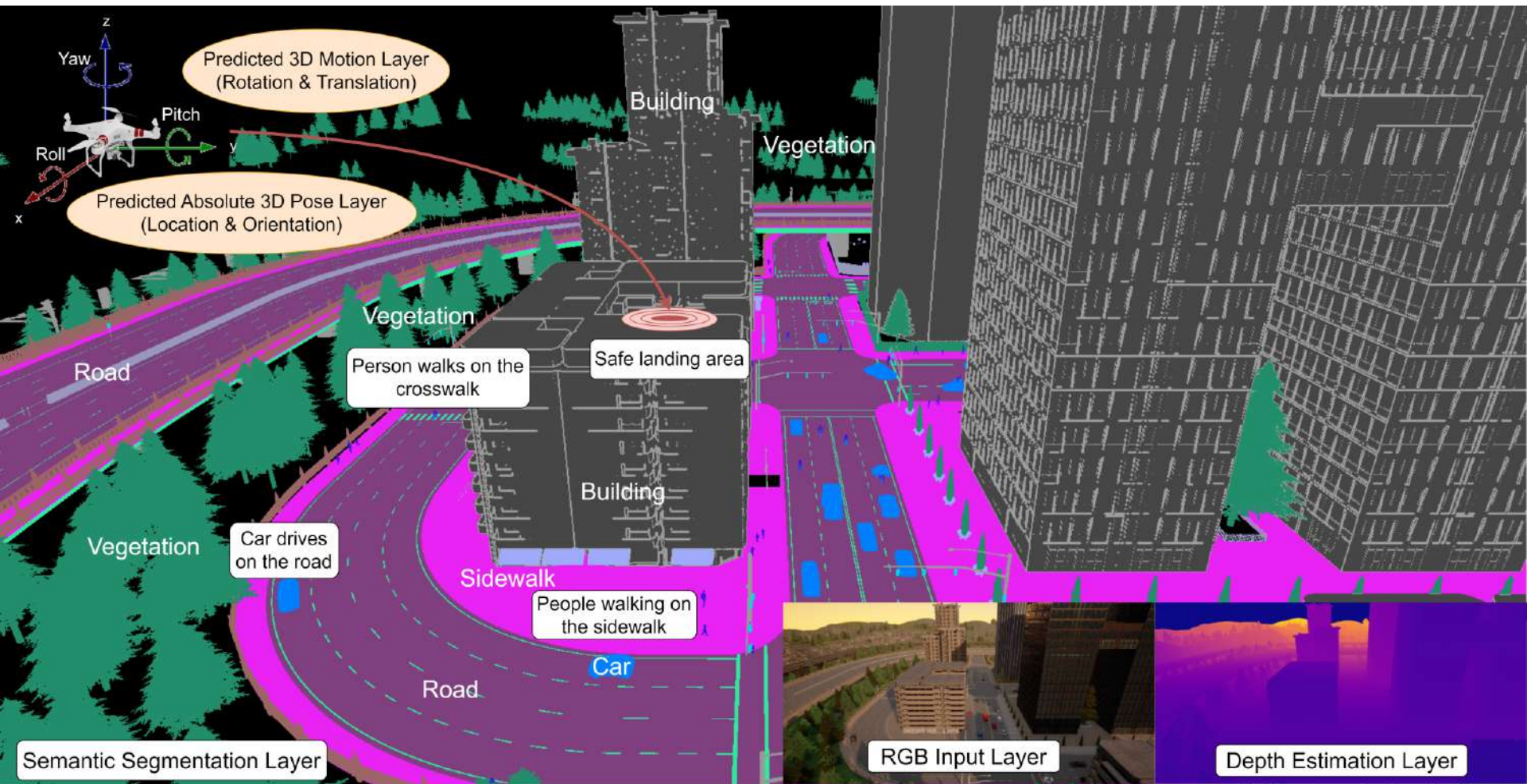
Collaboration, Networking and Exchange Programmes

UPB leads WP4: **Common Vision and Roadmaps** and co-leads the **Human-Centric AI** thematic area

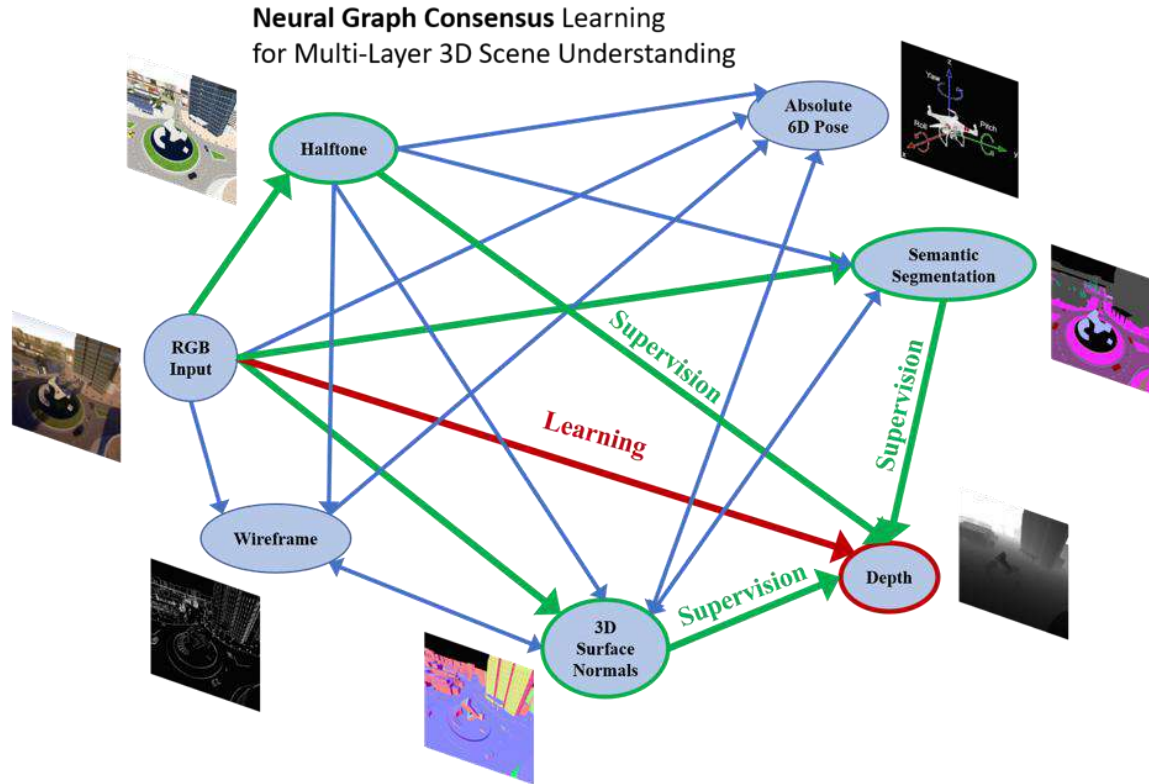
Consensus

in all Earth Systems,
at all scales, between
Different Views,
Modalities and Tasks





Unsupervised Learning by Neural Graph Consensus



Mihai Pirvu



Dragos Costea



Alina Marcu



Emil Slusanschi

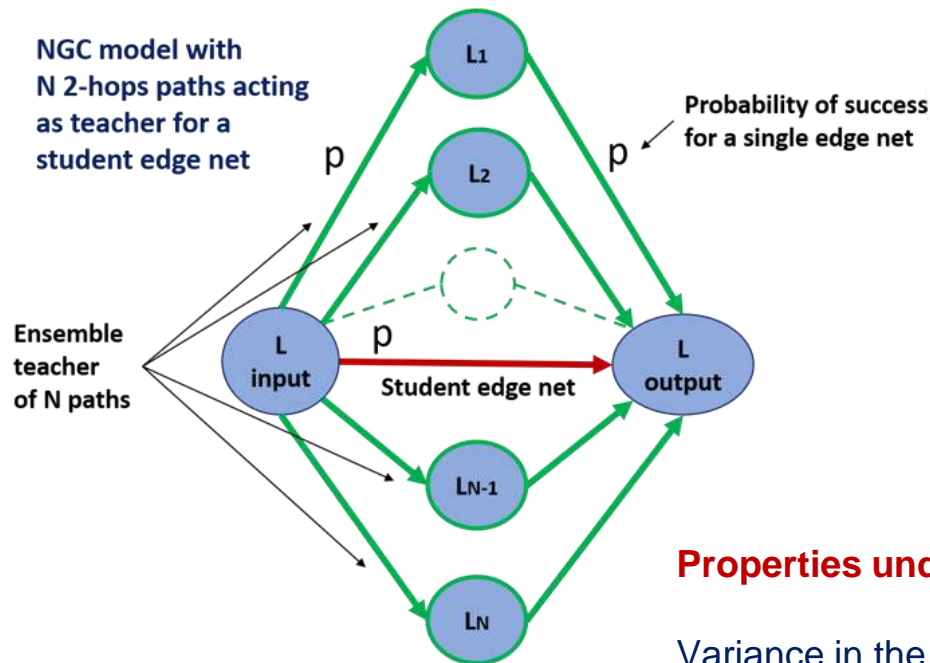


Rahul Sukthankar



Marius Leordeanu, Mihai Pirvu, Dragos Costea, Alina Marcu, Emil Slusanschi, Rahul Sukthankar
Semi-Supervised Learning for Multi-Task Scene Understanding by Neural Graph Consensus
Accepted at AAAI Conference on Artificial Intelligence (AAAI), 2021

Theoretical and numerical analysis



Mathematical intuition:

$$J_{\text{unsup}} = \sum (x_q^c - \frac{1}{N_q} \sum_{q=1}^{N_q} x_q^{(a)})^2$$

Output of one edge

Consensual output of path ensemble

Properties under independence assumptions:

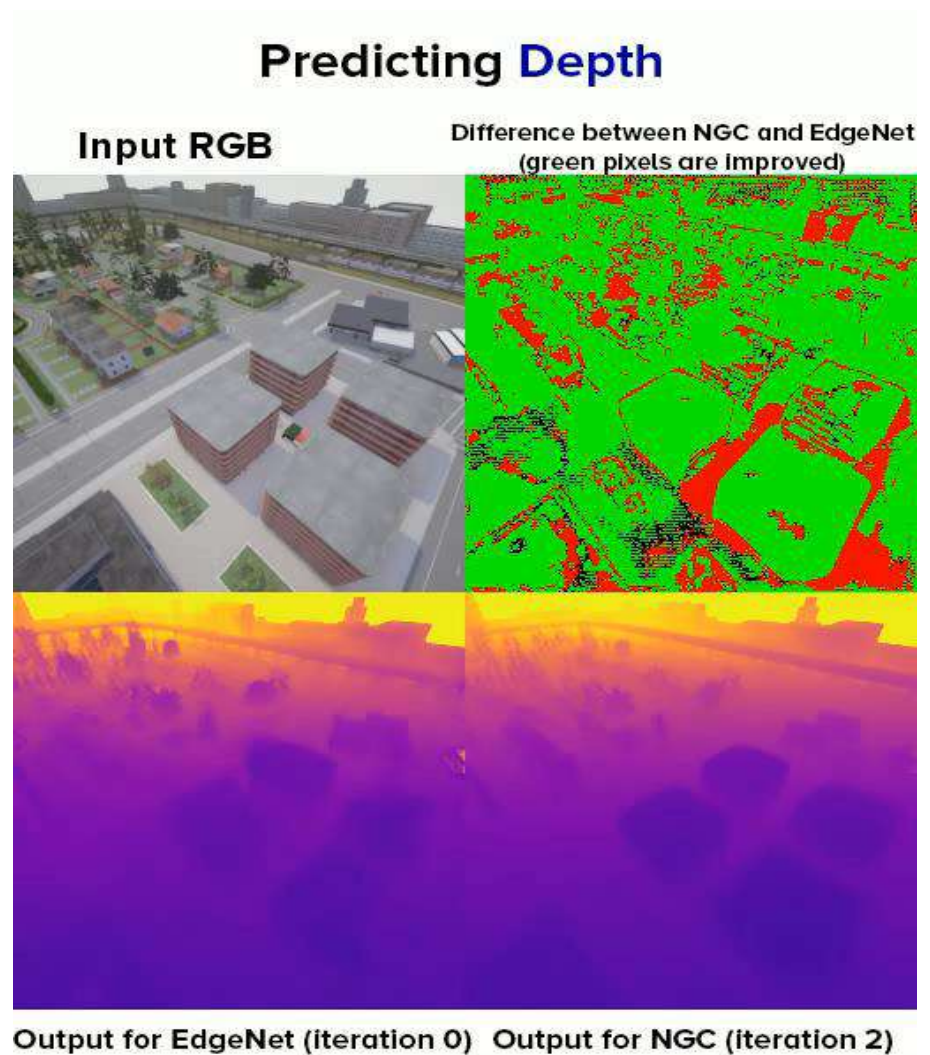
Variance in the graph will decrease

Over many iterations the model could converge to the truth

Results over several unsupervised learning iterations

Representation	Evaluation Metric	Iteration 0	Iteration 1		Iteration 2	
		EdgeNet	NGC	Distil. EdgeNet	NGC	Distil. EdgeNet
Depth	L1 (meters)	4.9844	3.4867	4.2802	3.2994	3.9508
	Pixels ↑ (%)	-	79.30	60.66	79.69	61.90
Surface Normals (C)	L1 (degrees)	8.4862	7.7914	8.2891	7.4503	7.6773
	Pixels ↑ (%)	-	74.18	53.59	74.61	53.94
Surface Normals (W)	L1 (degrees)	11.8859	8.8248	10.7500	8.5282	8.6714
	Pixels ↑ (%)	-	79.95	57.88	81.12	61.14
Semantic Segmentation	Accuracy	0.9001	0.9181	0.9019	0.9245	0.9283
	mIOU	0.4840	0.4978	0.4980	0.5258	0.5159
	Pixels ↑ (%)	-	79.46	69.62	81.49	71.95
Wireframe	Accuracy	0.9617	0.9655	0.9654	0.9661	0.9655
	Pixels ↑ (%)	-	77.71	72.57	78.02	73.46
Position	L2 (meters)	25.7597	15.5383	20.0204	12.0764	15.5599
Orientation	L1 (degrees)	3.8439	2.5001	3.3961	2.2088	3.0005

Consensus among multiple interpretations improves not only quality, but also space-time consistency, which makes the results more trustworthy



NGC learning is related to the idea of Homeostasis in living organisms

Homeostasis

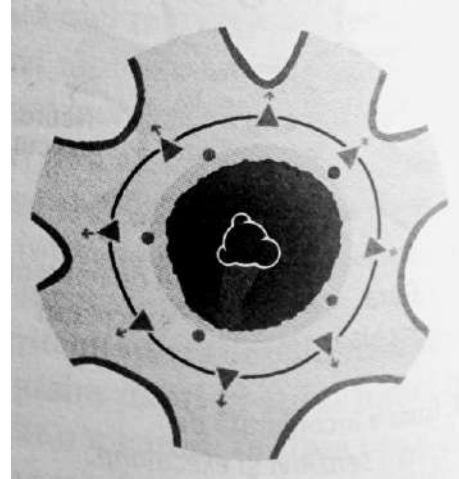
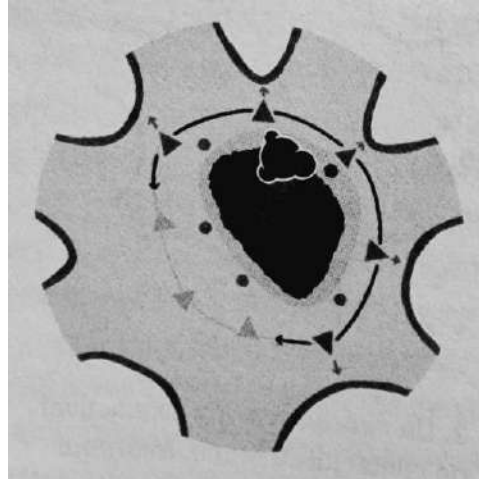
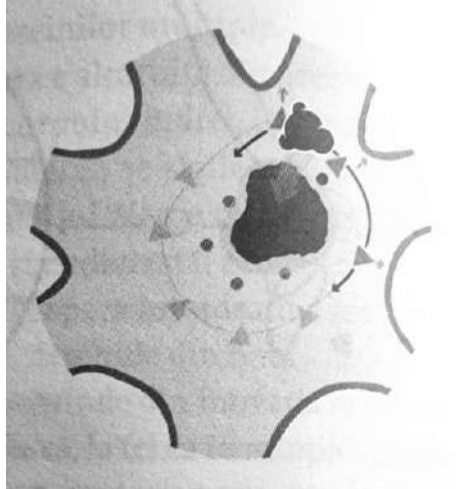
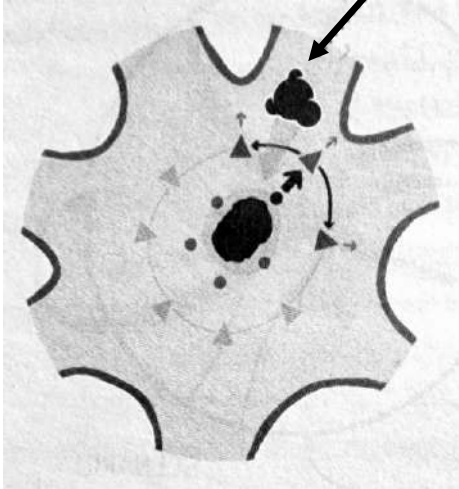
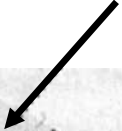
The innate tendency of all living organisms towards a relatively stable equilibrium between their many interdependent elements, in order to maintain their life (Betts et al. 2016).

Betts, J. G., P. Desaix, E. Johnson, J. E. Johnson, O. Korol, D. Kruse, and K. A. Young. "Anatomy and physiology. OpenStax." (2016).

Self-supervised Multi-task Consensus in the Hydra Nervous System

One of the first multi-neuron nervous systems

Food



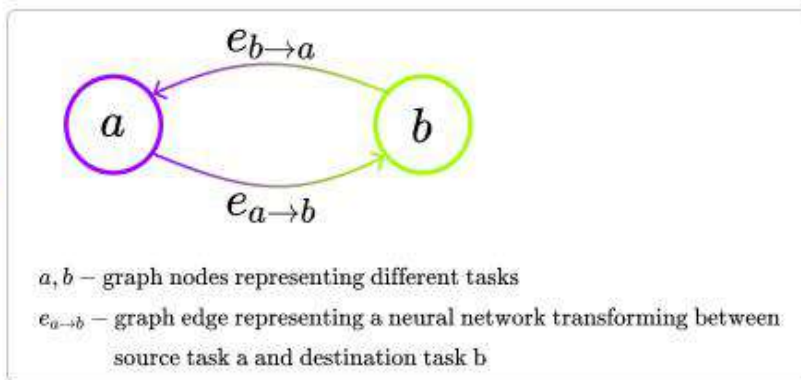
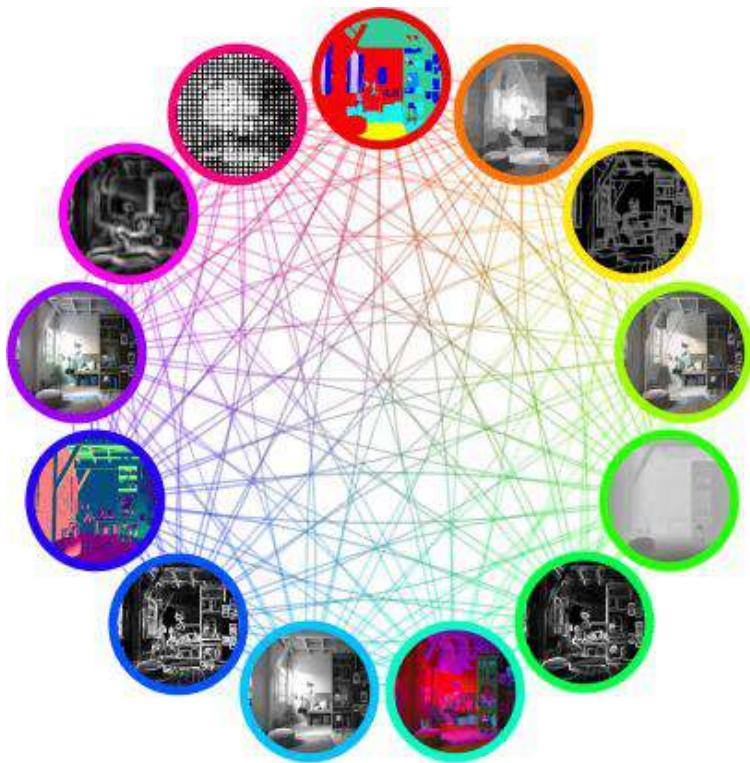
**We live in a
connected world!**

By having a connected mind!



**Multi-view and Multi-task Consensus could lead to
a self-regulatory and self-supervised way to achieve sustainability.**

Self-supervised consensus in fully connected multi-task graphs



Emanuela Haller

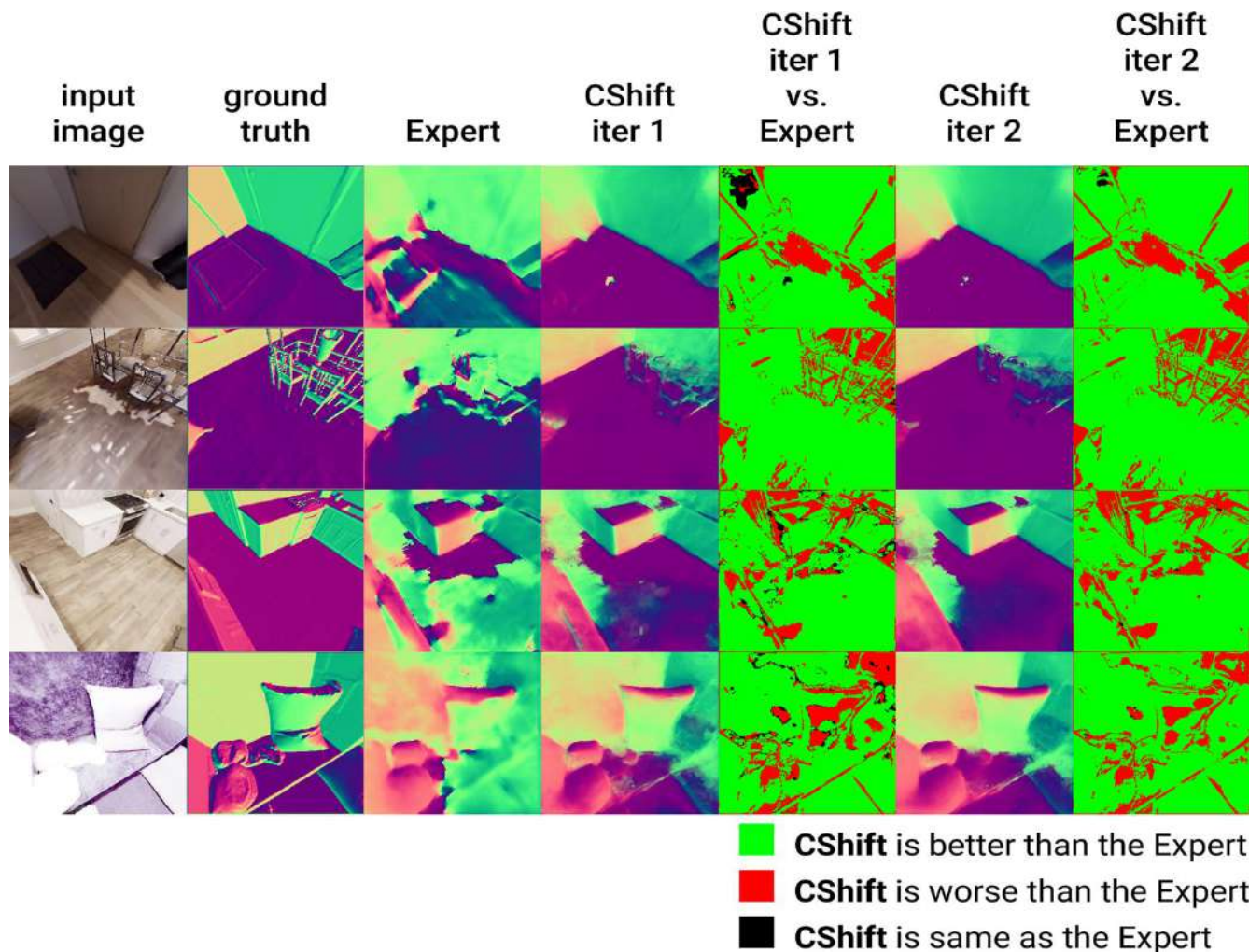


Elena Burceanu



Emanuela Haller, Elena Burceanu and Marius Leordeanu - *Self-Supervised Learning in Multi-Task Graphs through Iterative Consensus Shift* – British Machine Vision Conference (BMVC) 2021

Improving over unsupervised learning iterations



Consensus in real-world experiments with UAVs



DroneScapes Dataset

Atanasie



Gradistei



Jupiter



Barsana



Comana



Olanesti



Herculane



Slanic



Petrova



Norway

10 varied scenes, 9 in Romania and 1 in Norway

50 minutes of videos at 3840×2160 30 FPS

Includes GPS information, linear and angular velocities and absolute camera angles

Automatic Segmentation Propagation on Different Scenes



Only 1.6% of
of frames
are manually
labeled



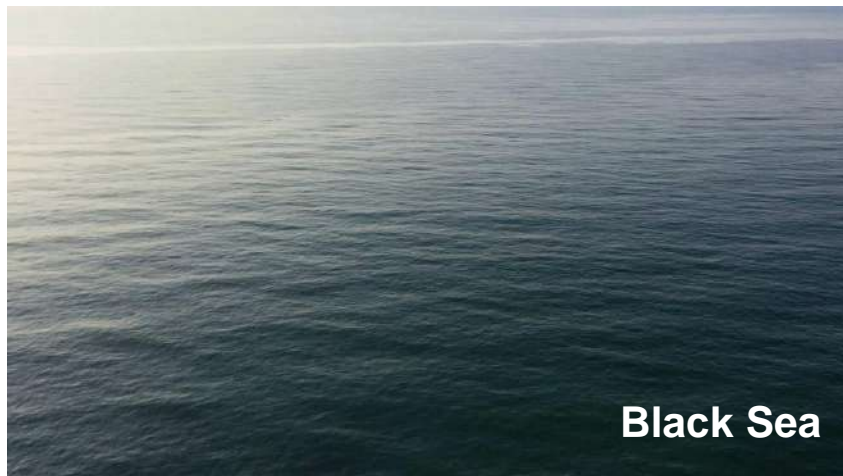
Alina Danciu



Alina Marcu

Marcu, Alina, Vlad Licaret, Dragos Costea and Marius Leordeanu. "Semantics through time: Semi-supervised segmentation of aerial videos with iterative label propagation." ACCV 2020.

Automatic Segmentation Propagation on Different Scenes



Only 1.6% of
of frames
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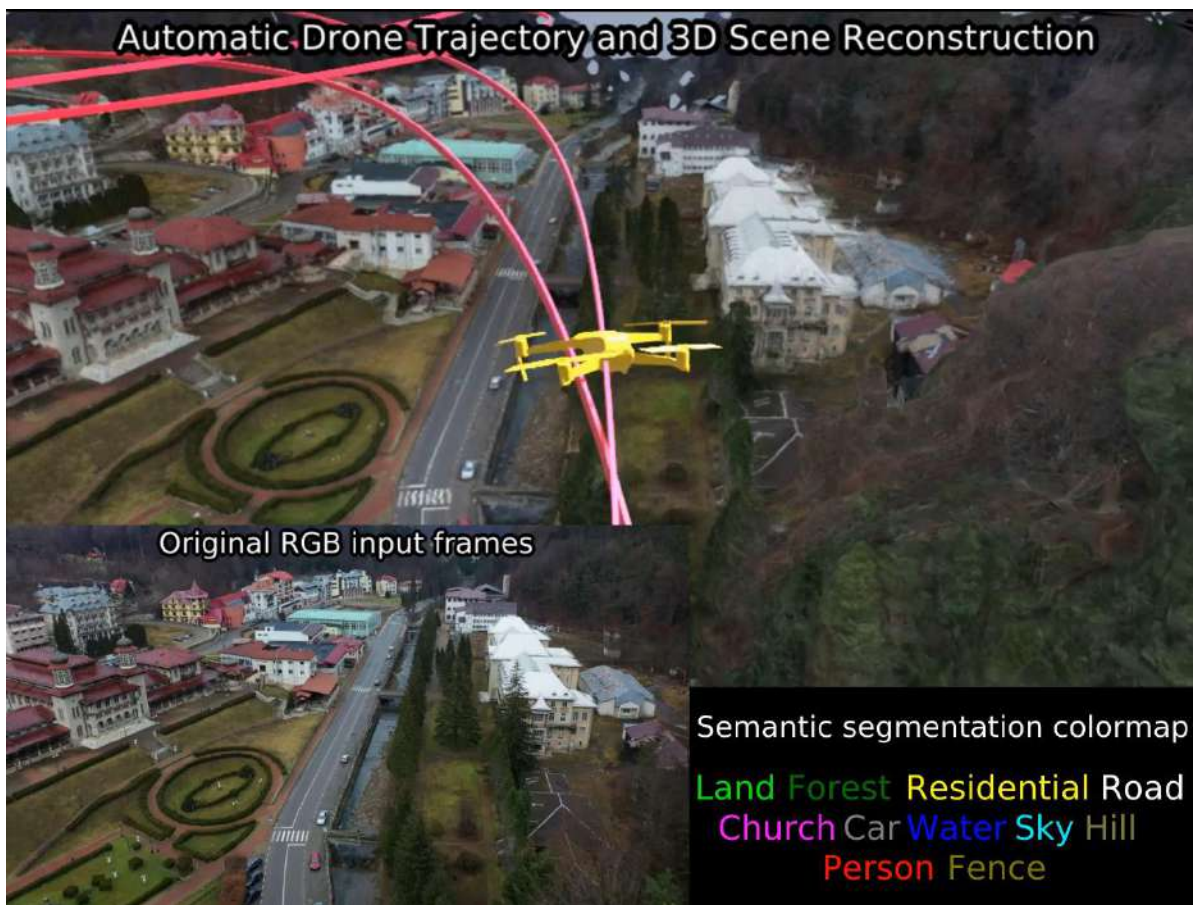


Alina Danciu



Alina Marcu

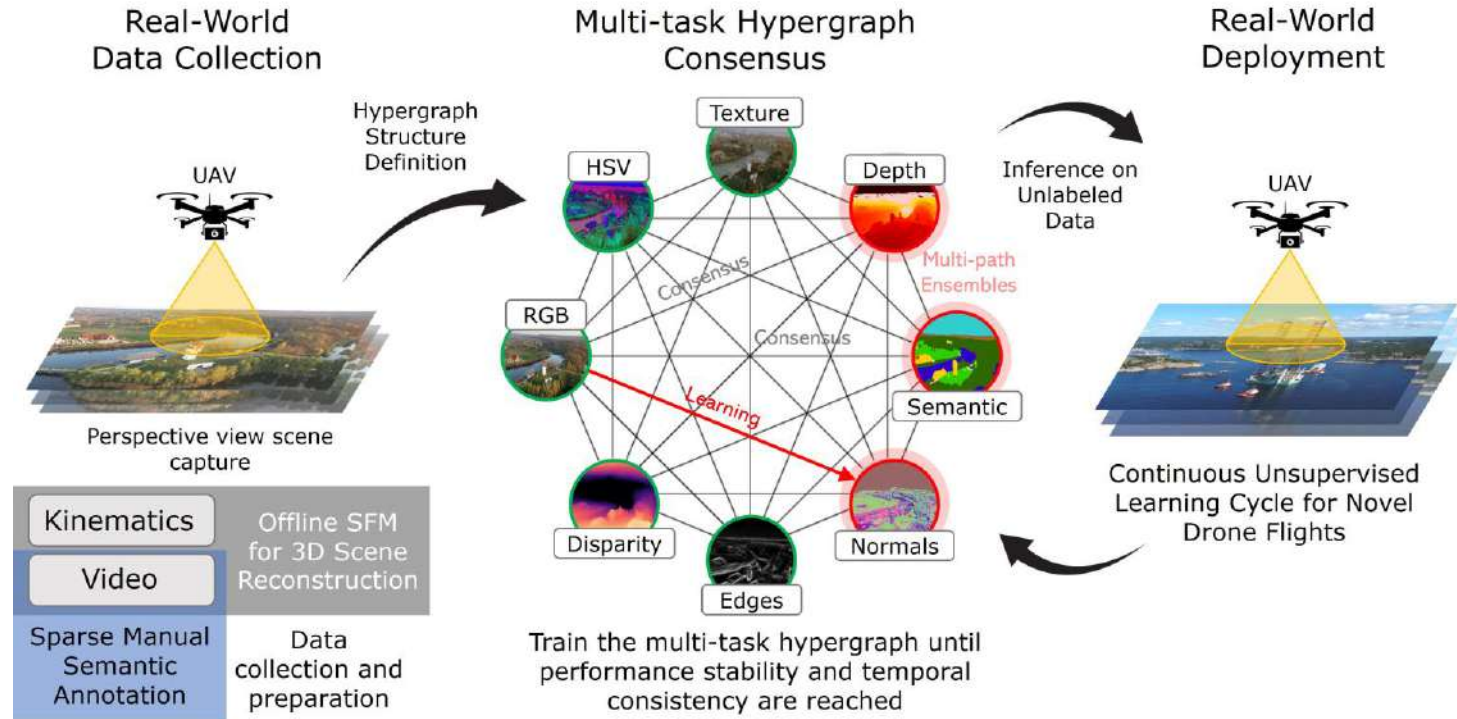
Towards
total scene
multi-view
understanding
in space
and time



Edges and soft segmentation: [Leordeanu et al, TPAMI 2014; Leordeanu et al, ECCV 2012]

Unsupervised metric monocular depth estimation: [Licaret et al, ICRA 2022; Pirvu et al, CVPRW 2021]

Self-supervised learning with multi-view hypergraph consensus in the real world



Alina Marcu



Mihai Pirvu



Dragos Costea



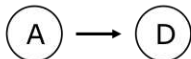
Emanuela Haller

Marcu, A, M. Pirvu, D. Costea, E. Haller, E. Slusanschi, AN Belbachir, R. Sukthankar and M. Leordeanu. **Self-supervised hypergraphs for learning multiple world interpretations.** In *Proceedings of the IEEE International Conference on Computer Vision*, 2023.

Types of Multi-modal Hyperedges

Edge (E)

Setup: Given A, B, C as input nodes and D, E as output nodes



Learn a transformation between a given input node to any output node through a neural network.

Dual-hop Edge (DH-E)



Learn a transformation between a given input node to an output node and then use the prediction to learn a connection to another output node.

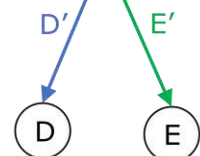
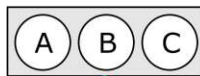
Aggregation Hyperedge (AH)



Learn the mapping from the concatenated volume of all input nodes to each output node.

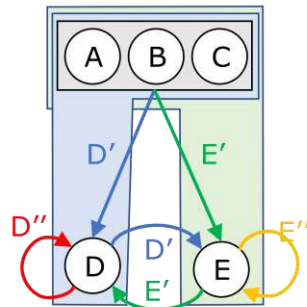
Cycle Hyperedge (CH)

T = 1



$ABC \rightarrow D'$
 $ABC \rightarrow E'$

T = 2



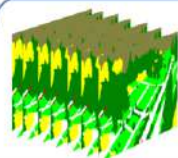
$ABCD'E' \rightarrow D''$
 $ABCD'E' \rightarrow E''$

At T=1, build aggregation hyperedges for all the output nodes. At T=2, learn a transformation between the concatenation of all input nodes together with the output nodes predictions from all aggregation hyperedges towards each output node.

Learning Hyperedge Consensus

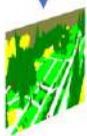
Version 1

N multi-path predictions



$H \times W \times N$
 $3 \times 3 \times 3$ Conv3D
 $H \times W \times 10$
 $3 \times 3 \times 3$ Conv3D
 $H \times W \times 5$

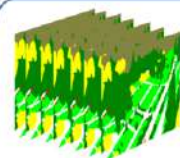
End-to-end Dense Map Learning



Ensemble Output

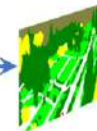
Version 2

N multi-path predictions



$H \times W \times N$
 $3 \times 3 \times 3$ Conv3D
 $H \times W \times 10$
 $3 \times 3 \times 3$ Conv3D
 $H \times W \times 5$
FC (N)
 $(\sigma_1, \sigma_2, \dots, \sigma_N)$

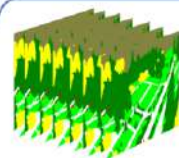
Map-wise weighted sum Σ



Ensemble Output

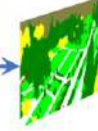
Version 3

N multi-path predictions



$H \times W \times N$
 $3 \times 3 \times 3$ Conv3D
 $H \times W \times 10$
 $3 \times 3 \times 3$ Conv3D
 $H \times W \times 5$
 $3 \times 3 \times 3$ Conv3D
 $H \times W \times N$

Pixel-wise weighted sum Σ



Ensemble Output

Improving accuracy and temporal consistency over iterations of self-supervised learning

Scene Name	Train Labeled	Train Unlabeled (iter 1)	Train Unlabeled (iter 2)	Train Unlabeled (iter 3)
Atanasie	76	4501 (76)	4500 (75)	-
Gradistei	18	726 (18)	484 (12)	-
Herculane	12	484 (12)	363 (9)	-
Jupiter	21	847 (21)	605 (15)	-
Olanesti	18	726 (18)	484 (12)	-
Petrova	12	484 (12)	363 (9)	-
Slanic	76	4501 (76)	4500 (75)	-
Barsana	-	-	-	1452 (36)
Comana	-	-	-	1210 (30)
Norway	-	-	-	2941 (50)
TOTAL	233	12269 (233)	11299 (207)	5603 (116)

Type	Semantic		Depth		Normals	
	IoU (↑)	Cons. (↑)	L1 (↓)	Cons. (↑)	L1 (↓)	Cons. (↑)
rgb-sup.	25.04	88.85	-	-	-	-
rgb-iter1	32.79	94.04	21.66	5.89	12.40	98.32
rgb-iter2	37.26	95.72	17.34	7.06	11.93	98.87
rgb-iter3	40.31	98.13	16.64	30.26	11.71	99.30

Input image



Mask2Former [Cheng et al, CVPR 2022]



Human



Ours

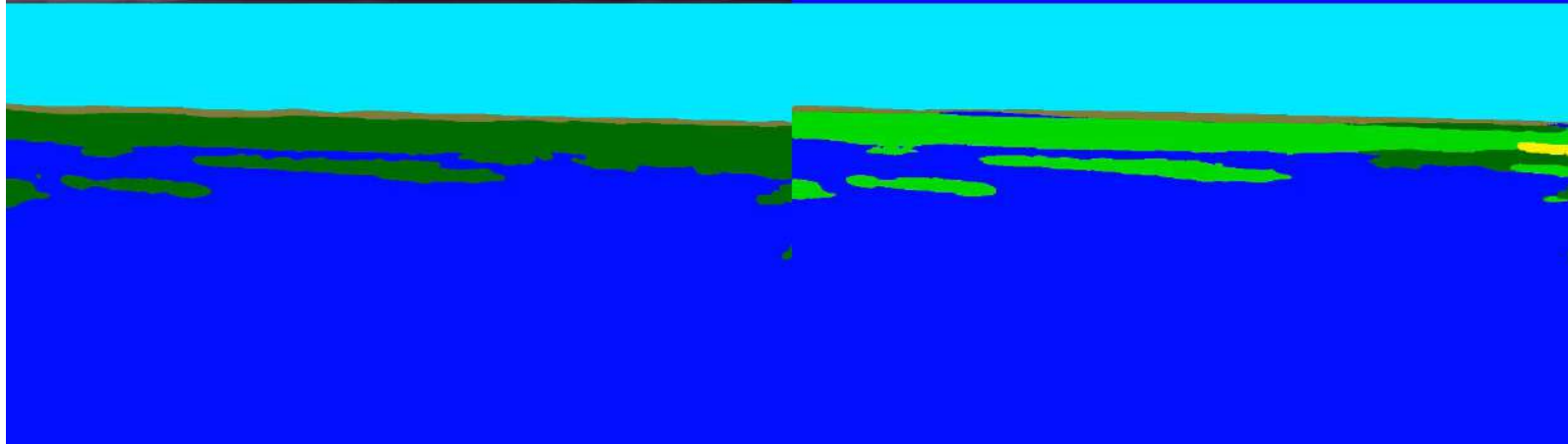


Input image

Mask2Former [Cheng et al, CVPR 2022]



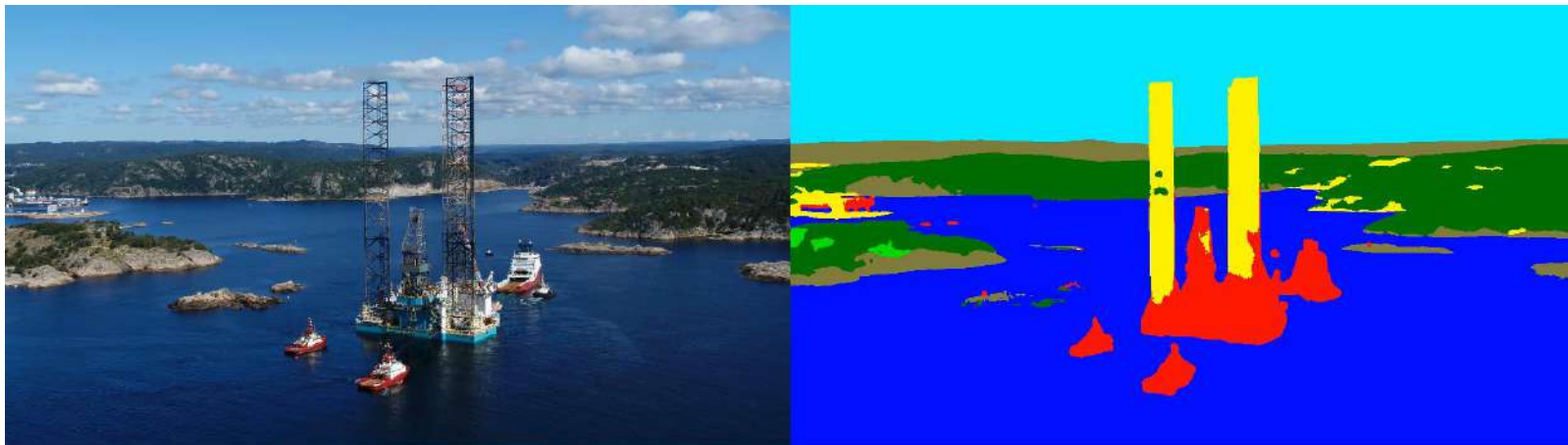
Human



Ours

Input image

Mask2Former [Cheng et al, CVPR 2022]

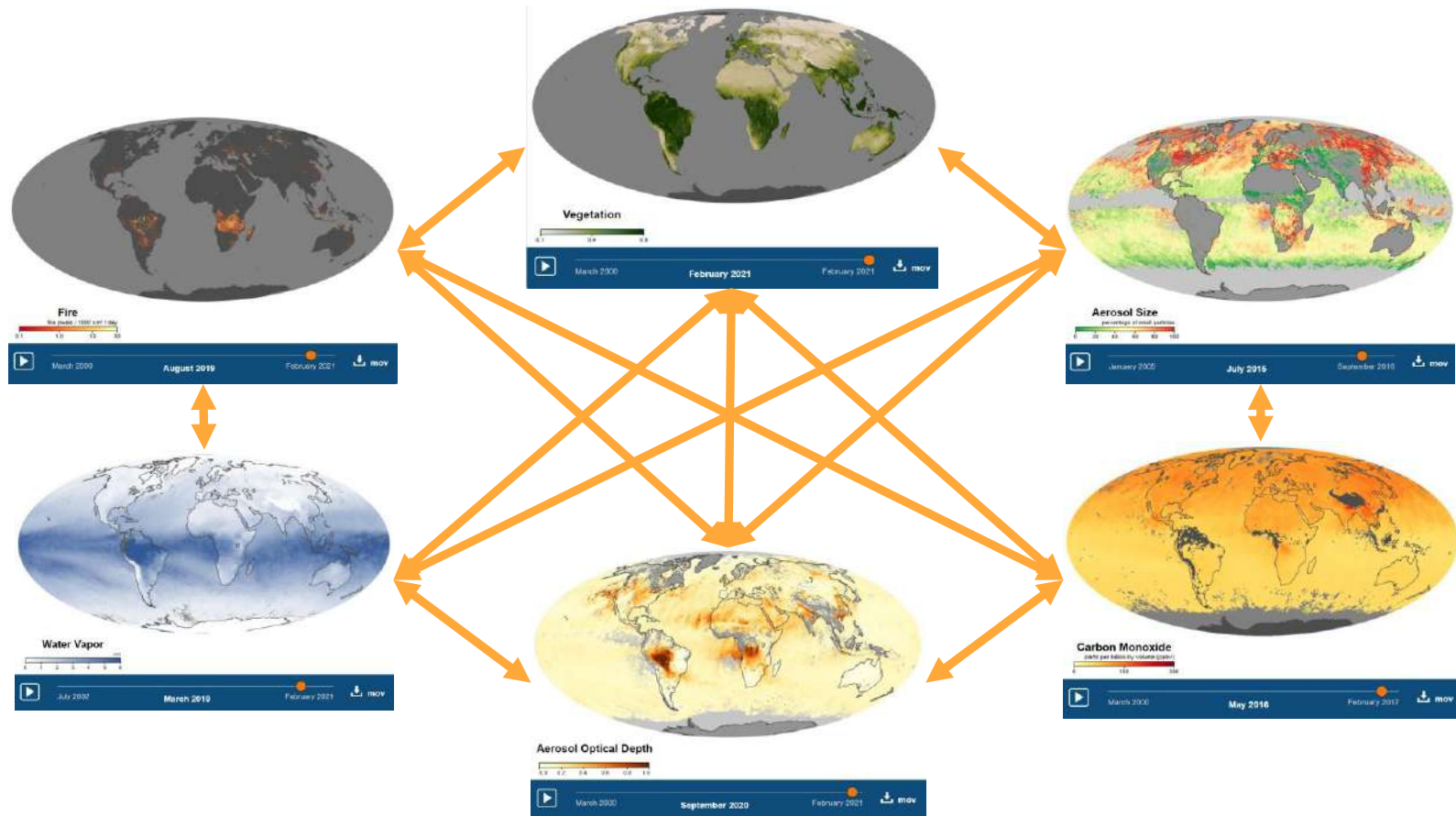


Human



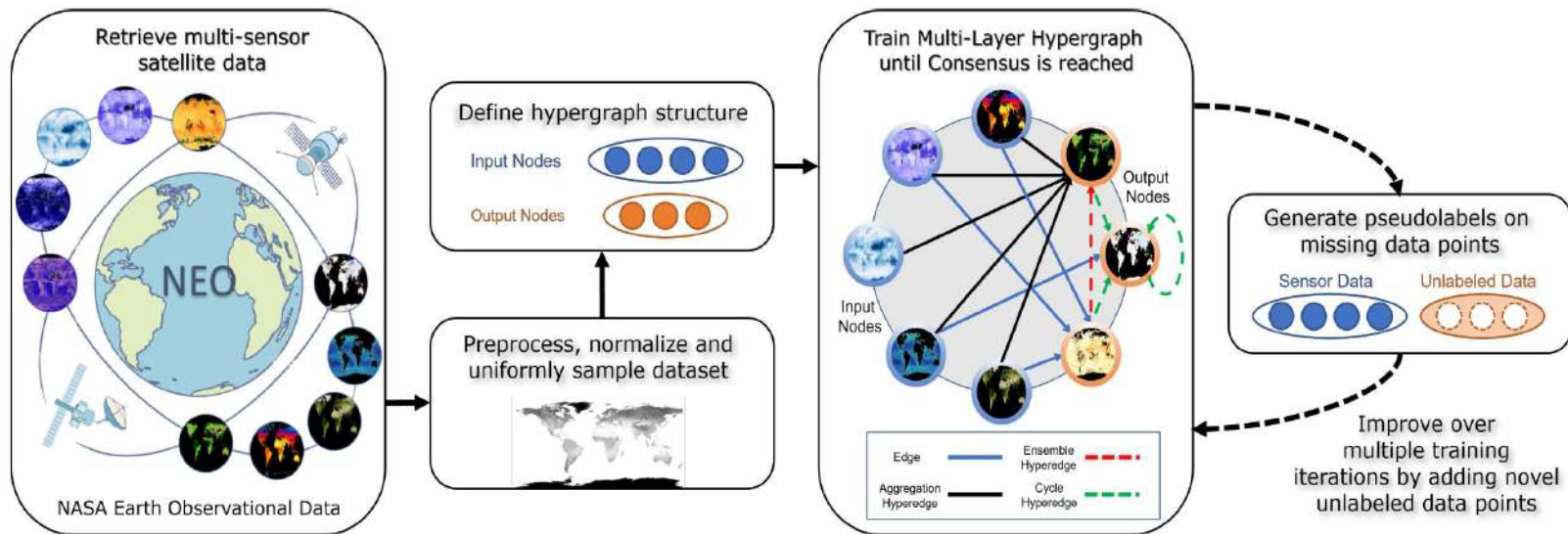
Ours

Learning Multi-view Earth Consensus for Predicting Climate



The Holocene period, representing the last 10 000 years (also marking the great development of human civilization), is a relatively stable period of the earth climate, in which different layers of the Earth System found a dynamic equilibrium (consensus) with average temperature varying less than 1 degree per year.

Consensus for Understanding Climate: A Multi-modal Hypergraph Approach



Mihai Pirvu



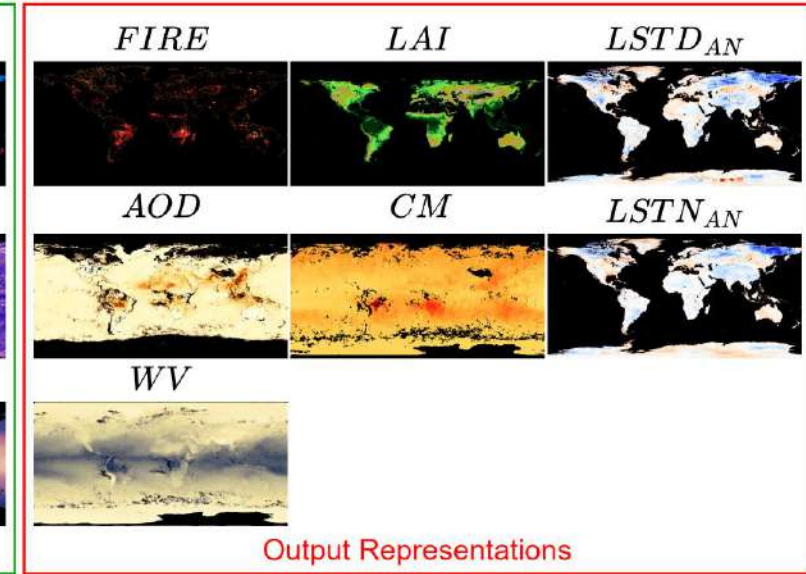
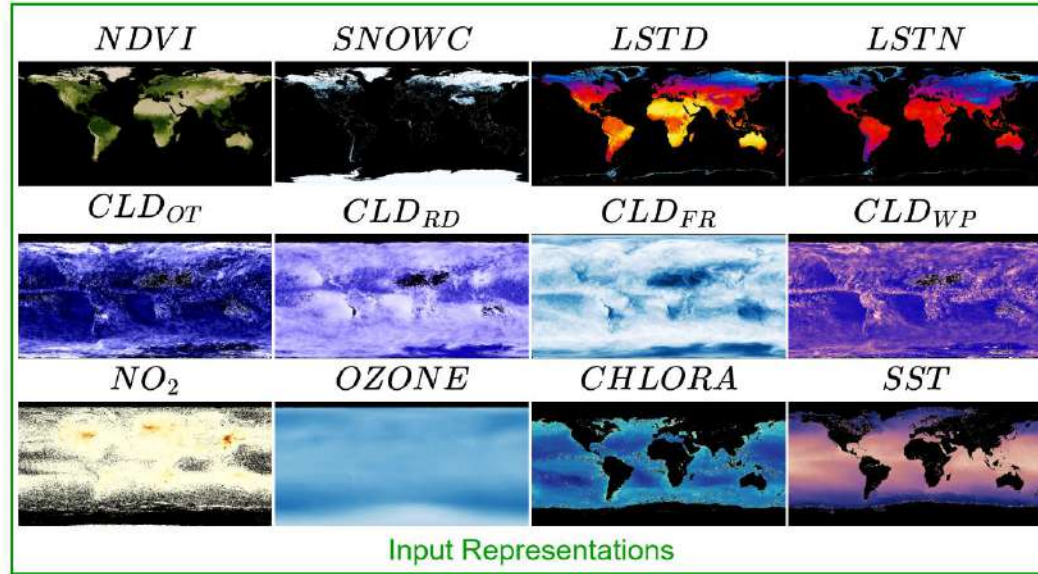
Alina Marcu

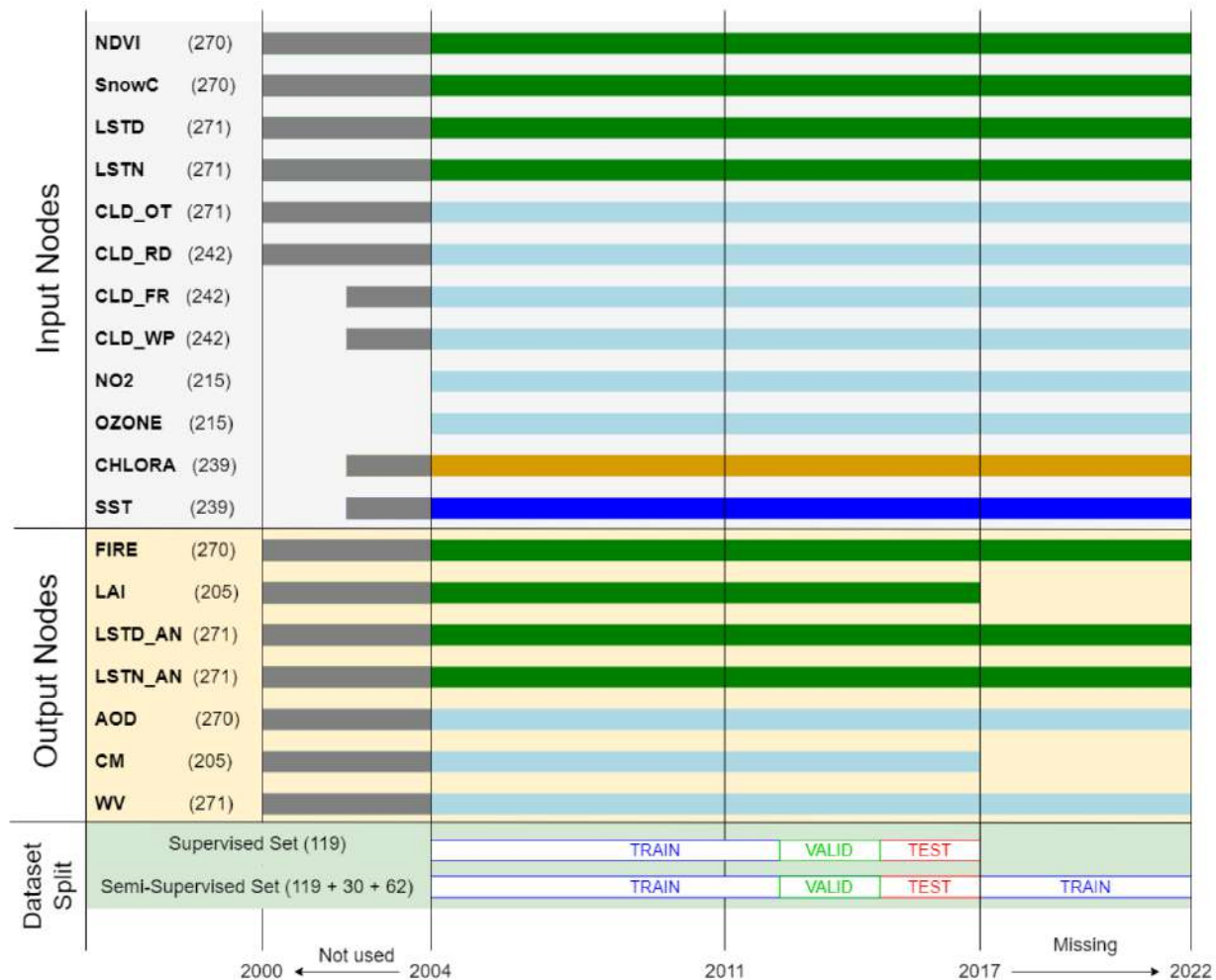


Alexandra Dobrescu

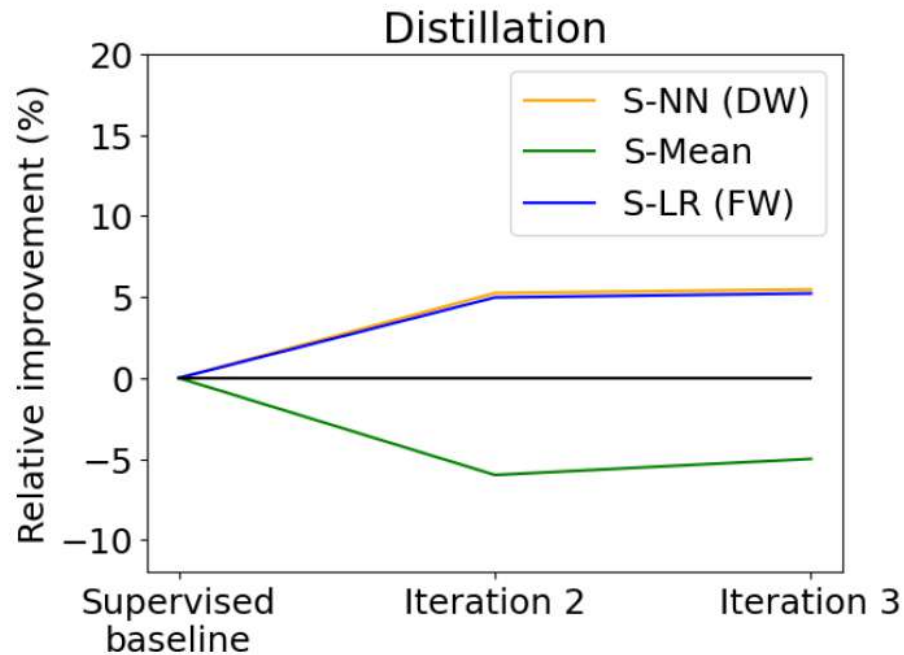
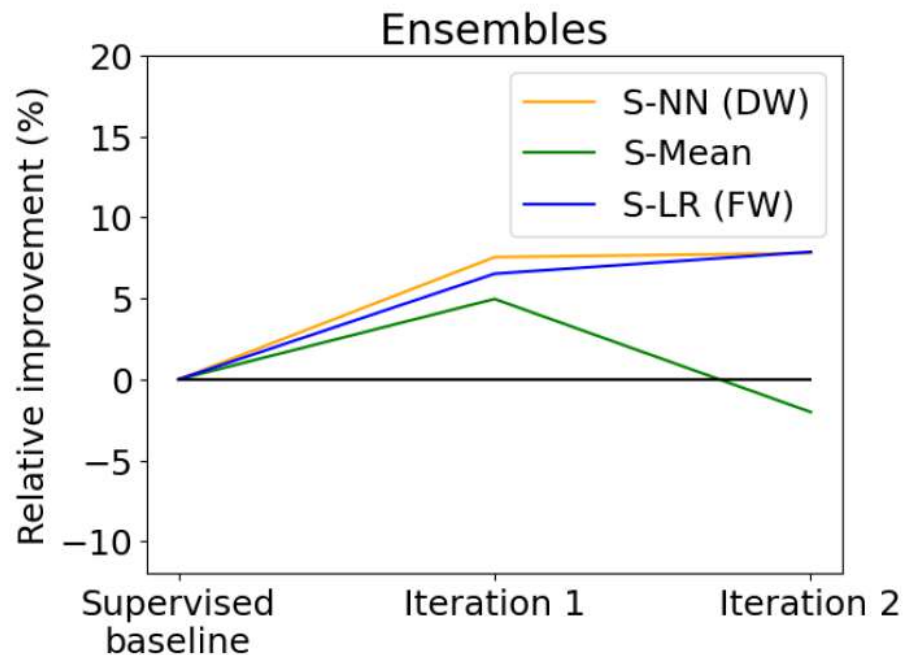
Pirvu, M., Alina M., A. Dobrescu, AN Belbachir and M. Leordeanu. **"Multi-Task Hypergraphs for Semi-supervised Learning using Earth Observations."** In Proceedings of the International Conference on Computer Vision, 2023.

Experiments on NASA NEO Dataset

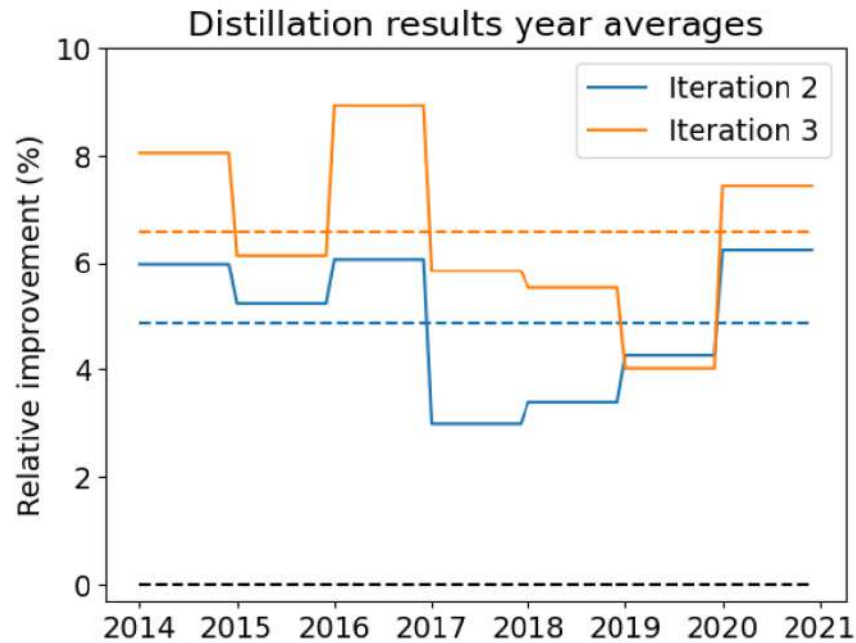
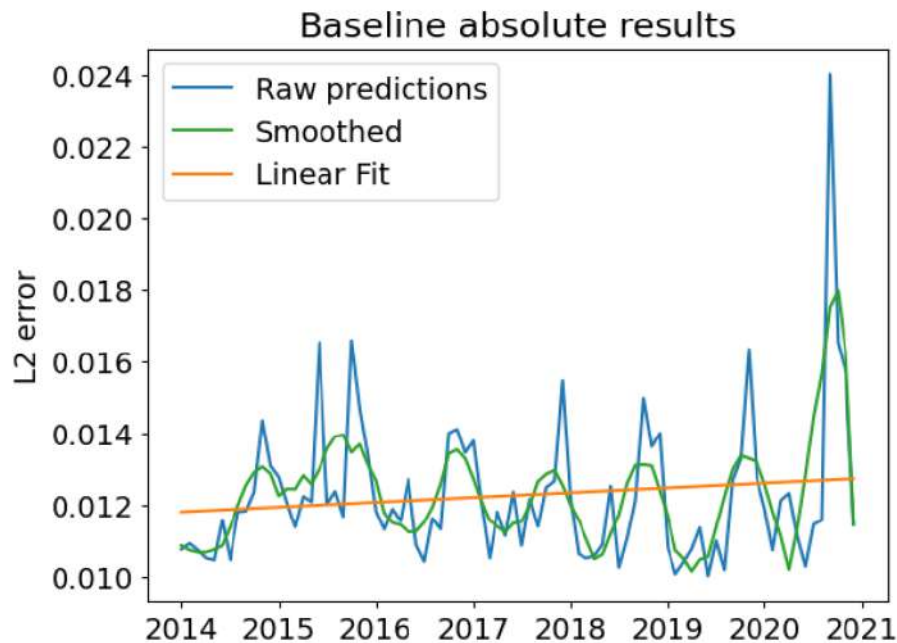




Learning Consensus Ensembles and Self-Distillation over Iterations



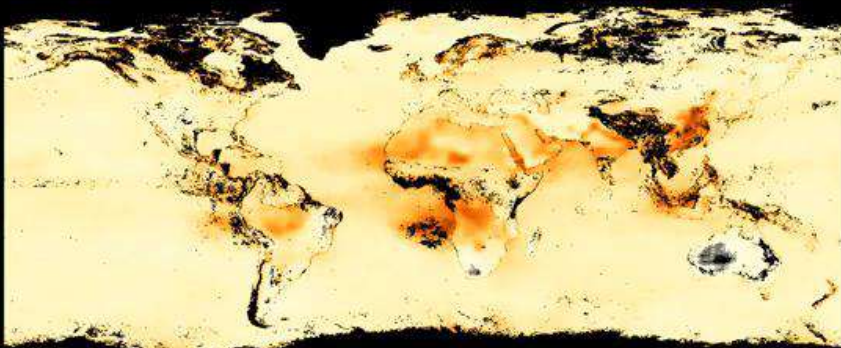
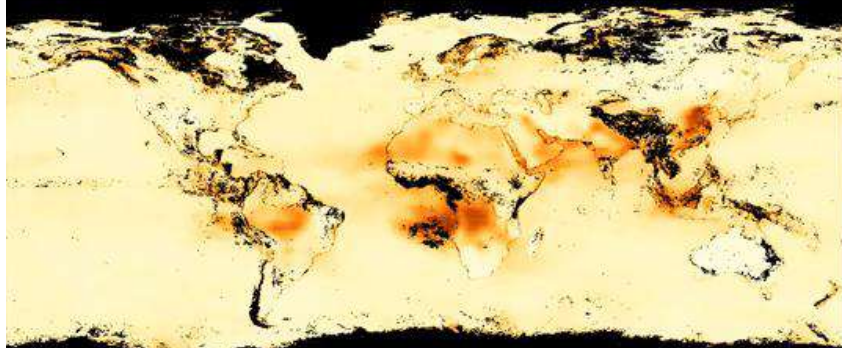
Self-supervised Learning Adapts to Climate Changes



Aerosol Optical Depth

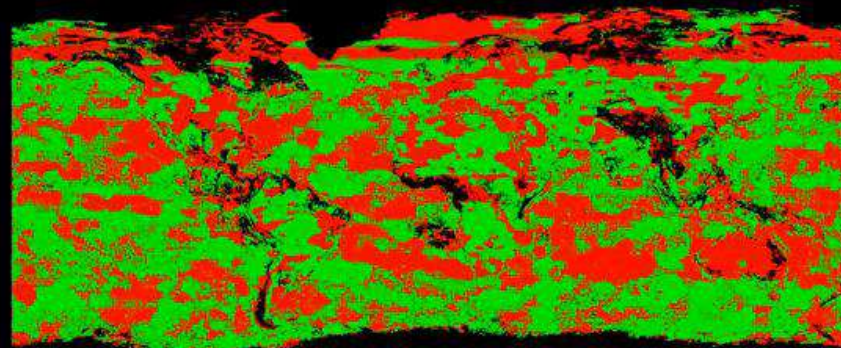
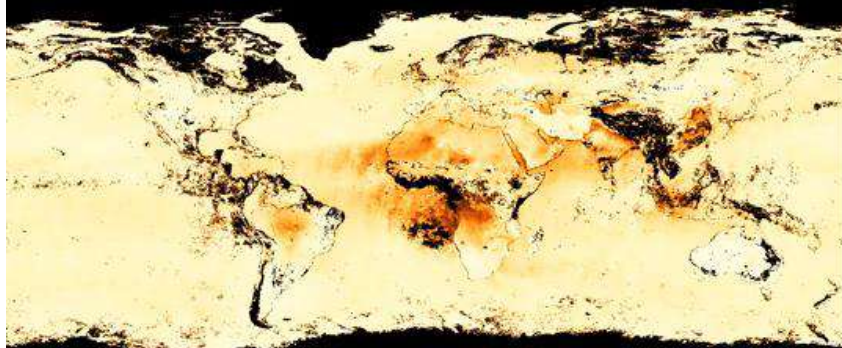
Supervised Edge

Semi-supervised Edge

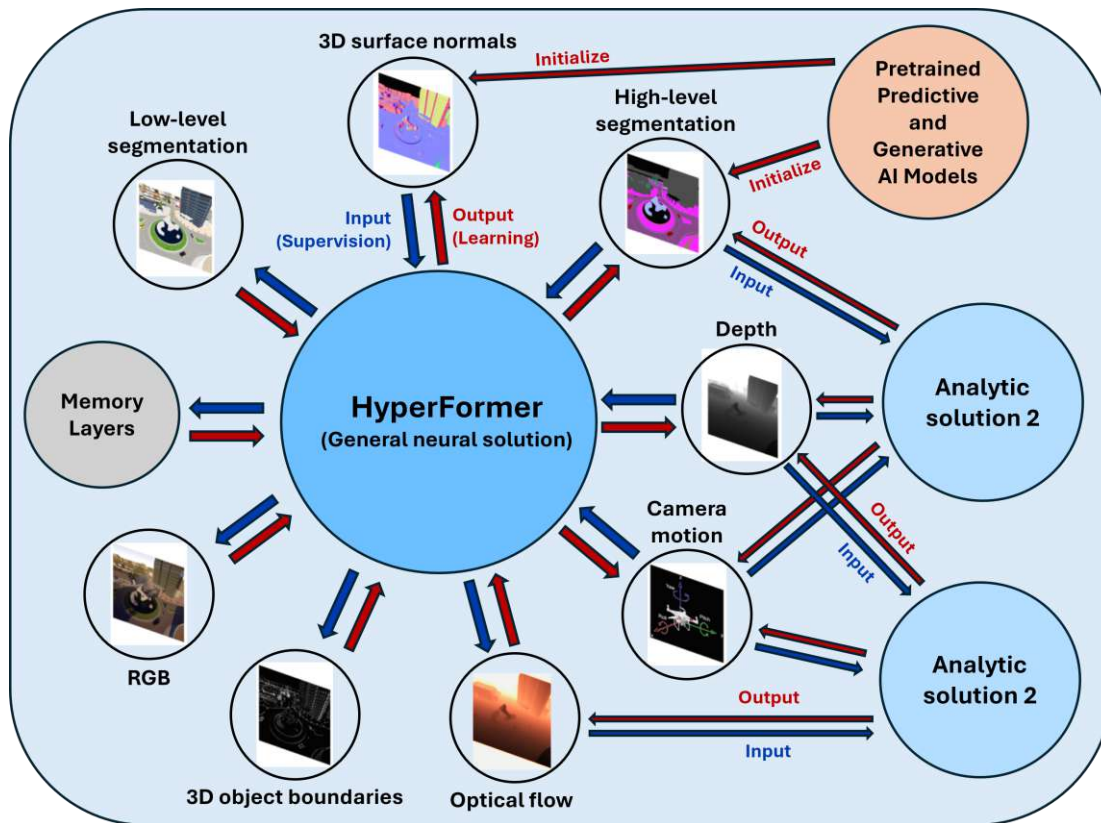


Ground Truth

58.4% (green) sem-sup more consistent than supervised

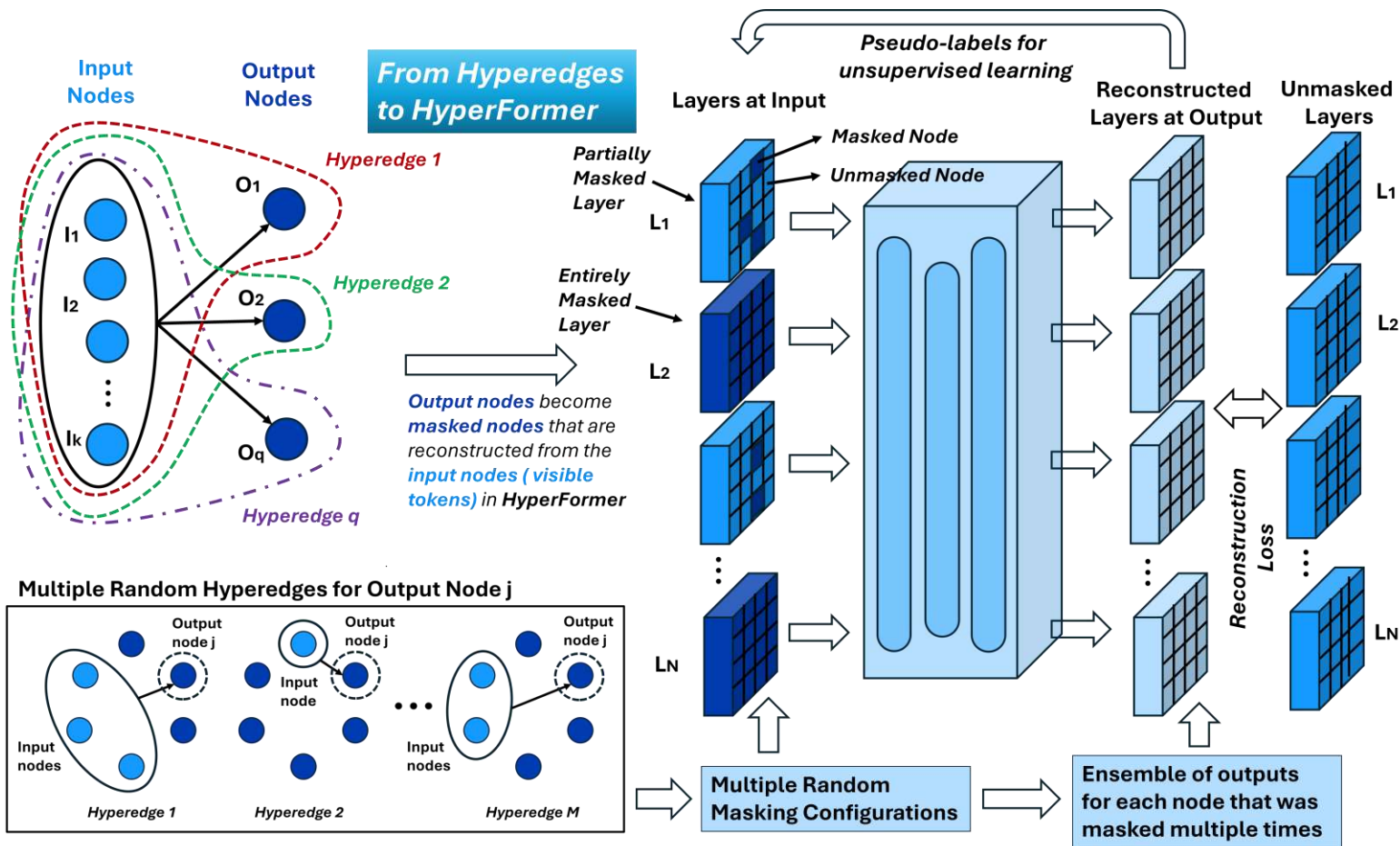


Multi-view Hypergraph Consensus with Multi-view Multiple Random Masking Auto-encoders



Mihai Pirvu

Introducing HyperFormer



Creating Multiple Views from RGB

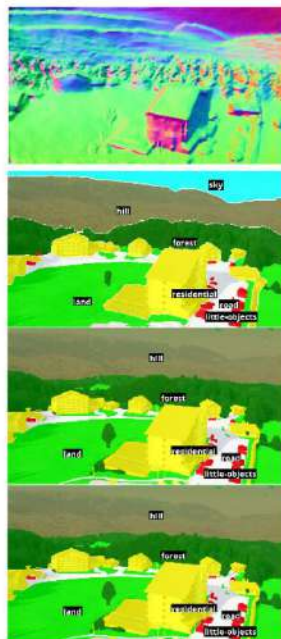
rgb (input)



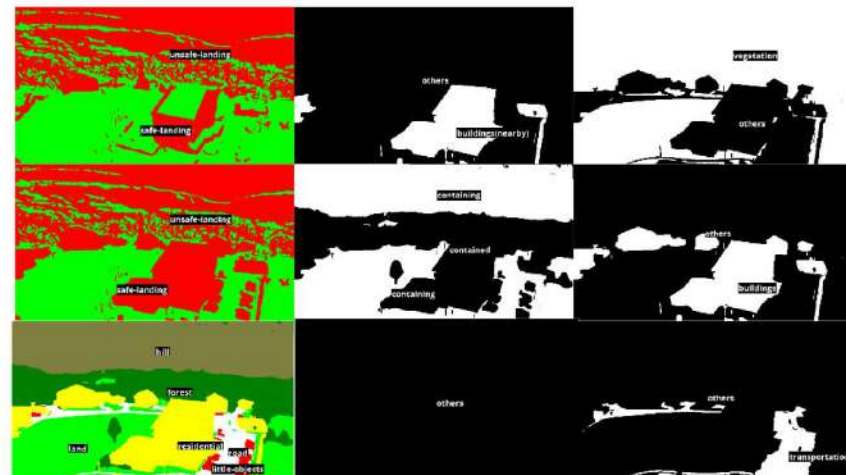
experts



derived level 1



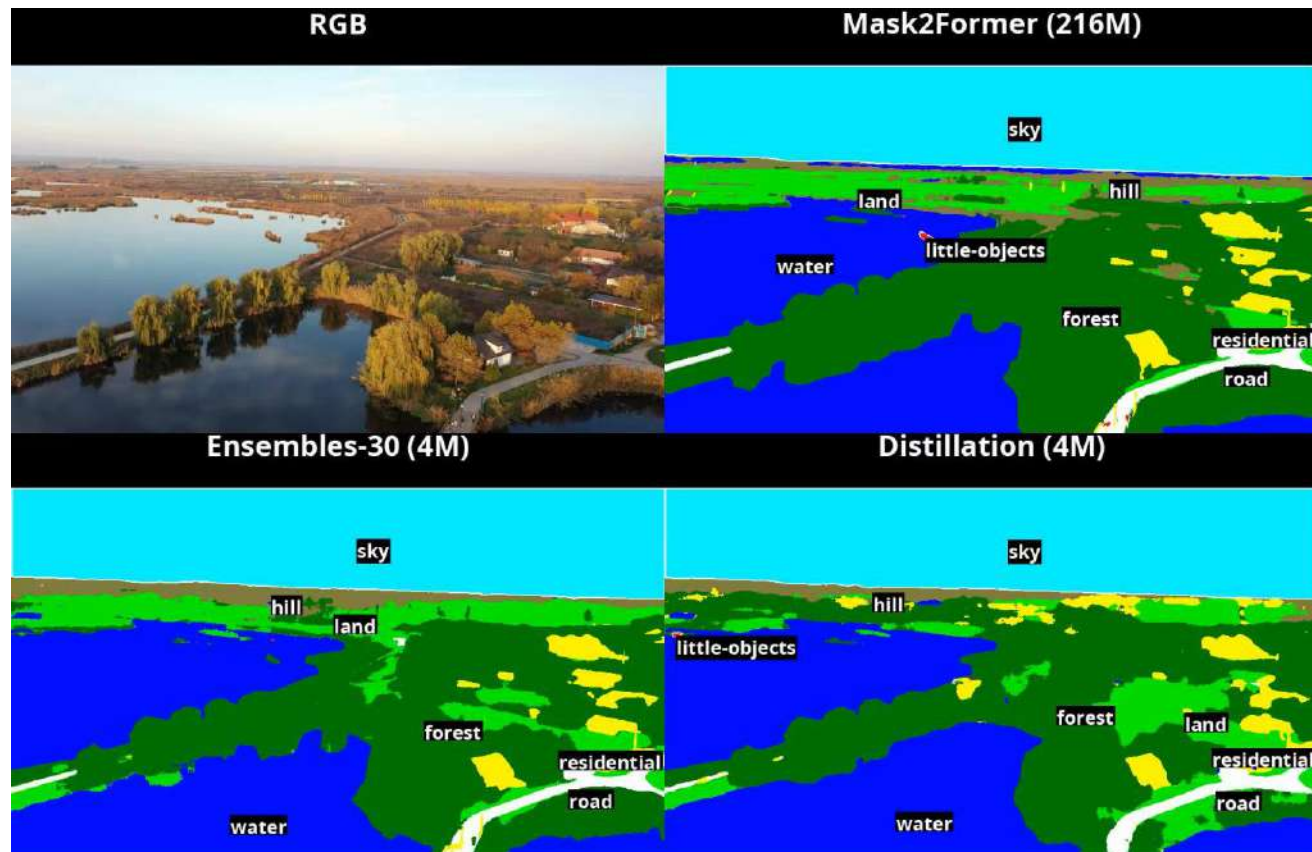
derived level 2



Experiments on extended DroneScapes++

Added **16 novel scenes**
to initial **DronesScapes**
with 10 scenes

**Comana
scene**



RGB

Mask2Former (216M)



Ensembles-30 (4M)

Distillation (4M)

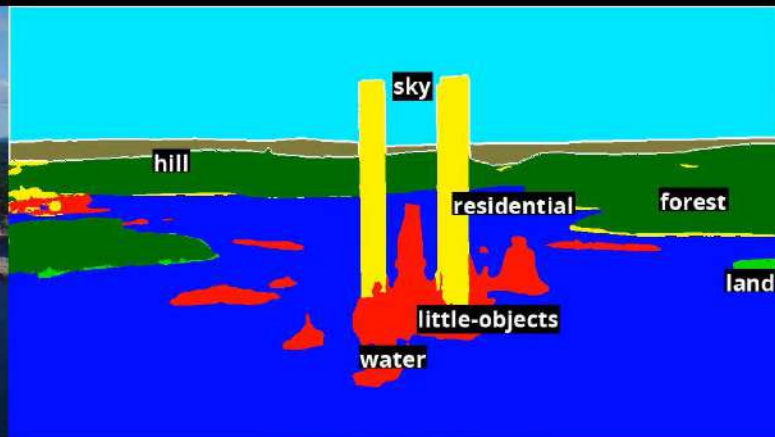


Barsana
scene

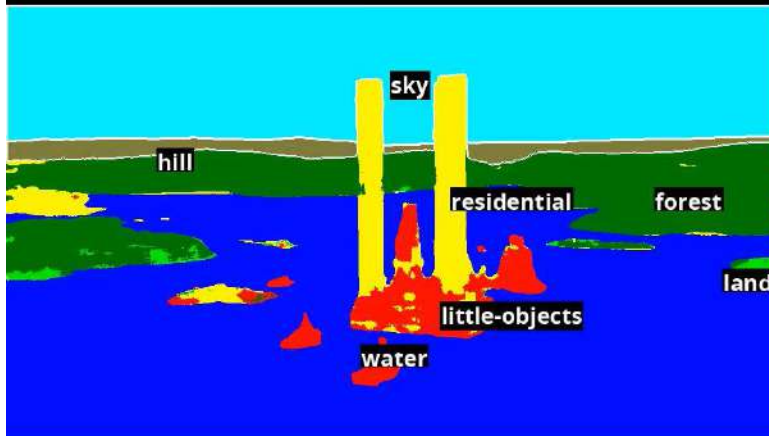
RGB



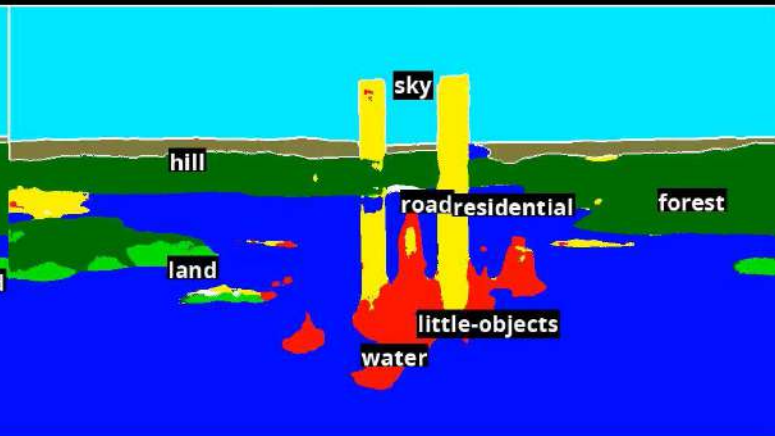
Mask2Former (216M)



Ensembles-30 (4M)



Distillation (4M)

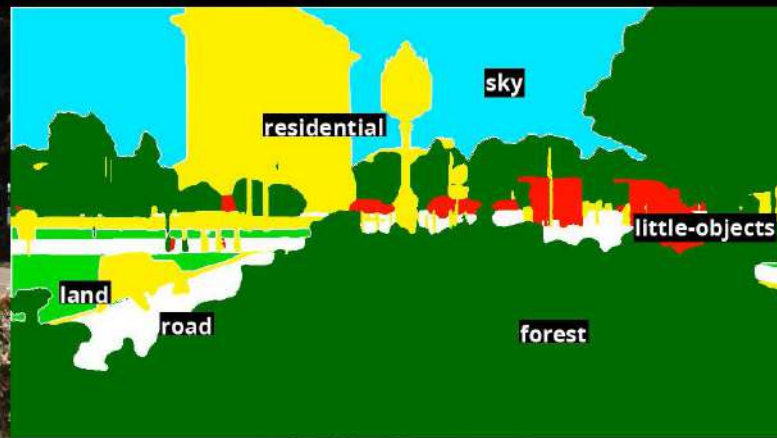


Norway
scene

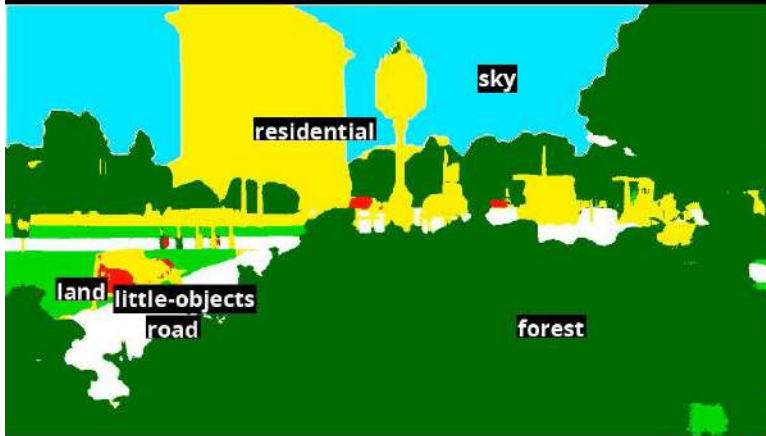
RGB



Mask2Former (216M)



Ensembles-30 (4M)



Distillation (4M)



Bucharest
scene

Self-supervised Multi-view Consensus improves both accuracy and consistency over time

Mean IoU	Barsana	Comana	Norway	Mean
NGC-LR ICCV-23 (32M)	46.51	45.59	30.17	40.76
Mask2Former (217M)	63.371	60.559	37.986	53.97
Ensembles-30 (4M)	63.806	63.186	39.981	55.324
Distillation (4M)	66.349	61.112	37.696	55.052

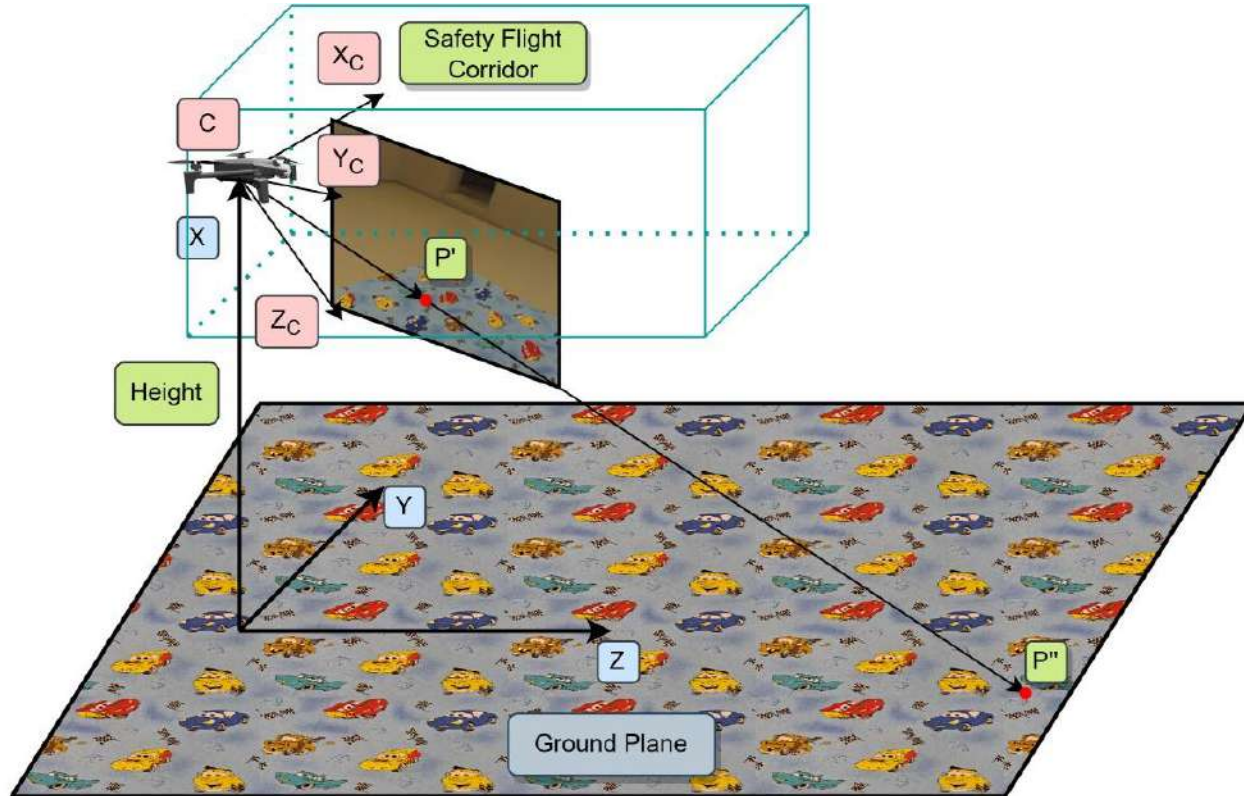
Consistency (%)	Barsana	Comana	Norway	Castelul Corvinilor	Bucharest Youtube	Mean
Mask2Former (217M)	93.97	94.68	98.42	98.37	96.79	96.44
Ensembles-30 (4M)	93.94	96.12	98.08	98.05	97.26	96.69
Distillation (4M)	98.16	98.04	99.02	99.13	98.15	98.5

Developing Self-flying Drones in Our SpaceTime Vision and Robotics Lab

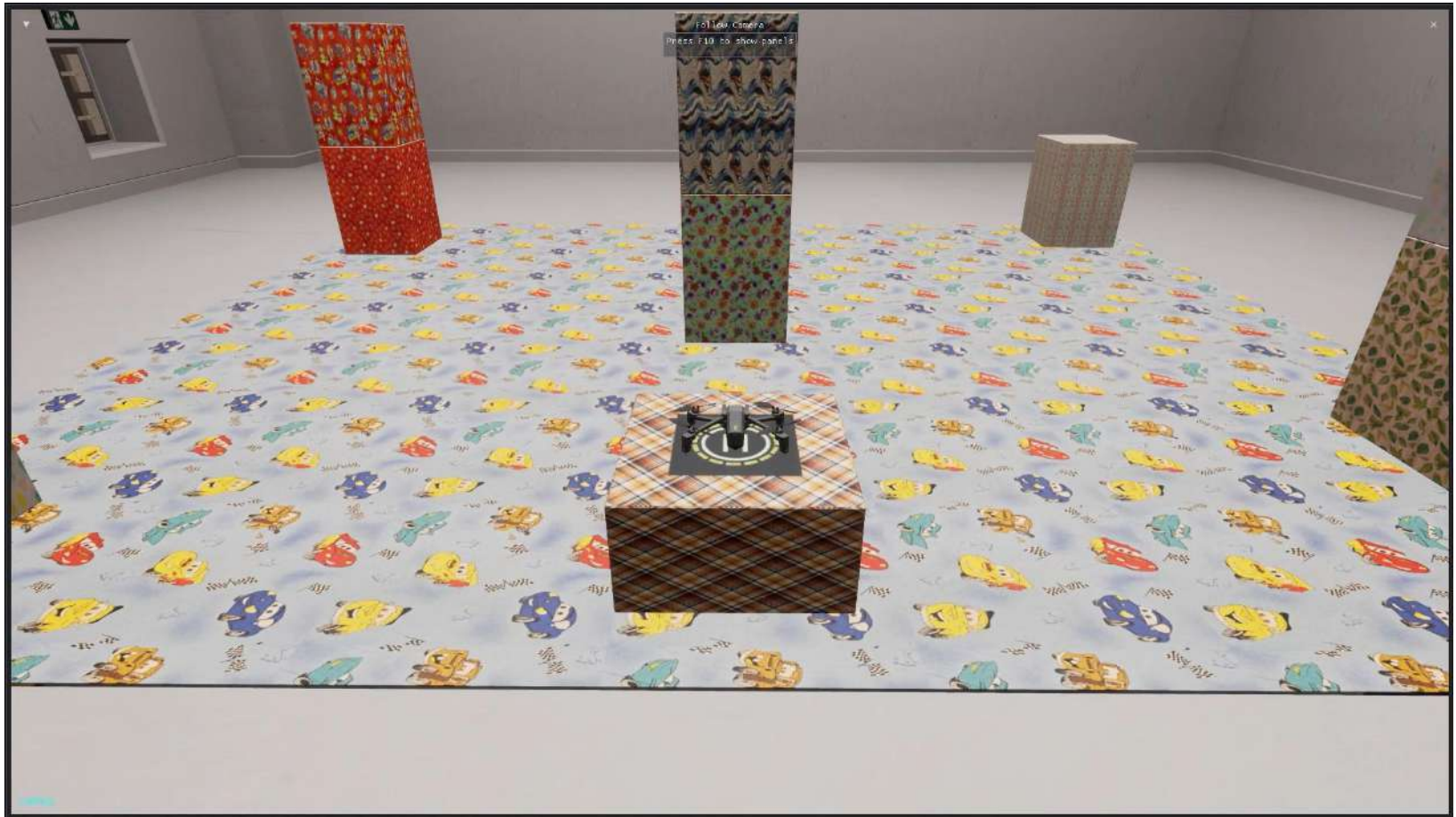


Music: “Fly to the Island” (Album: “Supersonic”) , composed, performed and co-produced by Marius Leordeanu

Key ideas: Learning semantic segmentation with minimal user labeling and
Unsupervised computation of metric depth

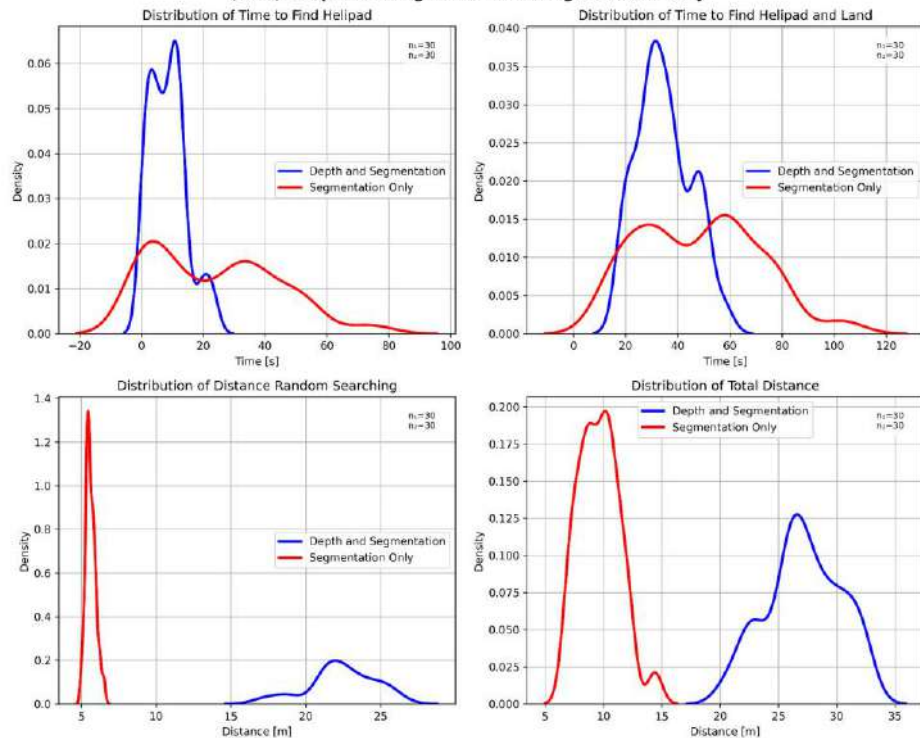


Learn and discover in the twin virtual scene – **Apply in the real scene**

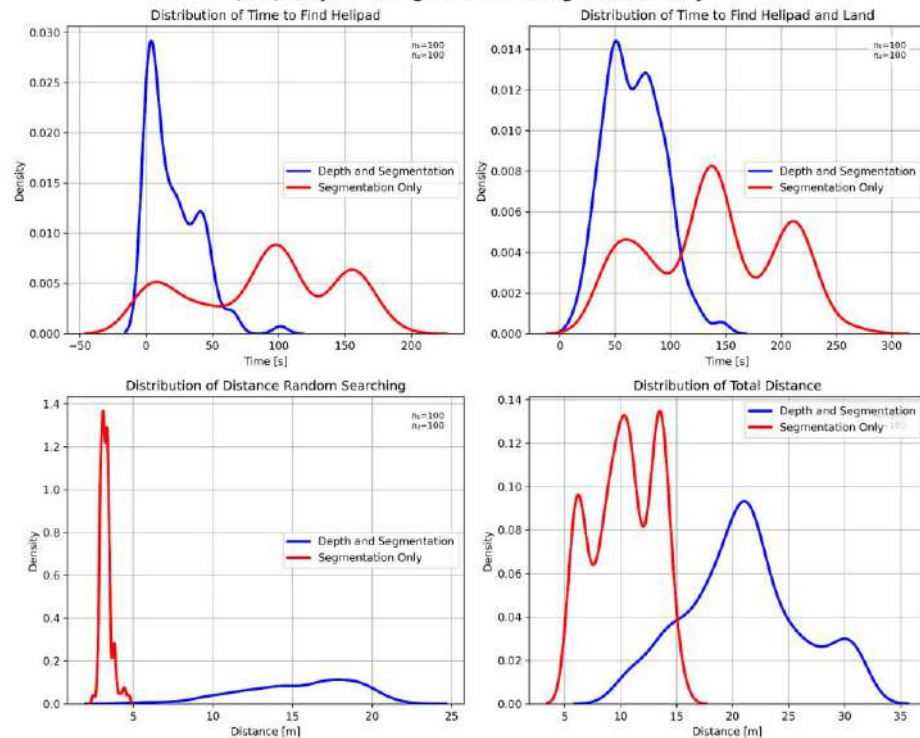


Consistency between tests in Real vs Virtual Scenes

(Real) - Depth and Segmentation vs Segmentation Only

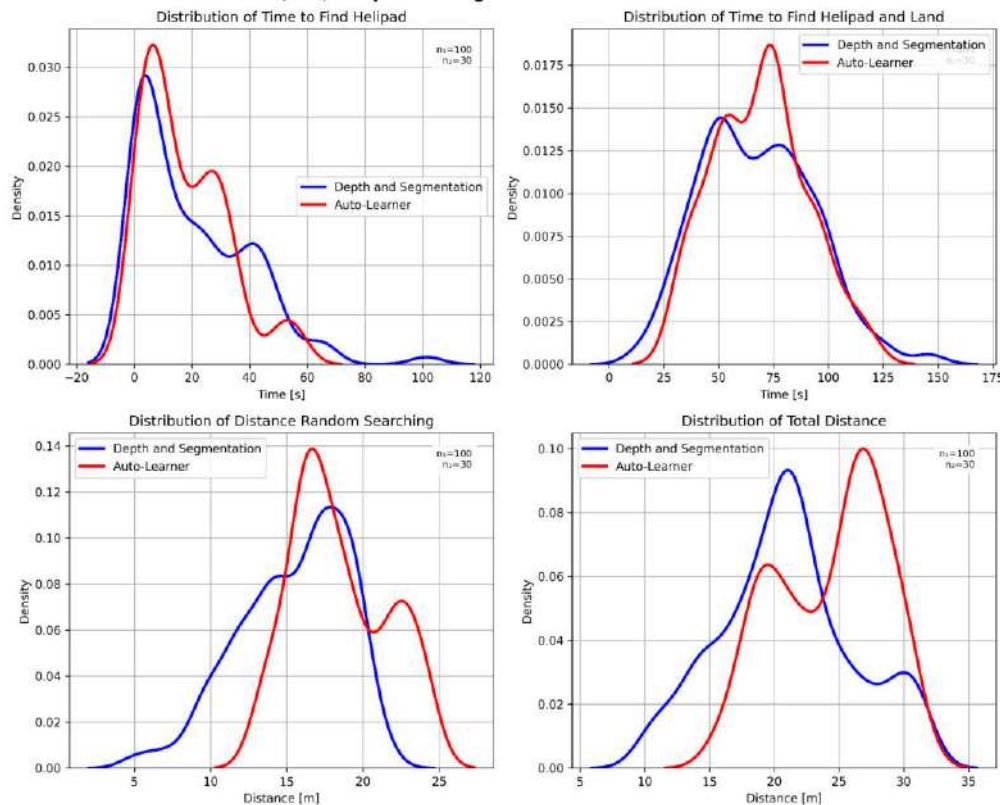


(Sim) - Depth and Segmentation vs Segmentation Only



Distill the complex Depth and Segmentation Auto-pilot into a single small neural net (1.3 M params U-Net)

(Sim) - Depth and Segmentation vs Auto-Learner

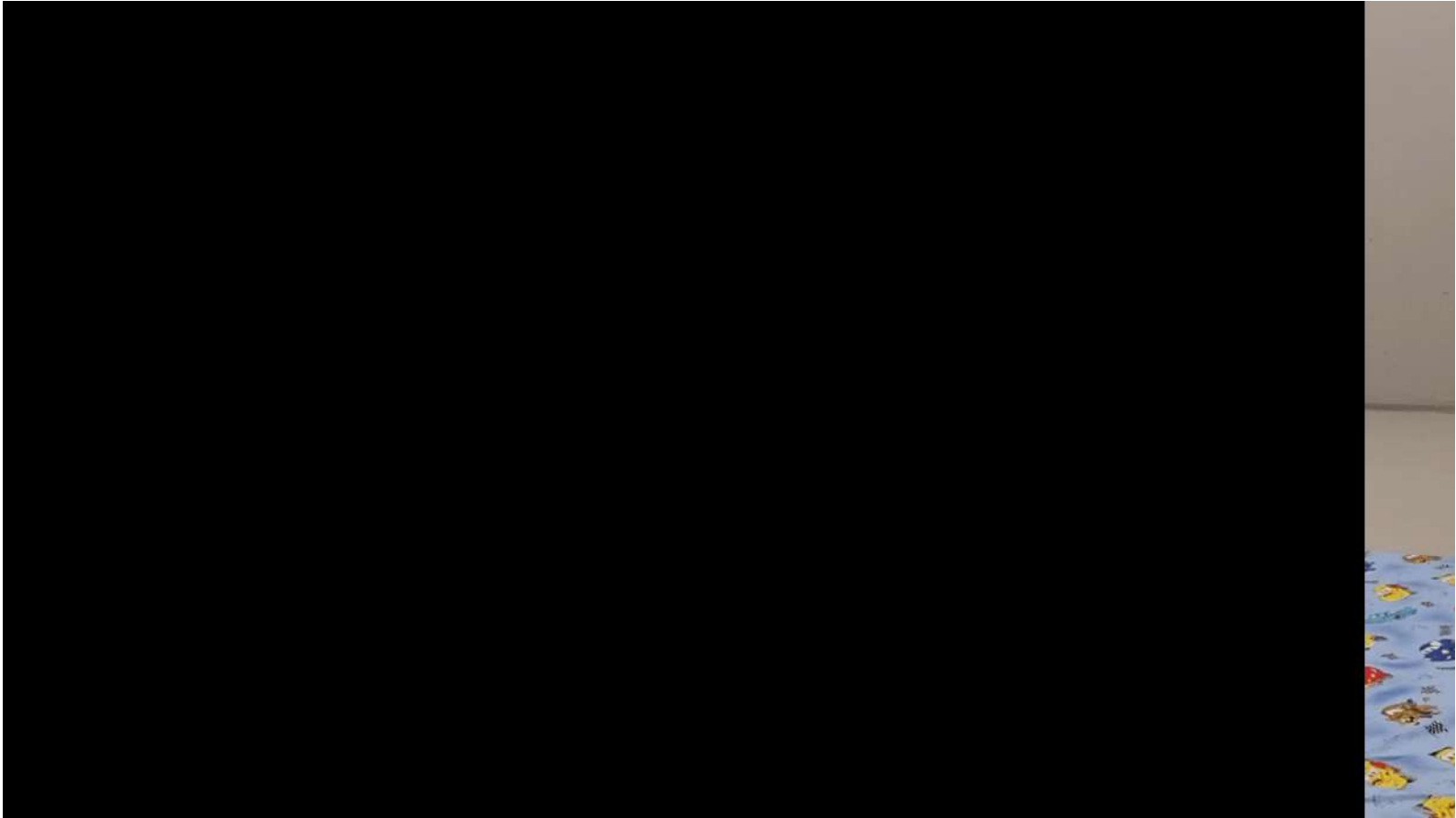


Final Small U-Net Architecture

Layer (type) (var_name)	Input Shape	Output Shape	Param #	Trainable
DroneMovementNet (DroneMovementNet)	(1, 9, 256, 256)	(1, 3)	--	True
↳ ConvolutionBlock (conv1)	(1, 9, 256, 256)	(1, 16, 256, 256)	--	True
↳ Sequential (double_conv)	(1, 9, 256, 256)	(1, 16, 256, 256)	--	True
↳ Conv2d (8)	(1, 9, 256, 256)	(1, 16, 256, 256)	1,312	True
↳ BatchNorm2d (1)	(1, 16, 256, 256)	(1, 16, 256, 256)	32	True
↳ ReLU (2)	(1, 16, 256, 256)	(1, 16, 256, 256)	--	True
↳ Conv2d (3)	(1, 16, 256, 256)	(1, 16, 256, 256)	2,308	True
↳ BatchNorm2d (4)	(1, 16, 256, 256)	(1, 16, 256, 256)	32	True
↳ ReLU (5)	(1, 16, 256, 256)	(1, 16, 256, 256)	--	True
↳ MaxPool2d (pool1)	(1, 16, 256, 256)	(1, 16, 128, 128)	--	True
↳ ConvolutionBlock (conv2)	(1, 16, 128, 128)	(1, 32, 128, 128)	--	True
↳ Sequential (double_conv)	(1, 16, 128, 128)	(1, 32, 128, 128)	--	True
↳ Conv2d (8)	(1, 32, 128, 128)	(1, 32, 128, 128)	4,648	True
↳ BatchNorm2d (1)	(1, 32, 128, 128)	(1, 32, 128, 128)	64	True
↳ ReLU (2)	(1, 32, 128, 128)	(1, 32, 128, 128)	--	True
↳ Conv2d (3)	(1, 32, 128, 128)	(1, 32, 128, 128)	9,248	True
↳ BatchNorm2d (4)	(1, 32, 128, 128)	(1, 32, 128, 128)	64	True
↳ ReLU (5)	(1, 32, 128, 128)	(1, 32, 128, 128)	--	True
↳ MaxPool2d (pool2)	(1, 32, 128, 128)	(1, 32, 64, 64)	--	True
↳ ConvolutionBlock (conv3)	(1, 32, 64, 64)	(1, 64, 64, 64)	--	True
↳ Sequential (double_conv)	(1, 32, 64, 64)	(1, 64, 64, 64)	--	True
↳ Conv2d (8)	(1, 64, 64, 64)	(1, 64, 64, 64)	18,496	True
↳ BatchNorm2d (1)	(1, 64, 64, 64)	(1, 64, 64, 64)	128	True
↳ ReLU (2)	(1, 64, 64, 64)	(1, 64, 64, 64)	--	True
↳ Conv2d (3)	(1, 64, 64, 64)	(1, 64, 64, 64)	36,928	True
↳ BatchNorm2d (4)	(1, 64, 64, 64)	(1, 64, 64, 64)	128	True
↳ ReLU (5)	(1, 64, 64, 64)	(1, 64, 64, 64)	--	True
↳ MaxPool2d (pool3)	(1, 64, 64, 64)	(1, 64, 32, 32)	--	True
↳ ConvolutionBlock (conv4)	(1, 64, 32, 32)	(1, 128, 32, 32)	--	True
↳ Sequential (double_conv)	(1, 64, 32, 32)	(1, 128, 32, 32)	--	True
↳ Conv2d (8)	(1, 128, 32, 32)	(1, 128, 32, 32)	73,856	True
↳ BatchNorm2d (1)	(1, 128, 32, 32)	(1, 128, 32, 32)	256	True
↳ ReLU (2)	(1, 128, 32, 32)	(1, 128, 32, 32)	--	True
↳ Conv2d (3)	(1, 128, 32, 32)	(1, 128, 32, 32)	147,584	True
↳ BatchNorm2d (4)	(1, 128, 32, 32)	(1, 128, 32, 32)	256	True
↳ ReLU (5)	(1, 128, 32, 32)	(1, 128, 32, 32)	--	True
↳ MaxPool2d (pool4)	(1, 128, 32, 32)	(1, 128, 16, 16)	--	True
↳ ConvolutionBlock (conv5)	(1, 128, 16, 16)	(1, 256, 16, 16)	--	True
↳ Sequential (double_conv)	(1, 128, 16, 16)	(1, 256, 16, 16)	--	True
↳ Conv2d (8)	(1, 256, 16, 16)	(1, 256, 16, 16)	295,168	True
↳ BatchNorm2d (1)	(1, 256, 16, 16)	(1, 256, 16, 16)	512	True
↳ ReLU (2)	(1, 256, 16, 16)	(1, 256, 16, 16)	--	True
↳ Conv2d (3)	(1, 256, 16, 16)	(1, 256, 16, 16)	598,880	True
↳ BatchNorm2d (4)	(1, 256, 16, 16)	(1, 256, 16, 16)	512	True
↳ ReLU (5)	(1, 256, 16, 16)	(1, 256, 16, 16)	--	True
↳ AdaptiveAvgPool2d (global_average_pooling)	(1, 256, 16, 16)	(1, 256, 1, 1)	--	True
↳ Linear (fc1)	(1, 256)	(1, 512)	131,584	True
↳ ReLU (relu)	(1, 512)	(1, 512)	--	True
↳ Dropout (dropout)	(1, 512)	(1, 512)	--	True
↳ Linear (fc2)	(1, 512)	(1, 3)	1,539	True

Total params: 1,314,739
Trainable params: 1,314,739
Non-trainable params: 0
Total multi-adds (G): 1.15

Dancing with the Drones - Towards Human-AI Art and Performance



Music: “Emergence” (Album: “Supersonic”) , composed, performed and co-produced by Marius Leordeanu

Fly to the Sky – A Cosmic Attraction



Music: “Cosmic Attraction”, composed, performed and co-produced by Marius Leordeanu