

A satellite view of Earth showing the Middle East, North Africa, and parts of Europe and Asia. The image is dark, with the text overlaid in white. The text is centered on the left side of the image.

Machine Learning and Climate Change

David Rolnick

McGill University

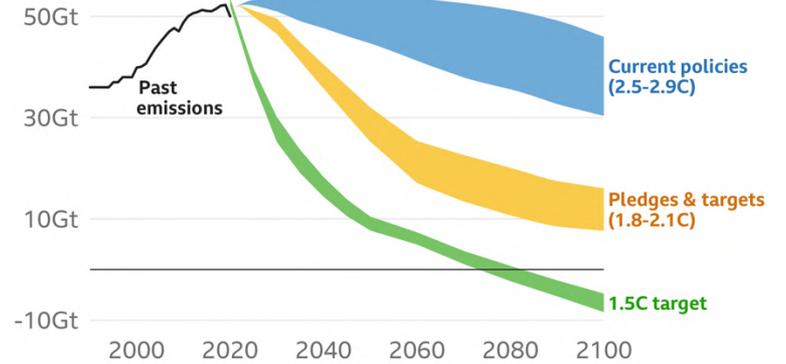
Mila – Quebec AI Institute

Climate Change AI



How close is the world to its 1.5C target?

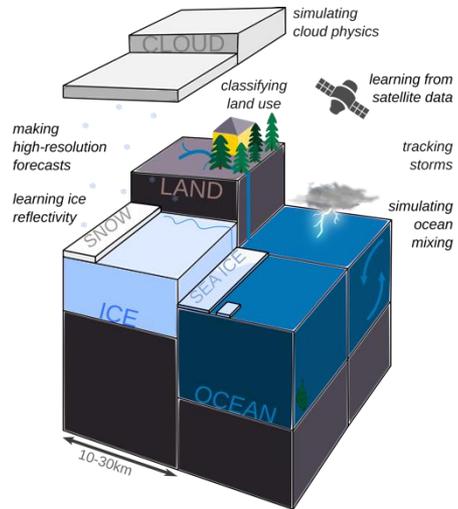
Projected greenhouse gas emissions and future warming levels vary by actions taken



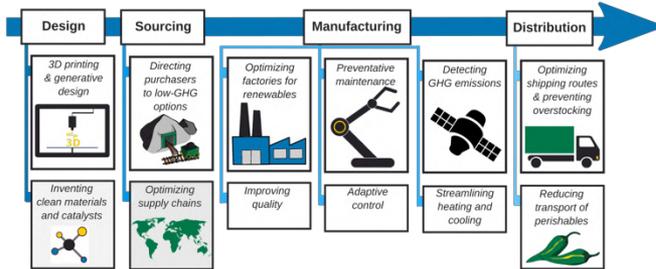
Emissions measured in gigatonnes of carbon dioxide equivalent

Source: Climate Action Tracker, Dec 2023. Broad lines show possible range **B B C**

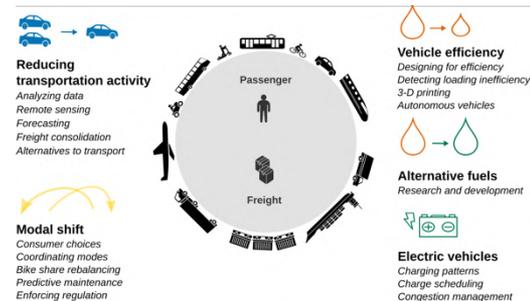
Climate prediction



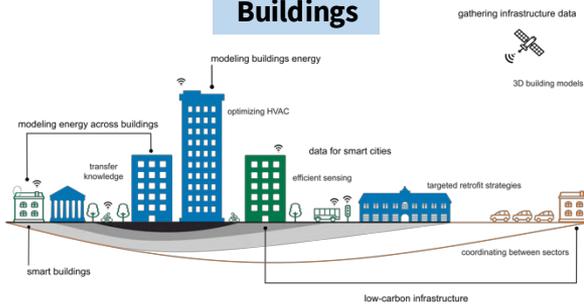
Industry



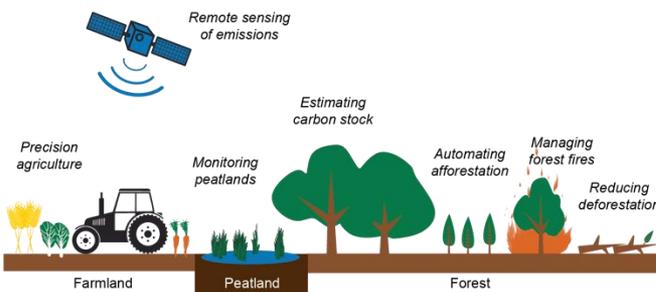
Transportation



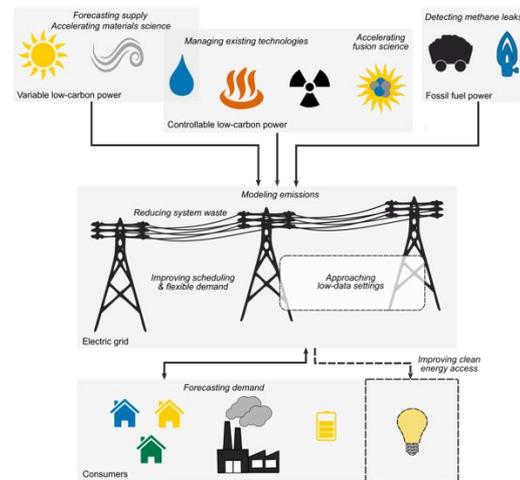
Buildings



Societal adaptation

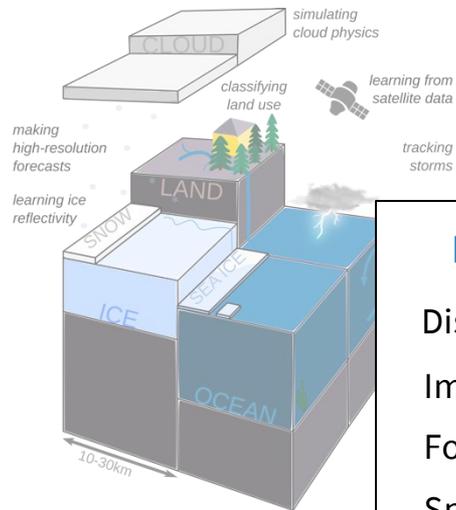


Land use

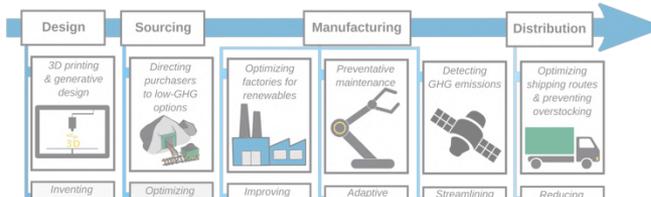


Electricity systems

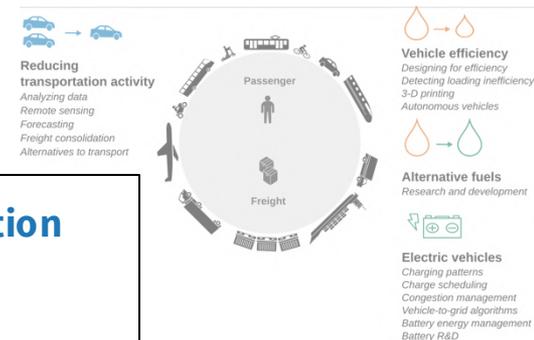
Climate prediction



Industry



Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

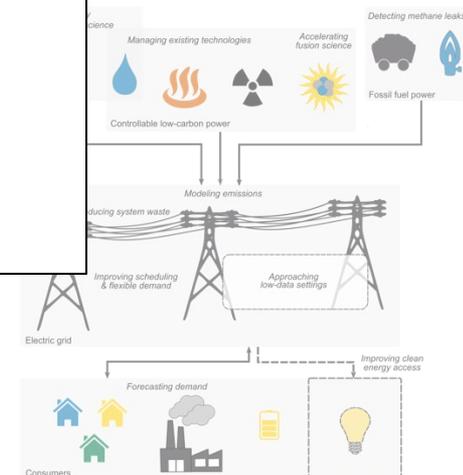
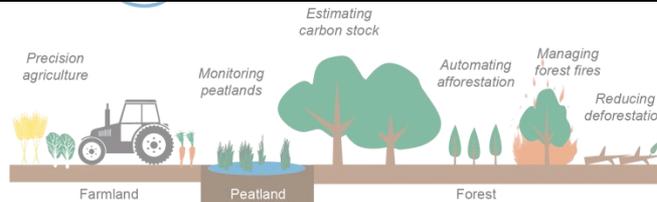
Improving operational efficiency

Forecasting

Speeding up time-intensive simulations

Accelerating scientific discovery

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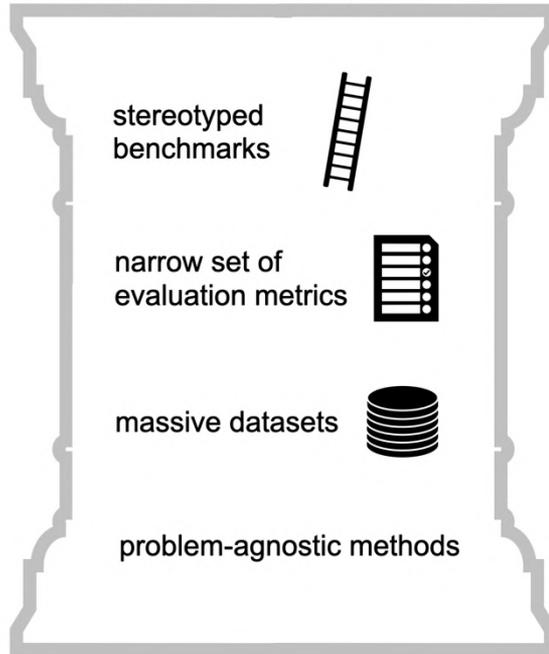
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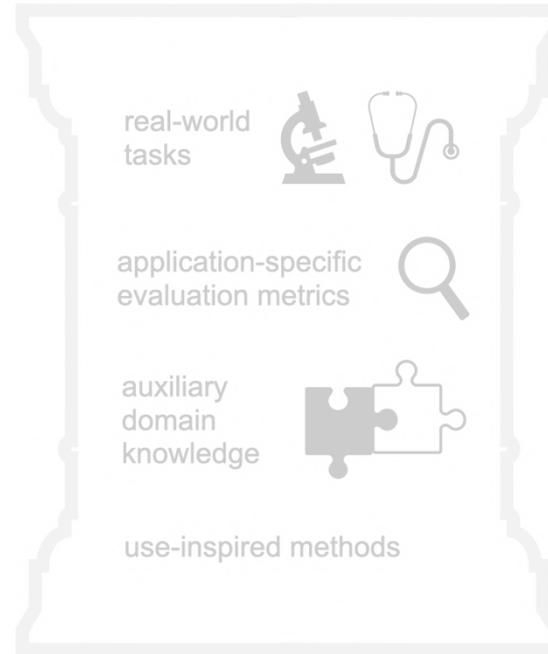
Methods-Driven ML

algorithms that perform well on benchmarks or admit theoretical guarantees.



Application-Driven ML

algorithms and systems that address challenges in real-world applications.



Rolnick, et al. "Application-driven Innovation in Machine Learning",
International Conference on Machine Learning (ICML) 2024.

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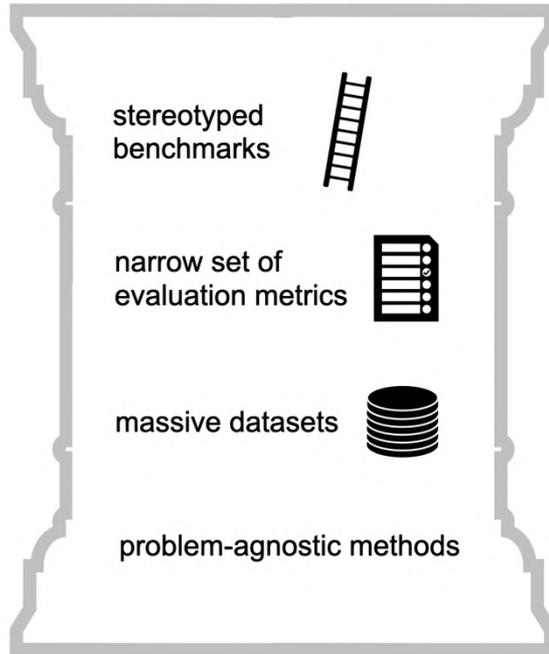
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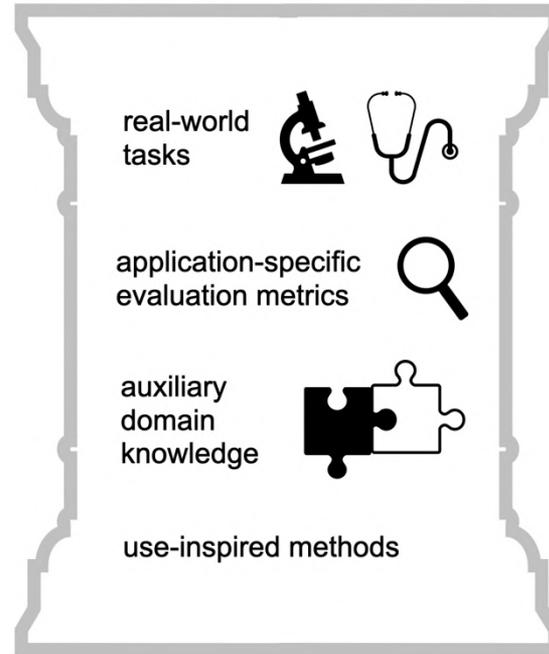
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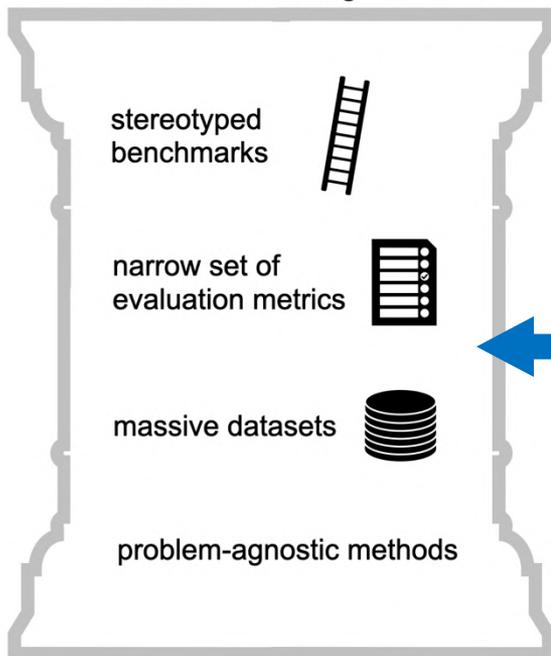
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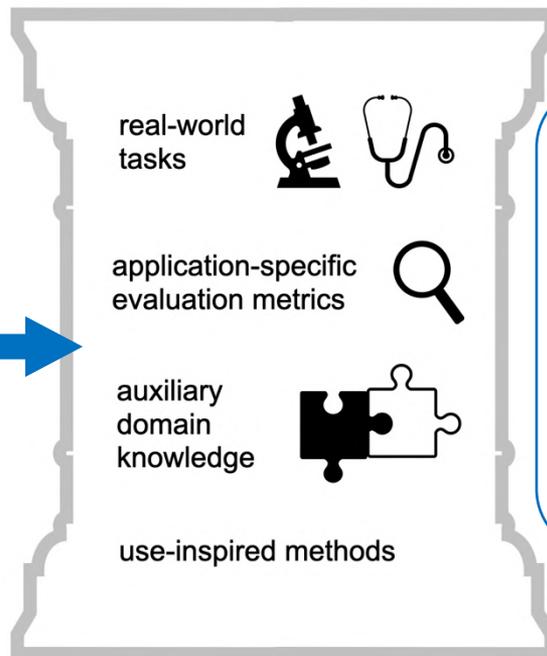
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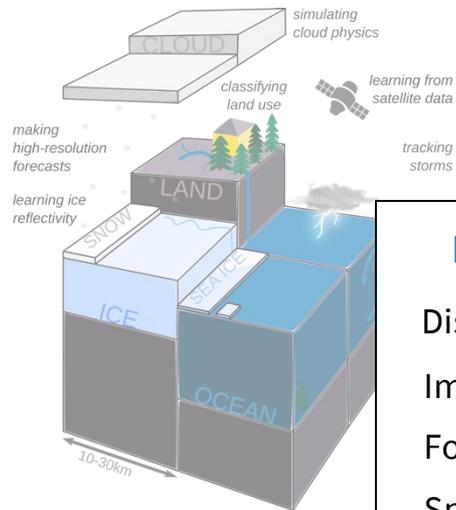
Challenges for ML

- OOD generalization
- Interpretability
- Lightweight models
- Physical constraints
- Limited labels
- Multi-modal data

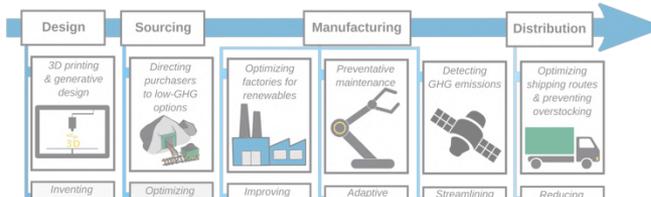
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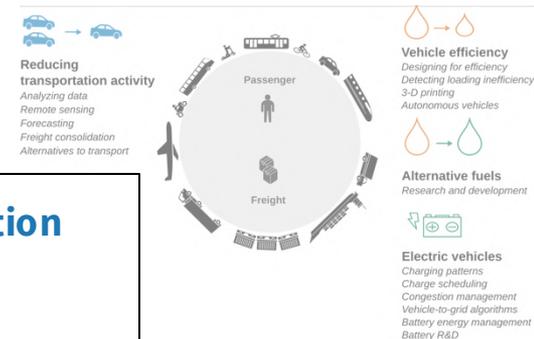
Climate prediction



Industry



Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

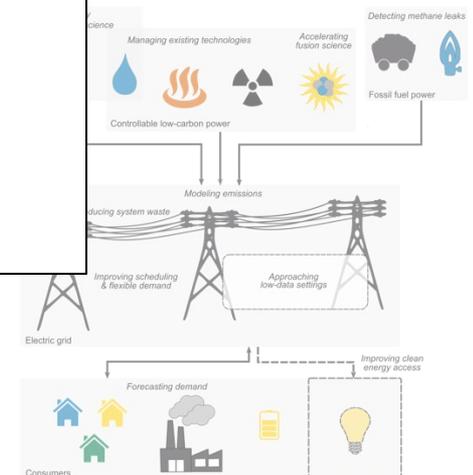
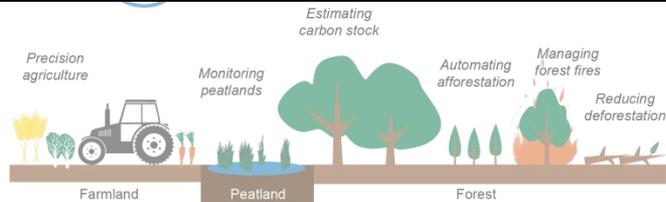
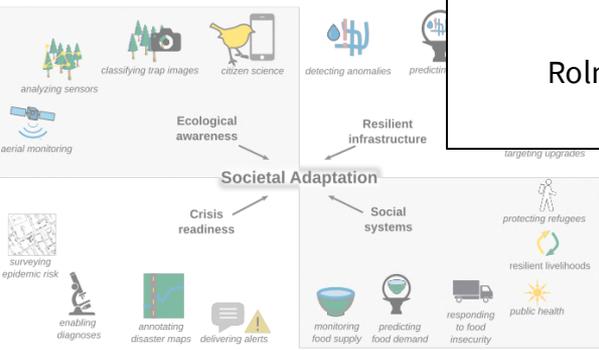
Improving operational efficiency

Forecasting

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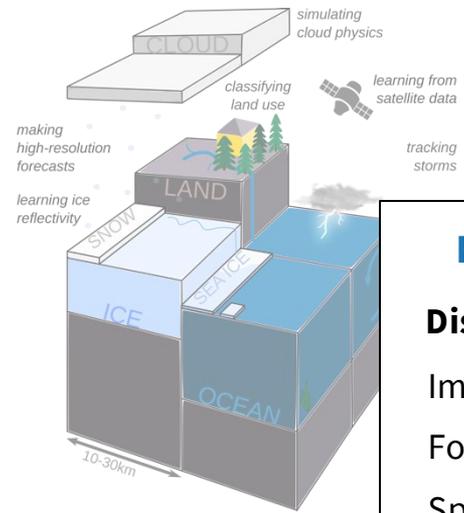


Societal adaptation

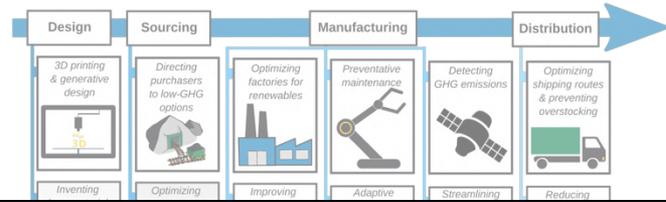
Land use

Electricity systems

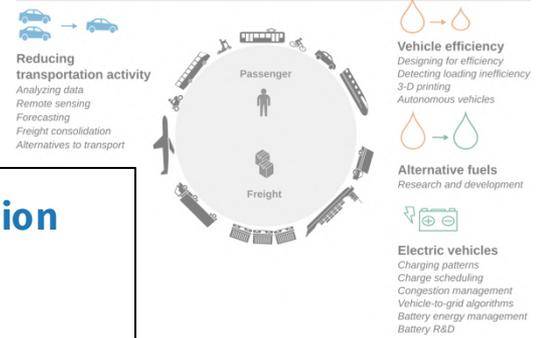
Climate prediction



Industry



Transportation

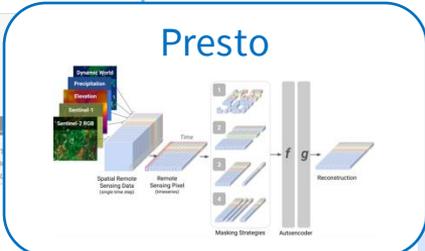


How machine learning can advance climate action

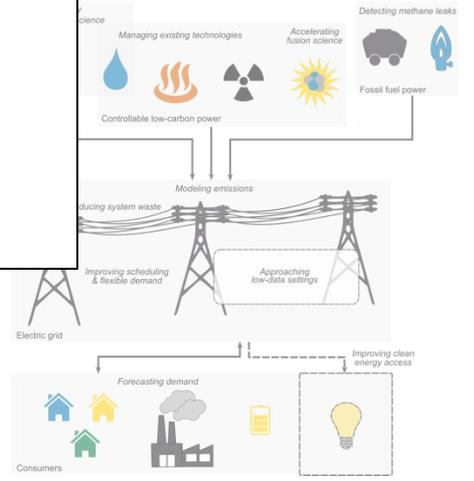
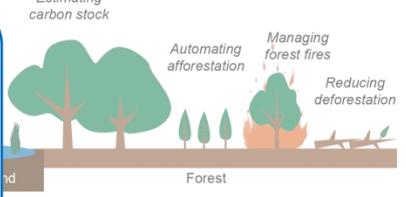
Distilling raw data into actionable information

- Improving operational efficiency
- Forecasting
- Speeding up time-intensive simulations
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Land use



Electricity systems

Societal adaptation

ML for agricultural remote sensing



CropHarvest dataset, Togo



Crop Probability
0 1

Kerner et al. (2020)

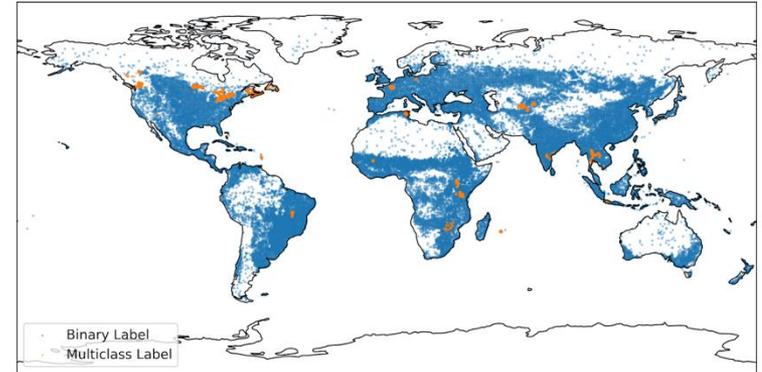


WorldCereal

ML for agricultural remote sensing

Key challenges

Sparse labeled data



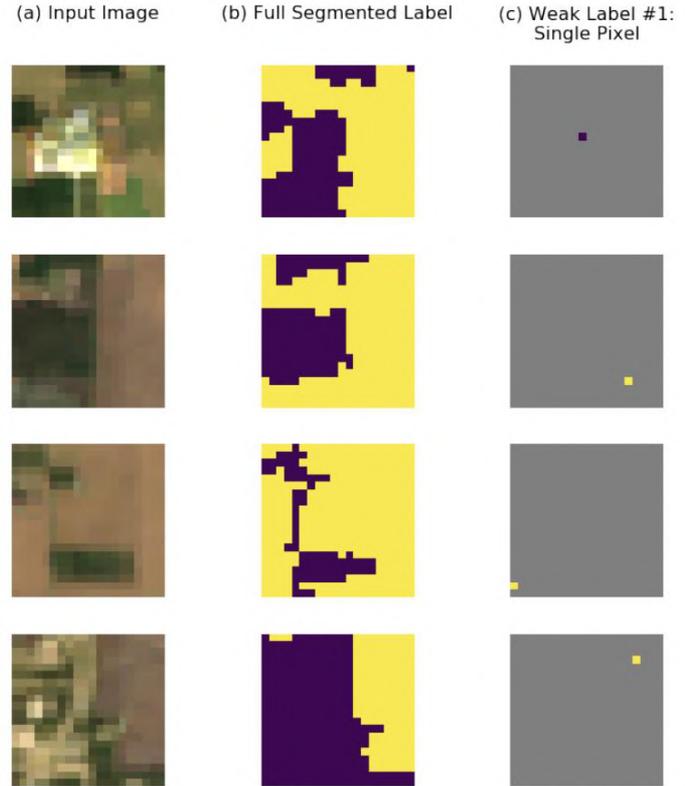
CropHarvest dataset

ML for agricultural remote sensing

Key challenges

Sparse labeled data

Irregularly shaped data



Wang et al. (2020)

ML for agricultural remote sensing

Key challenges

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Irregularly shaped data

Limited computational budget



ML for agricultural remote sensing

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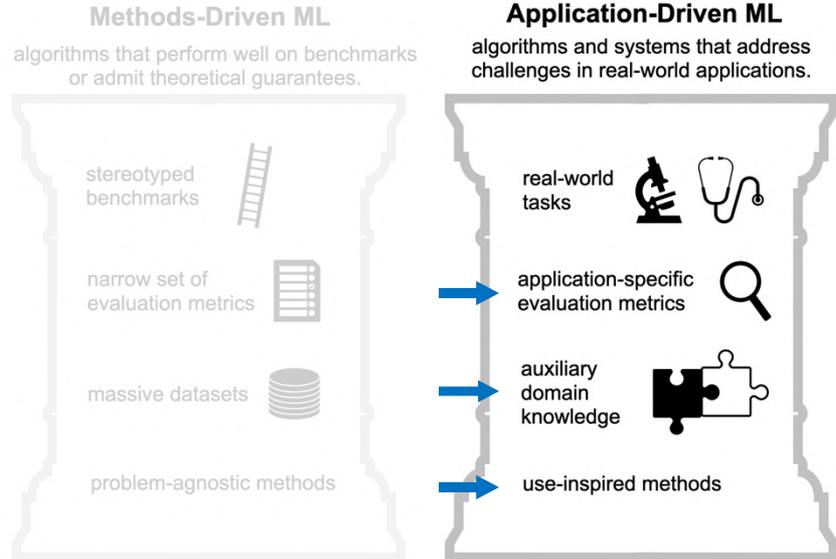
→ Limited computational budget

Problem-relevant information

Geographic structure

Large amount of unlabeled data

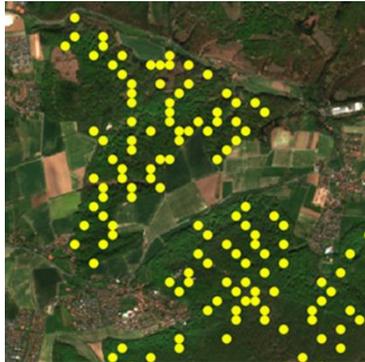
Diversity of input sensors/features



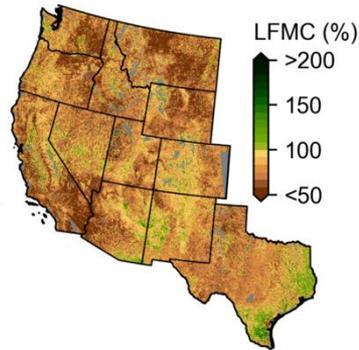
Many related problems



CropHarvest dataset



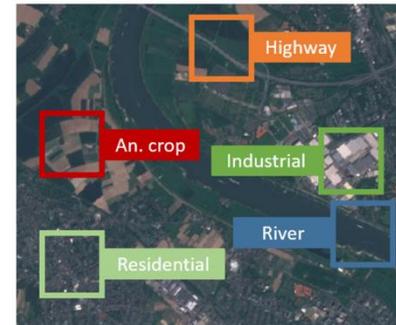
TreeSatAI dataset



Fuel moisture content
(Rao et al. 2020)



“Tick tick bloom”: Algae



EuroSat dataset

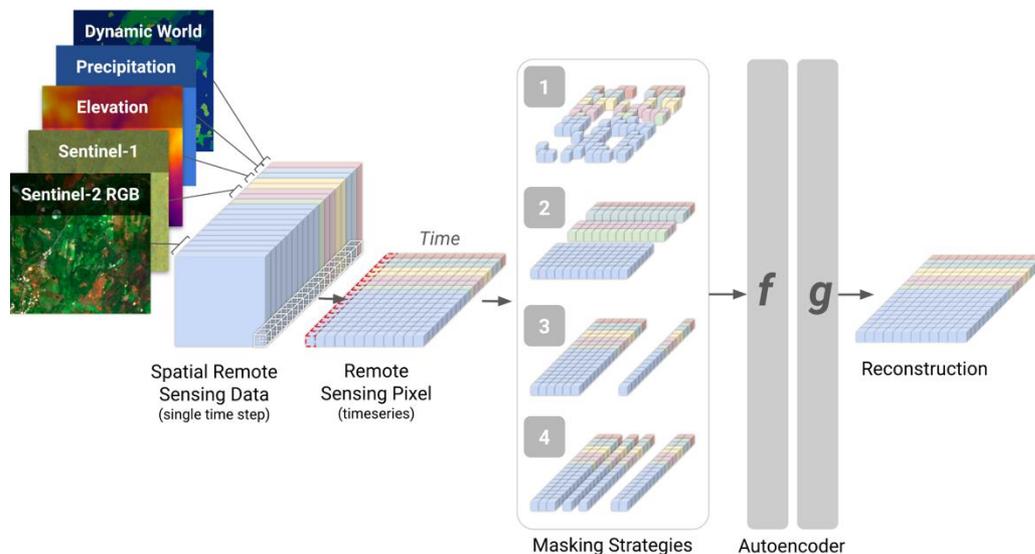
Presto algorithm – self-supervised learning

Presto algorithm leverages structure of remote sensing data

Input at pre-training time:

- Pixel time-series of sensor data and derived data products
- Lat-lon / temporal encodings

Idea: mask out timesteps and input features, train to reconstruct them



Tseng, Cartuyvels, Zvonkov, Purohit, Rolnick, Kerner, “Lightweight, pre-trained transformers for remote sensing timeseries”, preprint arXiv:2304.14065.

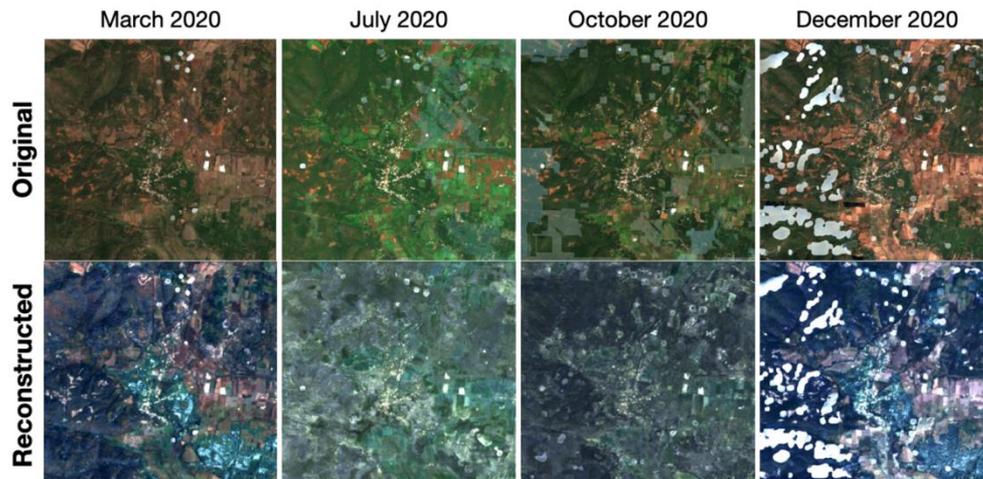
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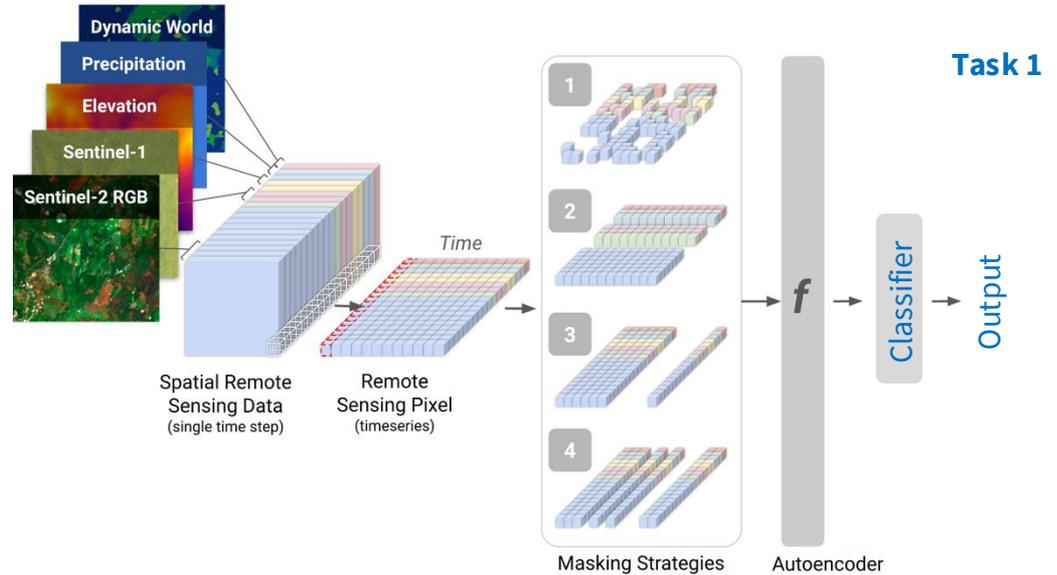
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Presto algorithm – use case

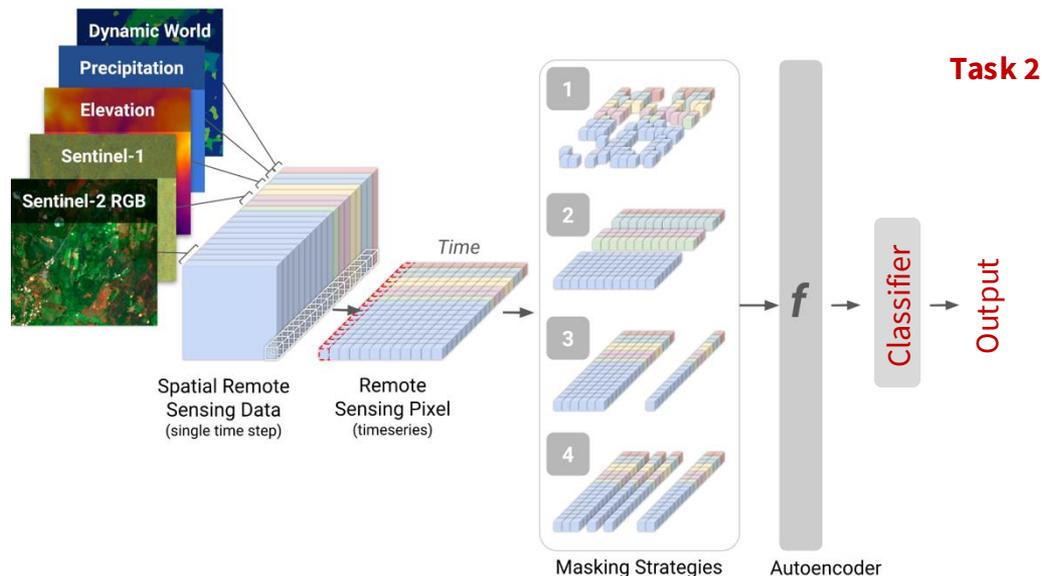
Learned encodings can then be used in solving downstream task
With limited labeled data, train a lightweight classifier (linear regression, random forest, kNN)



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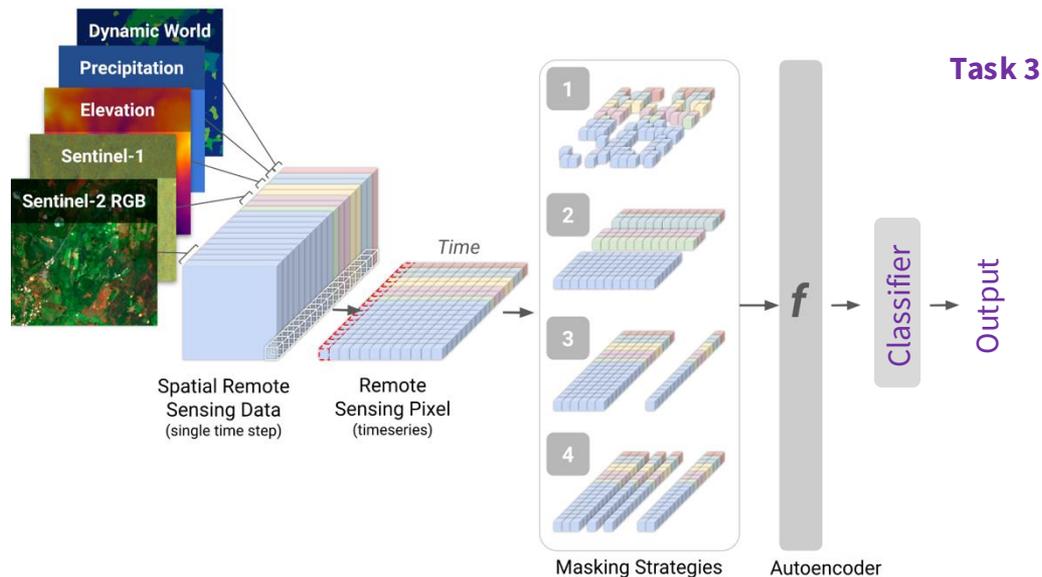
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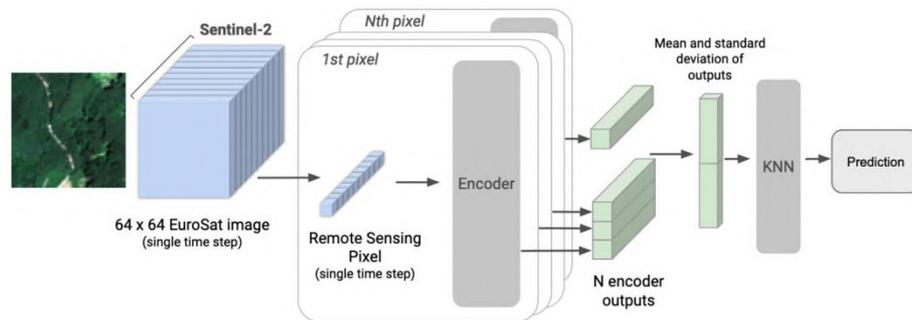
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Results

- Accuracy matches/exceeds larger models
- Competitive with image-structured algorithms
- Effective with single RGB timepoints



CropHarvest

Model	#. parameters		Mean F1
	Total	Adapted	
Random Forest			0.441
MOSAIKS-1D _R	418K	8193	0.738
TIML	91K	91K	0.802
Presto _R no DW	402K	129	0.835 0.836

EuroSat

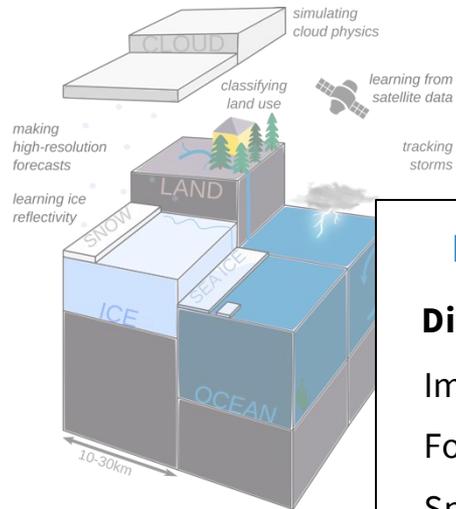
	Backbone	Inputs	Params (M)	Accuracy
GASSL	ResNet-18	RGB	11.69	0.895
SeCo	ResNet-18	RGB	11.69	0.931
SatMAE	ViT-Large	RGB	303.10	0.955
SatMAE	ViT-Large	MS	305.96	0.990
Random init.	Presto	RGB MS	0.40	0.745 0.924
Presto	Presto	RGB MS	0.40	0.849 0.953

TreeSatAI

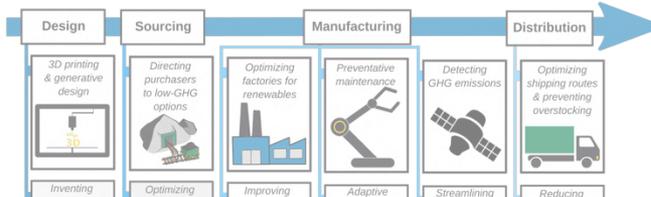
Model	Data	Weighted		Micro	
		F ₁	mAP	F ₁	mAP
MLP		10.09	29.42	12.82	33.09
LightGBM	S1	11.86	32.79	14.07	35.11
Presto _{RF}		38.34	35.45	40.79	38.64
MLP		51.97	64.19	54.59	65.83
LightGBM	S2	48.17	61.99	52.52	61.66
Presto _{RF}		55.29	61.53	58.29	63.31

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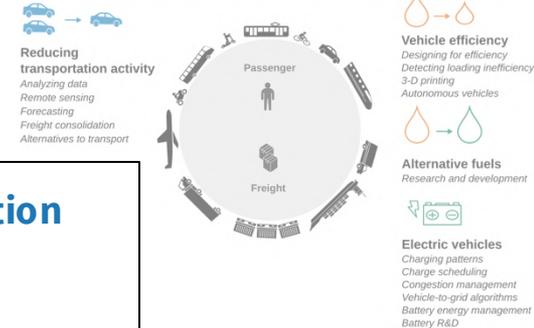
Climate prediction



Industry



Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

Improving operational efficiency

Forecasting

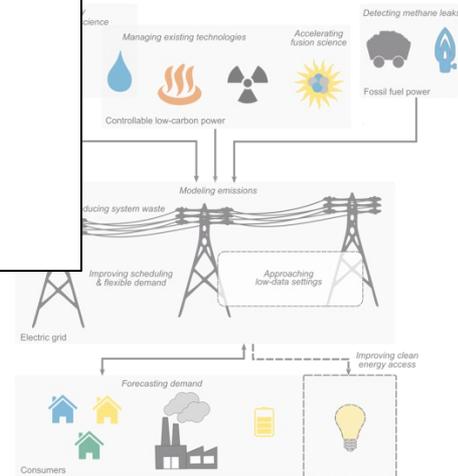
Speeding up time-intensive simulations

Accelerating scientific discovery

Rolnick, et al. Tackling Climate Change with Machine Learning, ACM Computing Surveys, first released 2019.



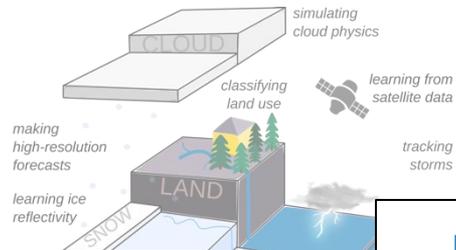
Land use



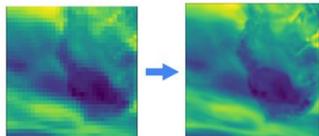
Electricity systems

Societal adaptation

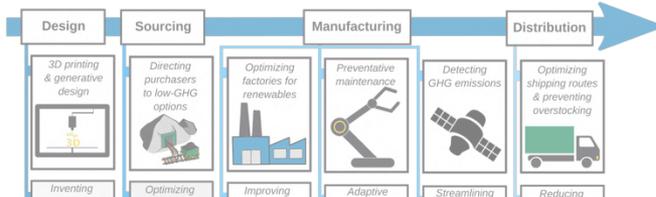
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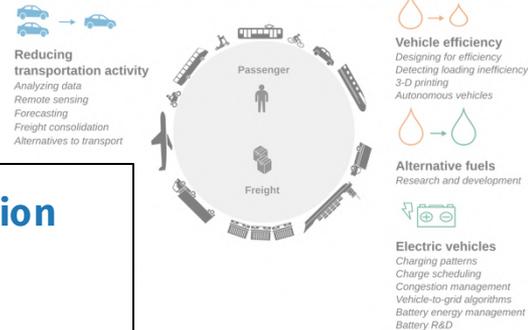
Downscaling FNO



Industry



Transportation



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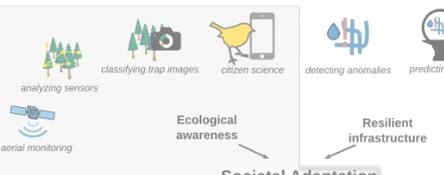
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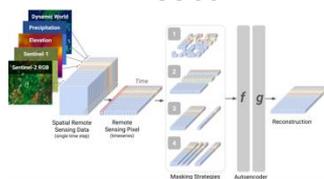
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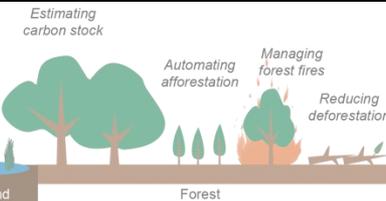
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Presto



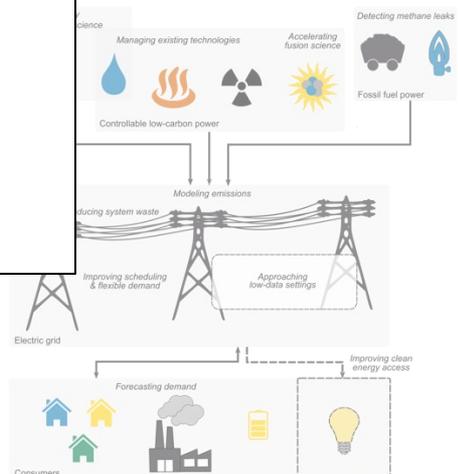
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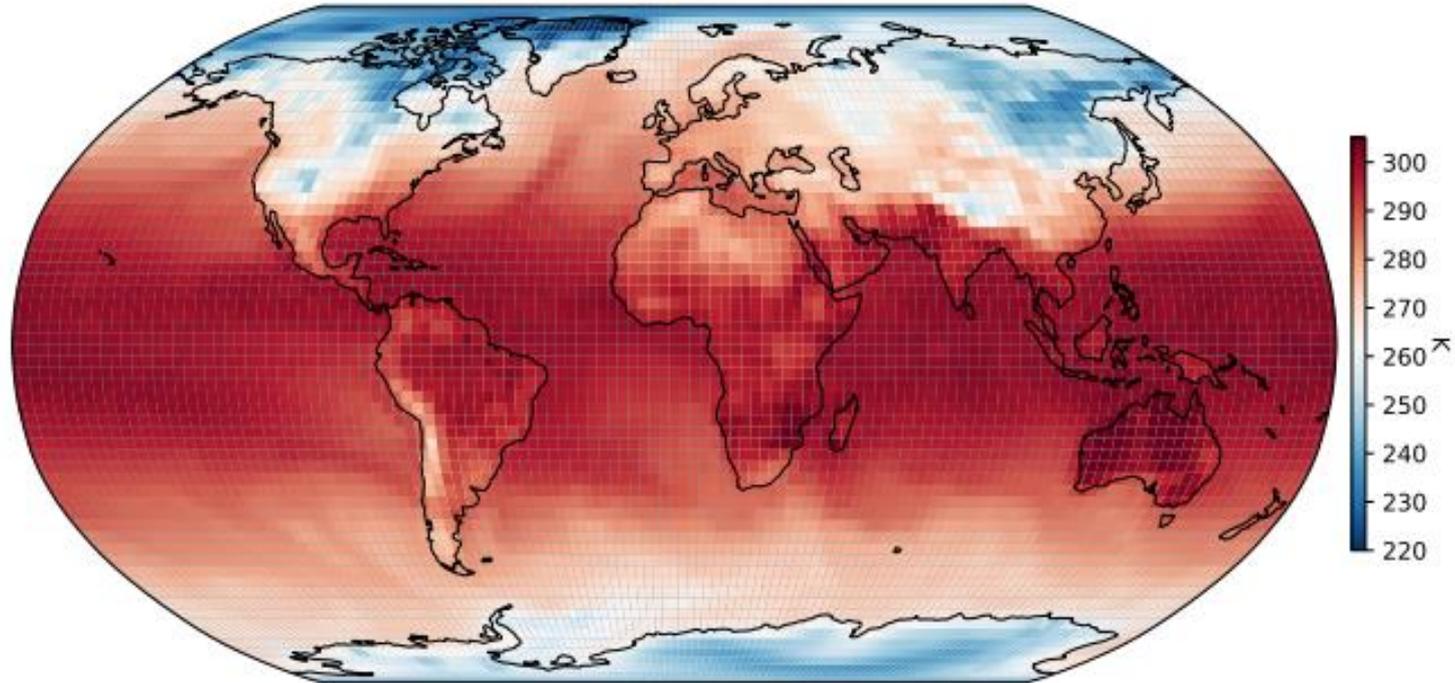
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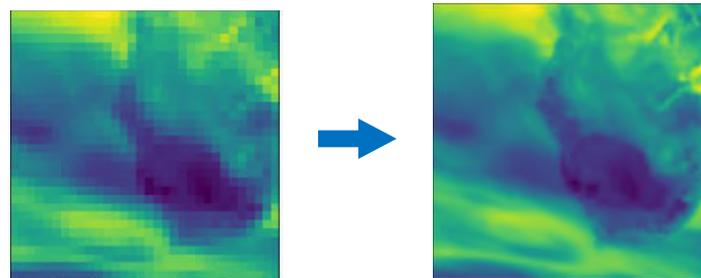
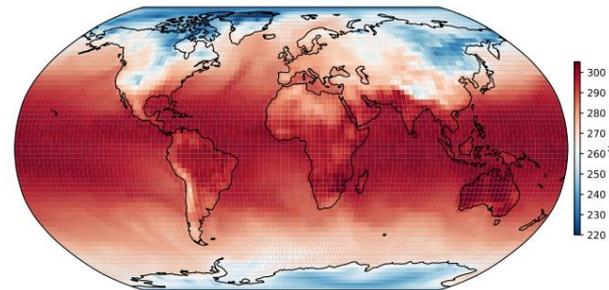
High-resolution climate data on demand



High-resolution climate data on demand

Two directions for ML:

- Climate model emulators
- Statistical downscaling = super-resolution



ERA5 reanalysis data = remote sensing +
ground sensor data + climate models

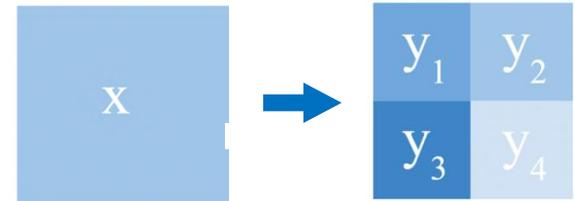
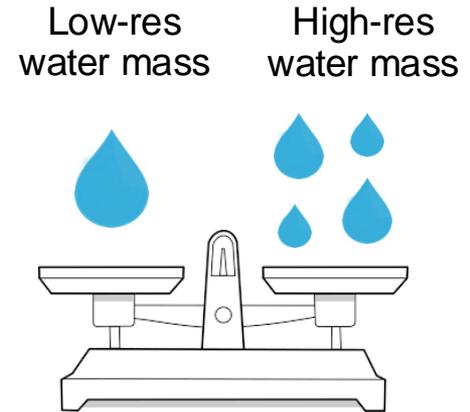
Machine learning for downscaling climate data

Standard ML super-resolution methods:

- Generative adversarial networks (GANs)
- Super-res convolutional neural networks (SR-CNNs)
- Vision transformers

Key challenges:

- Physical constraints



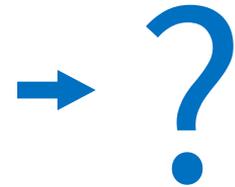
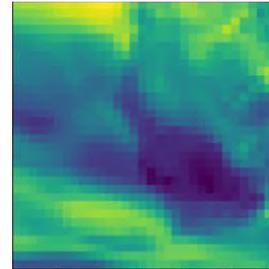
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- Differences from “natural” images

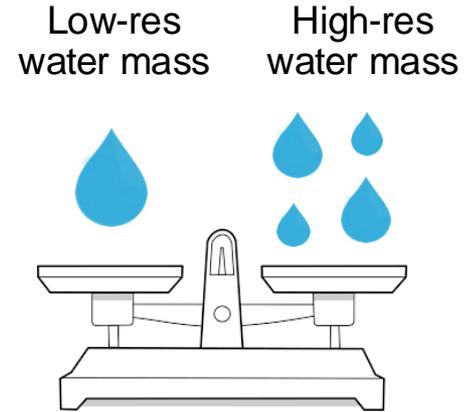
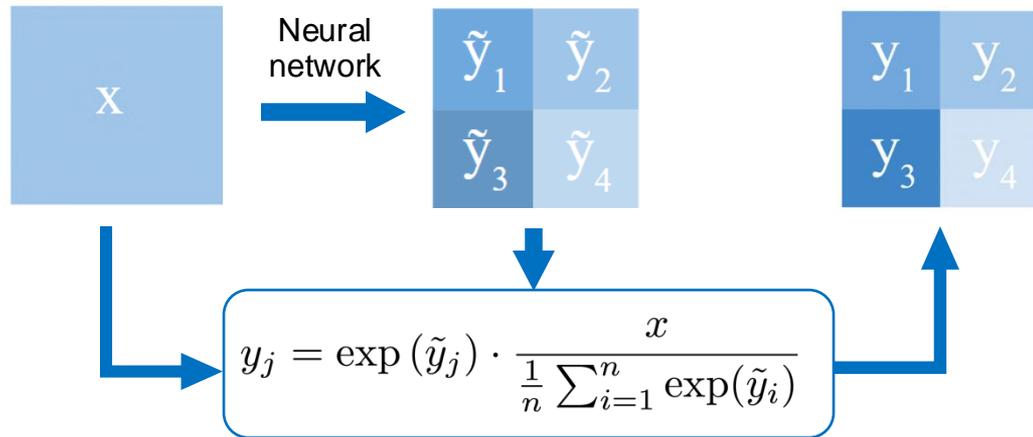


Part 1: physical constraints

Physical constraints - e.g. conservation of mass, energy, or momentum

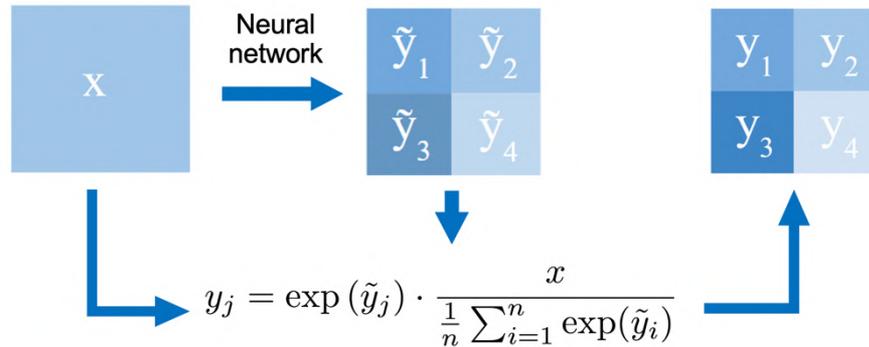
Typical ML approach: Try to learn from data, or add a loss penalty

Our approach: enforce via a hard constraint layer

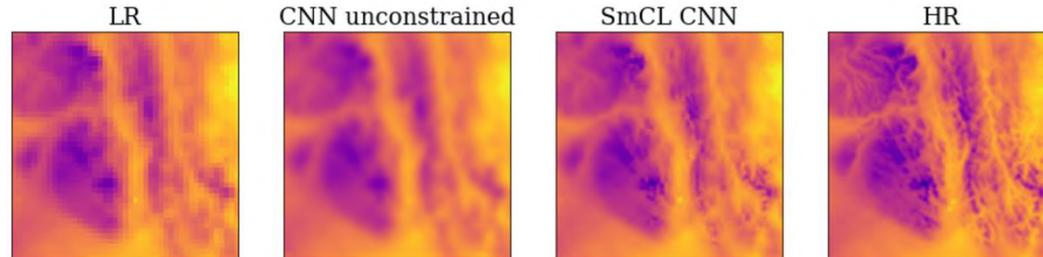


Harder, Yang, Ramesh, Sattigeri, Hernandez-Garcia, Watson, Szwarcman, Rolnick, "Generating physically-consistent high-resolution climate data with hard-constrained neural networks", Journal of Machine Learning Research (JMLR) 2023.

Part 1: physical constraints

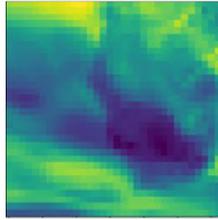


- ✓ Physical realism
- ✓ Accuracy
- ✓ Visual quality

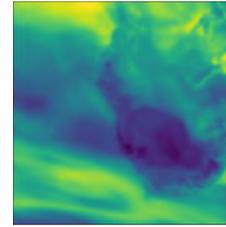


Harder, Yang, Ramesh, Sattigeri, Hernandez-Garcia, Watson, Swarcman, Rolnick, “Generating physically-consistent high-resolution climate data with hard-constrained neural networks”, Journal of Machine Learning Research (JMLR) 2023.

Part 2: arbitrary resolution downscaling

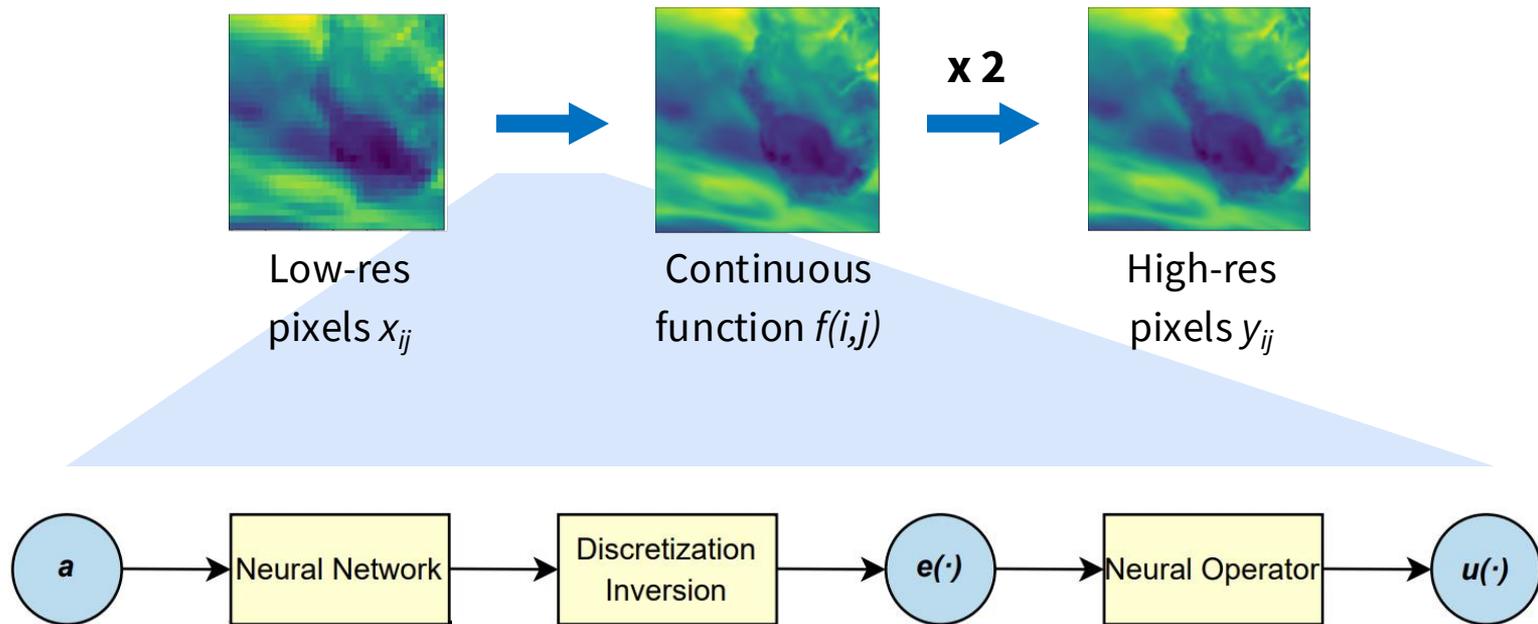


Low-res
pixels x_{ij}



High-res
pixels y_{ij}

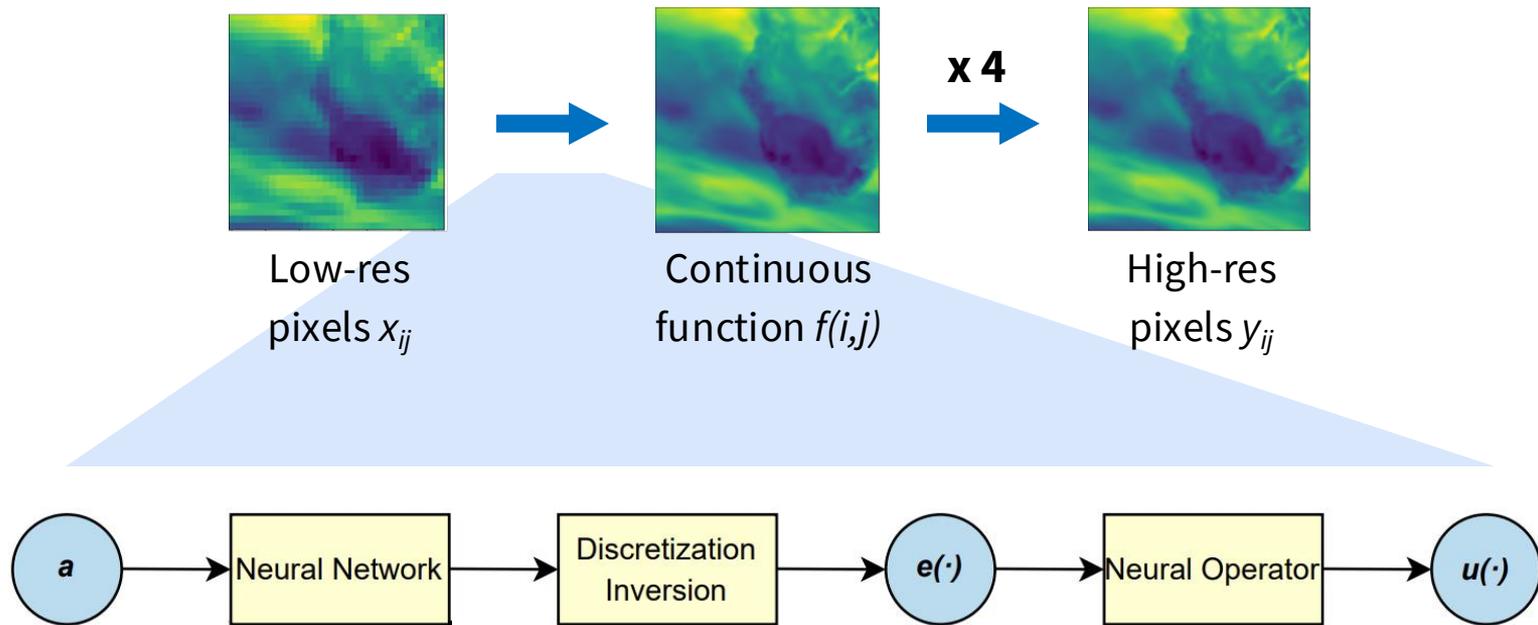
Part 2: arbitrary resolution downscaling



Yang, Hernandez-Garcia, Harder, Ramesh, Sattegeri, Swarcman, Watson, Rolnick, “Fourier Neural Operators for arbitrary resolution climate data downscaling”, preprint arXiv:2305.14452.

Fourier neural operator parametrizes map between functions in Fourier domain

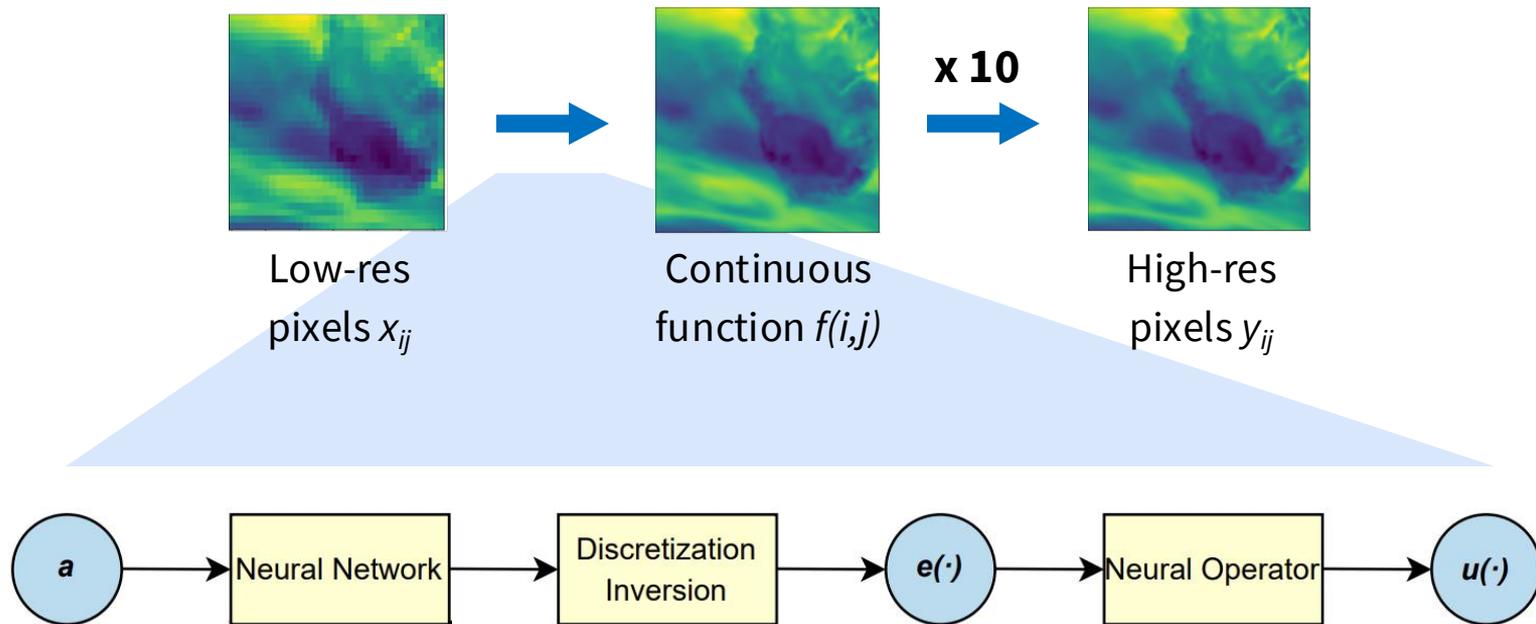
Part 2: arbitrary resolution downscaling



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Fourier neural operator parametrizes map between functions in Fourier domain

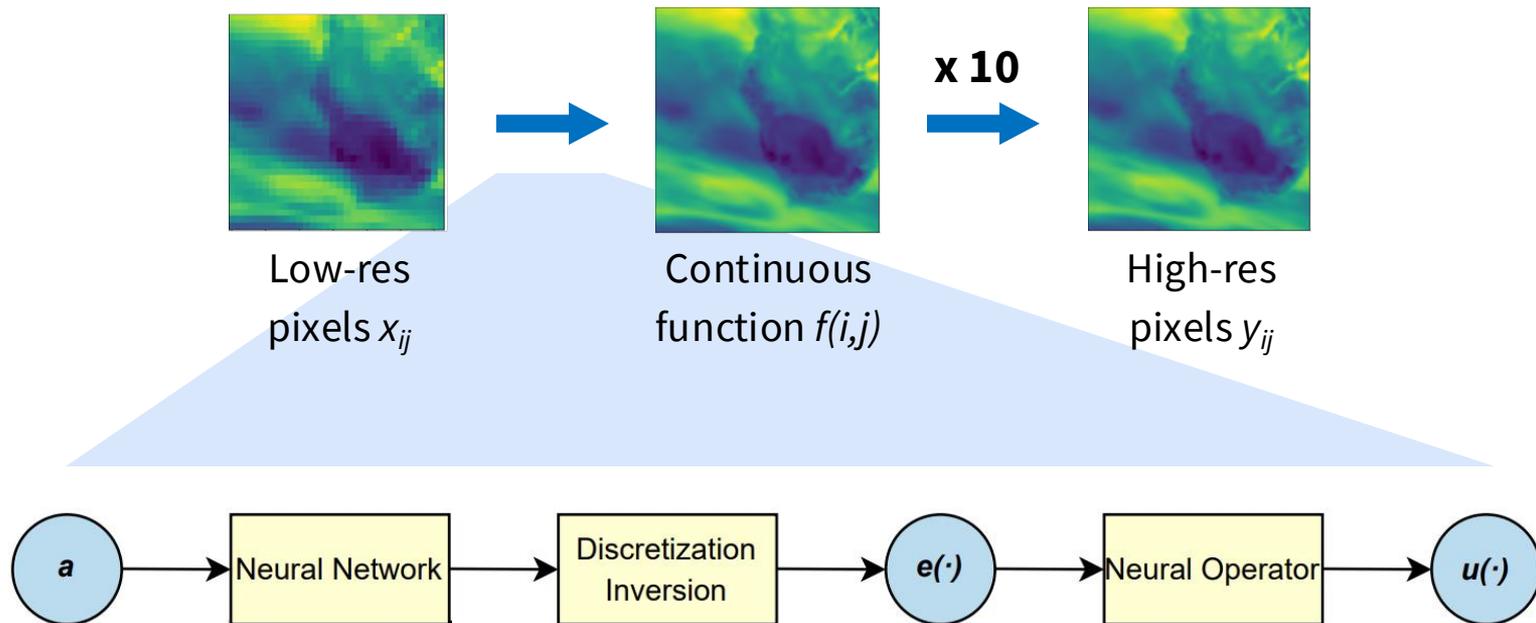
Part 2: arbitrary resolution downscaling



Yang, Hernandez-Garcia, Harder, Ramesh, Sattegeri, Szwarcman, Watson, Rolnick, “Fourier Neural Operators for arbitrary resolution climate data downscaling”, preprint arXiv:2305.14452.

Fourier neural operator parametrizes map between functions in Fourier domain

Part 2: arbitrary resolution downscaling



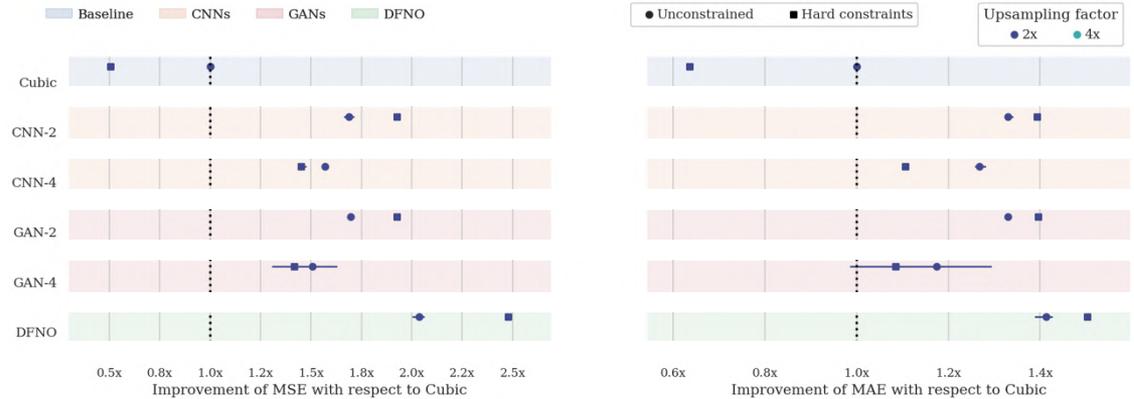
Generalizes without need for high-res data

Fourier domain well-matched to fluid dynamics

Fourier neural operator parametrizes map between functions in Fourier domain

Experimental results

ERA5 reanalysis data
Total column water

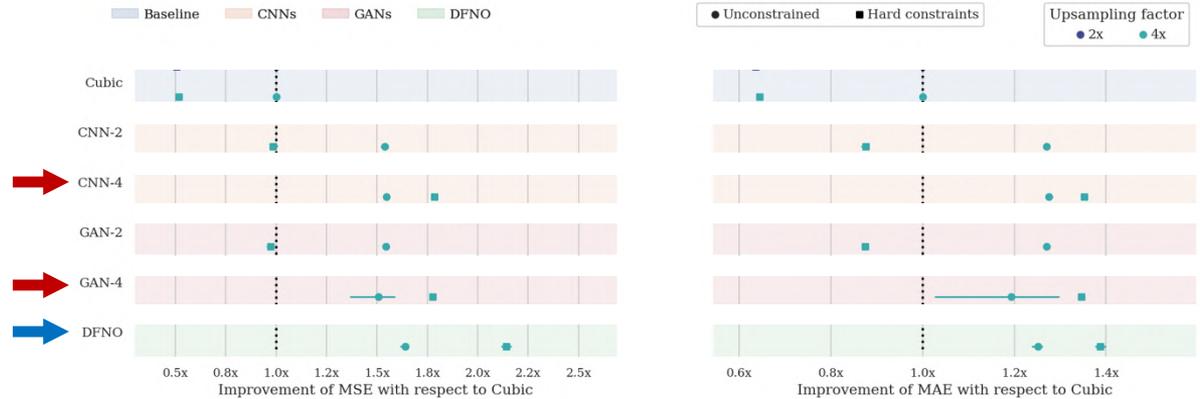


Experimental results

ERA5 reanalysis data
Total column water

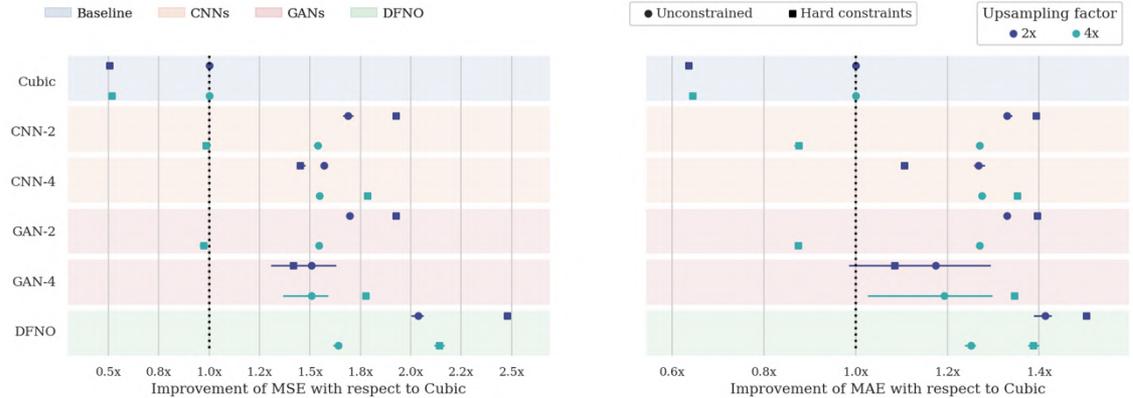
Trained
specifically
on 4x task

Zero-shot
generalization
from 2x task

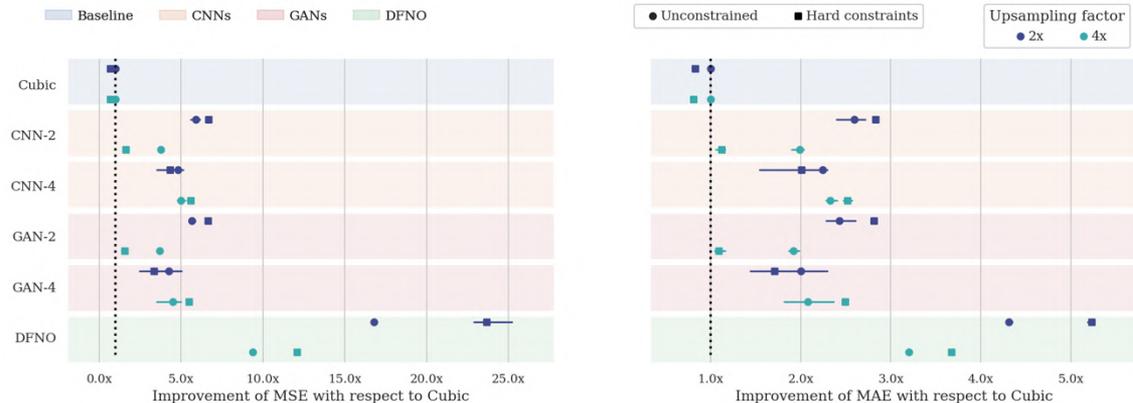


Experimental results

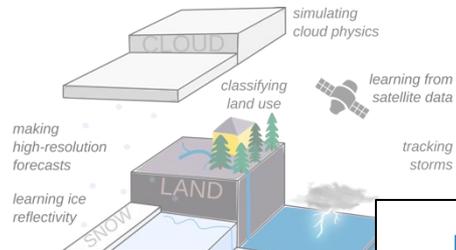
ERA5 reanalysis data
Total column water



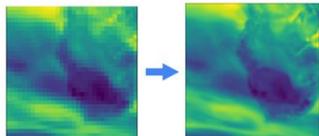
Navier-Stokes eqn.
viscous, incompressible
fluid in vorticity form
(original FNO problem)



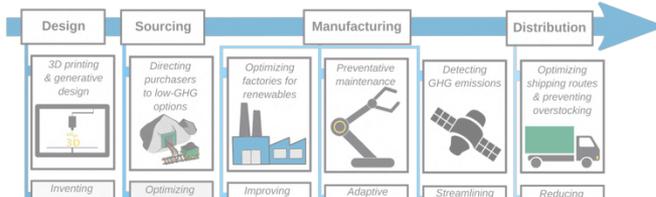
Climate prediction



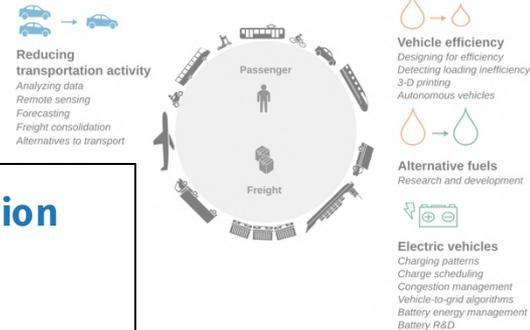
Downscaling FNO



Industry



Transportation



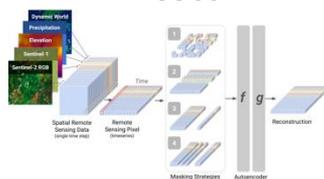
How machine learning can advance climate action

- Distilling raw data into actionable information
- Improving operational efficiency
- Forecasting
- Speeding up time-intensive simulations
- Accelerating scientific discovery

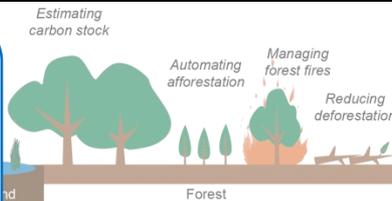
Rolnick, et al. Tackling Climate Change with Machine Learning, ACM Computing Surveys, first released 2019.



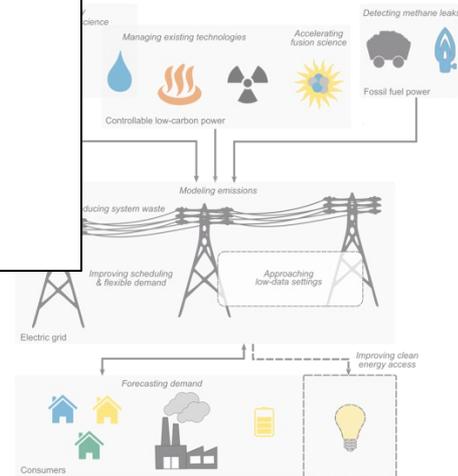
Presto



Land use



Electricity systems

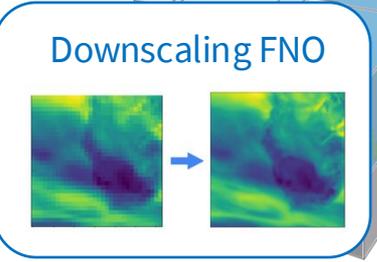
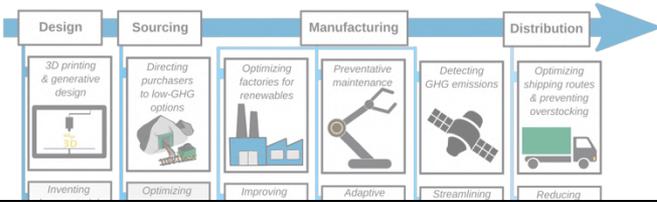
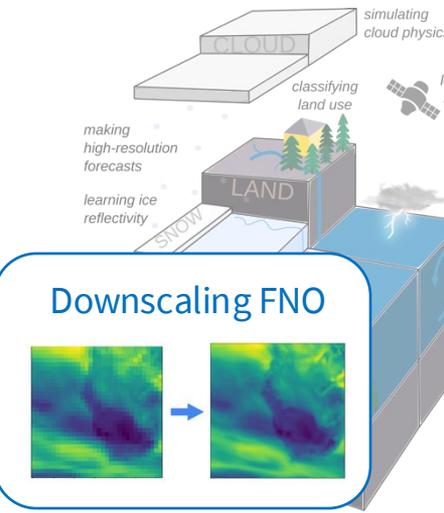


Societal adaptation

Climate prediction

Industry

Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

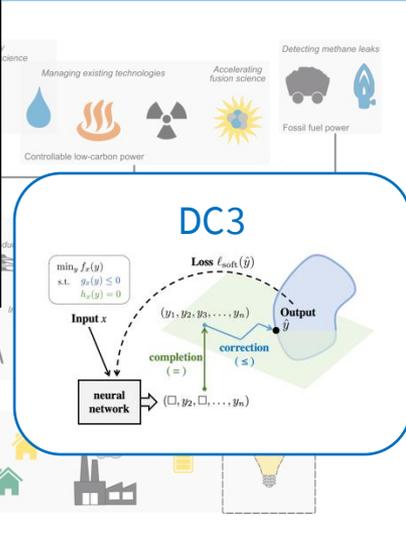
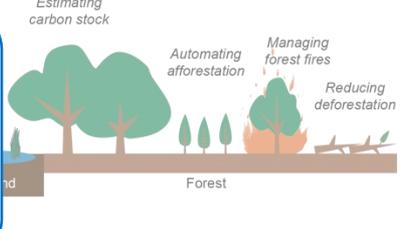
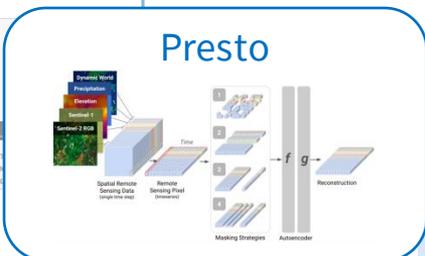
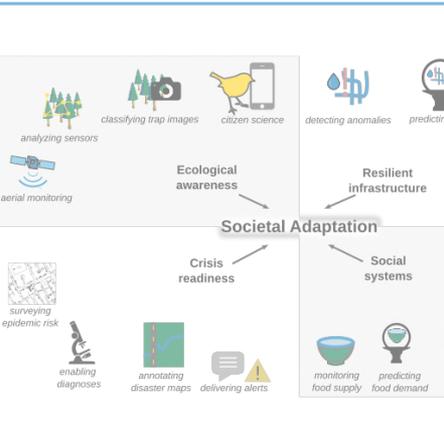
Improving operational efficiency

Forecasting

Speeding up time-intensive simulations

Accelerating scientific discovery

Rolnick, et al. Tackling Climate Change with Machine Learning, ACM Computing Surveys, first released 2019.



Societal adaptation

Land use

Electricity systems

Constrained deep learning for grid optimization

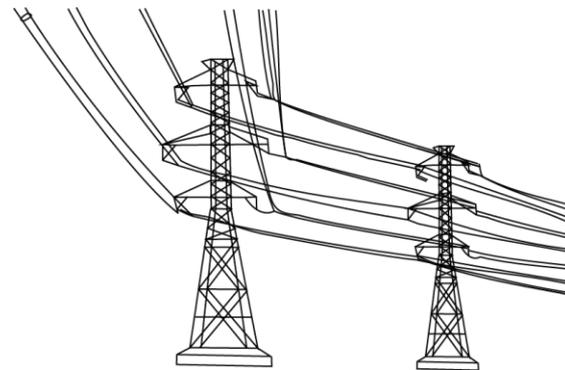
Balancing the electrical grid requires solving a nonconvex opt problem, AC Optimal Power Flow

Exact solutions take too long, so typically grid operators simplify the problem, wasting large amounts of power, especially w/ solar and wind

Typical DL uses soft penalty for constraint violation

But since even slight infeasibility renders useless

We design a DL approach to approximately solve non-convex optimization problems while satisfying hard constraints.



$$\begin{aligned} & \underset{p_g \in \mathbb{R}^b, q_g \in \mathbb{R}^b, v \in \mathbb{C}^b}{\text{minimize}} && p_g^T A p_g + b^T p_g \\ & \text{subject to} && p_g^{\min} \leq p_g \leq p_g^{\max} \\ & && q_g^{\min} \leq q_g \leq q_g^{\max} \\ & && v^{\min} \leq |v| \leq v^{\max} \\ & && (p_g - p_d) + (q_g - q_d)i = \text{diag}(v) \overline{W} \overline{v}. \end{aligned}$$

Approximate optimization w/ hard constraints

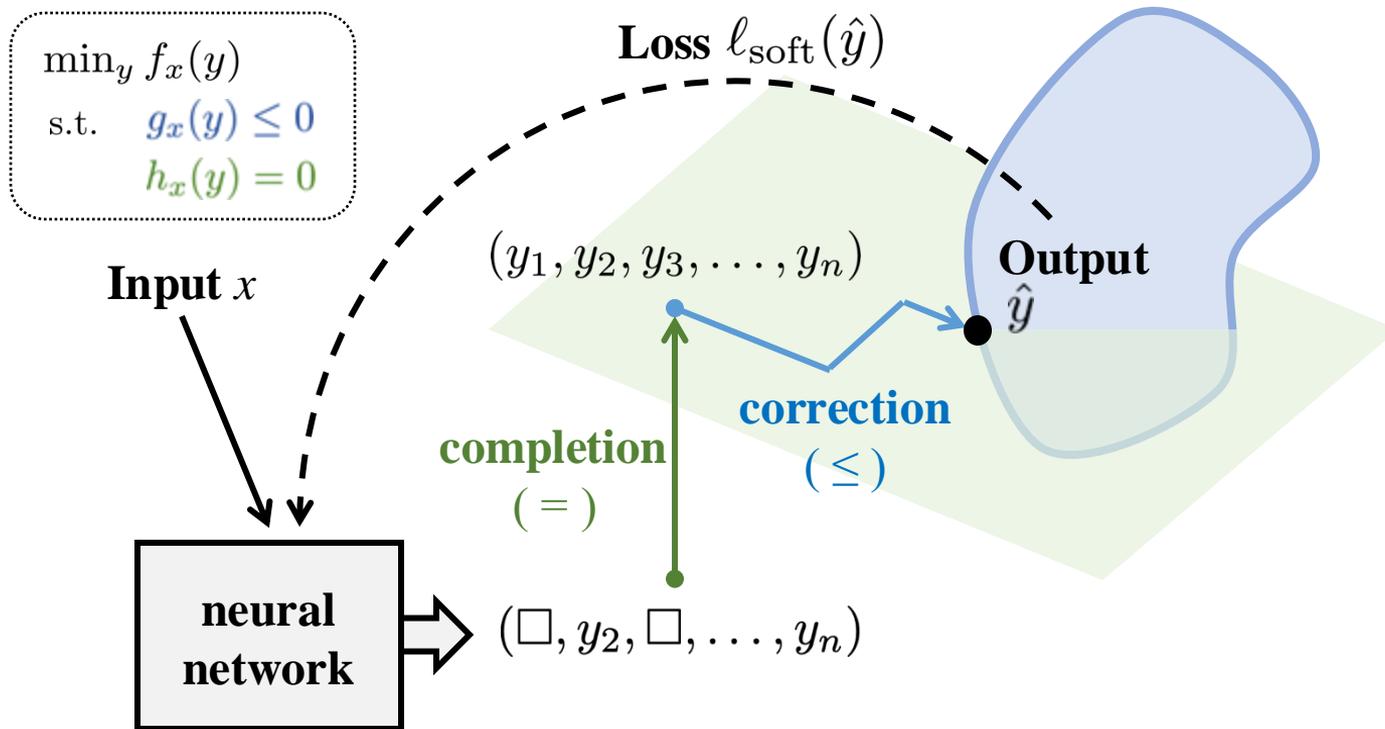
Goal: Approximate mapping from x to y , while satisfying constraints

$$\min_y f_x(y)$$

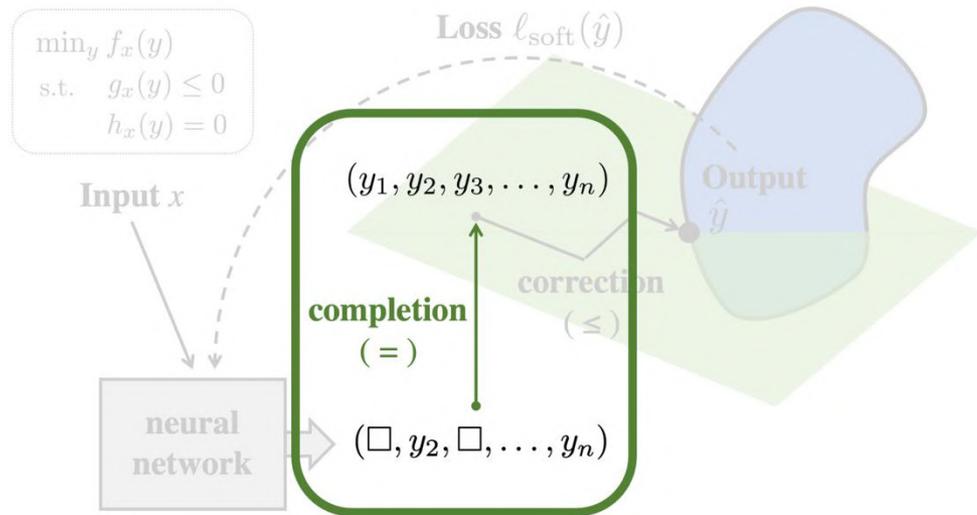
$$\text{s.t. } g_x(y) \leq 0$$

$$h_x(y) = 0$$

DC3: Deep Constraint Completion & Correction



Equality completion



Output **subset of variables**

$$z = N_{\theta}(x)$$

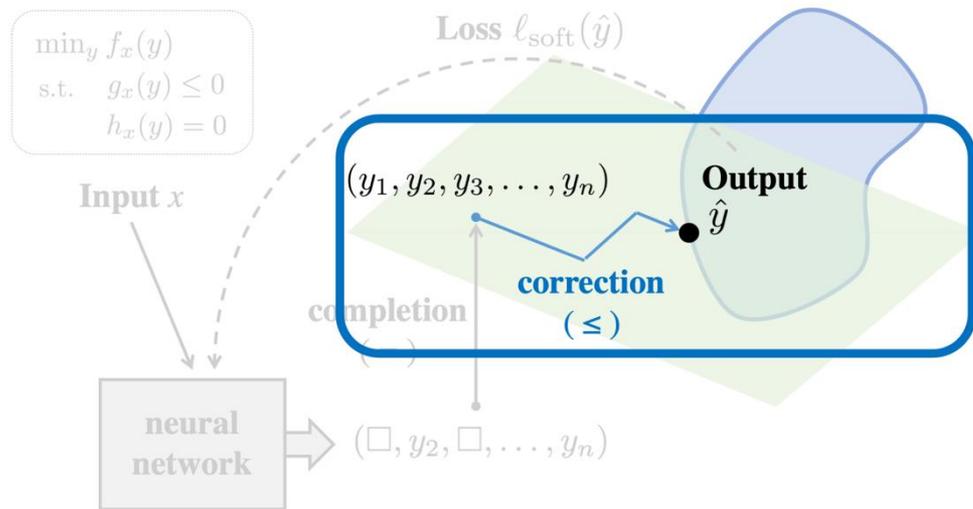
Then **solve for rest**: $\varphi_x(z)$

where $\varphi_x : \mathbb{R}^m \rightarrow \mathbb{R}^{n-m}$

$$\text{s.t. } h_x([z^T \ \varphi_x(z)^T])^T = 0$$

Procedure is **differentiable** (either explicitly or via implicit function thm)

Inequality correction



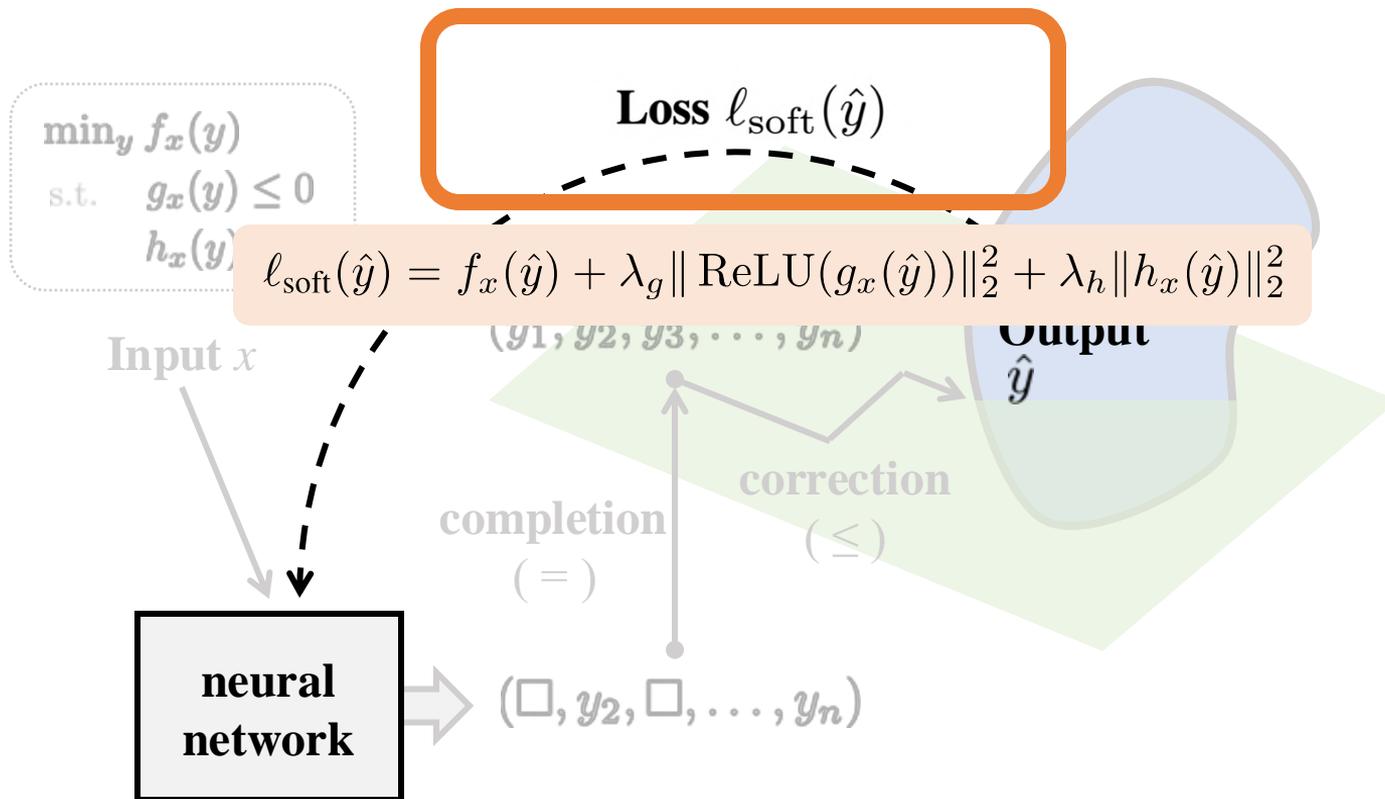
Gradient steps along manifold defined by equality constraints:

$$\rho_x \left(\begin{bmatrix} z \\ \varphi_x(z) \end{bmatrix} \right) = \begin{bmatrix} z - \gamma \Delta z \\ \varphi_x(z) - \gamma \Delta \varphi_x(z) \end{bmatrix},$$

$$\text{for } \Delta z = \nabla_z \left\| \text{ReLU} \left(g_x \left(\begin{bmatrix} z \\ \varphi_x(z) \end{bmatrix} \right) \right) \right\|_2^2,$$

$$\Delta \varphi_x(z) = \frac{\partial \varphi_x(z)}{\partial z} \Delta z$$

End-to-end training with soft loss



Performance on AC Optimal Power Flow

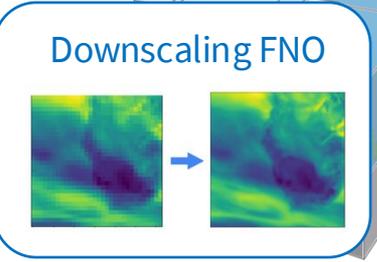
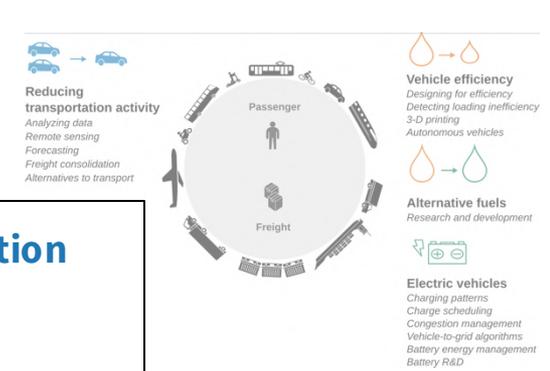
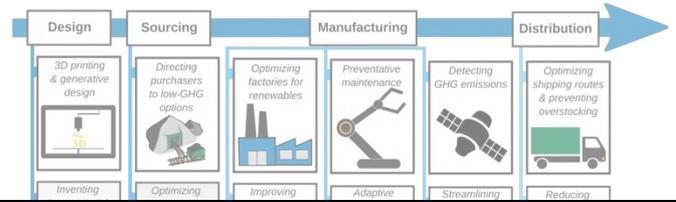
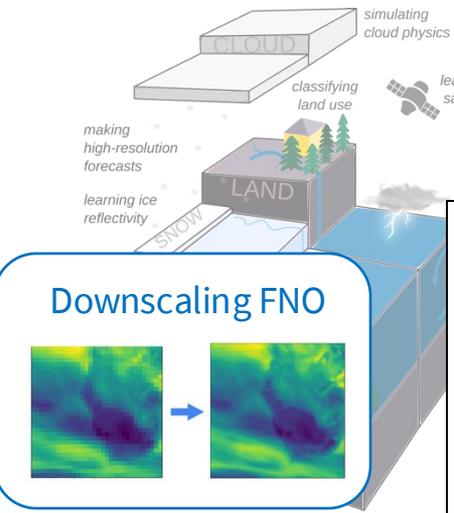
Satisfies all constraints (unlike other DL methods)
10x faster than optimizer, 0.22% optimality gap
and even faster in practice thanks to GPU parallelization

	Obj. value	Max eq.	Mean eq.	Max ineq.	Mean ineq.	Time (s)
Optimizer	3.81 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.949 (0.002)
DC3	3.82 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.089 (0.000)
DC3, \neq	3.67 (0.01)	0.14 (0.01)	0.02 (0.00)	0.00 (0.00)	0.00 (0.00)	0.040 (0.000)
DC3, $\not\leq$ train	3.82 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.089 (0.000)
DC3, $\not\leq$ train/test	3.82 (0.00)	0.00 (0.00)	0.00 (0.00)	0.01 (0.00)	0.00 (0.00)	0.039 (0.000)
DC3, no soft loss	3.11 (0.05)	2.60 (0.35)	0.07 (0.00)	2.33 (0.33)	0.03 (0.01)	0.088 (0.000)
NN	3.69 (0.02)	0.19 (0.01)	0.03 (0.00)	0.00 (0.00)	0.00 (0.00)	0.001 (0.000)
NN, \leq test	3.69 (0.02)	0.16 (0.00)	0.02 (0.00)	0.00 (0.00)	0.00 (0.00)	0.040 (0.000)
Eq. NN	3.81 (0.00)	0.00 (0.00)	0.00 (0.00)	0.15 (0.01)	0.00 (0.00)	0.039 (0.000)
Eq. NN, \leq test	3.81 (0.00)	0.00 (0.00)	0.00 (0.00)	0.15 (0.01)	0.00 (0.00)	0.078 (0.000)

Climate prediction

Industry

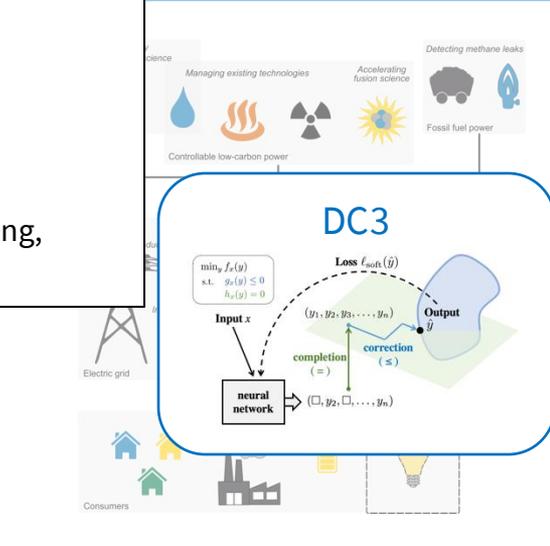
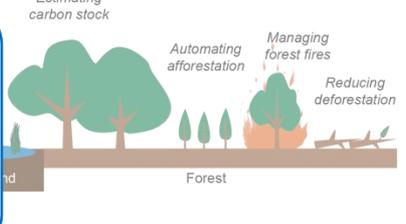
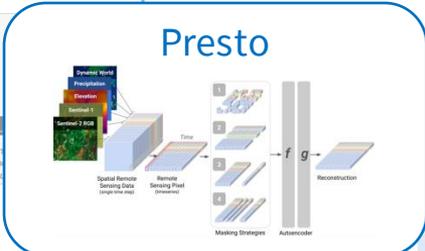
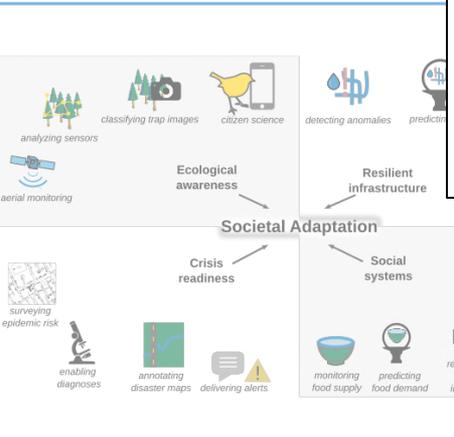
Transportation



How machine learning can advance climate action

- Distilling raw data into actionable information
- Improving operational efficiency
- Forecasting
- Speeding up time-intensive simulations
- Accelerating scientific discovery

Rolnick, et al. Tackling Climate Change with Machine Learning, ACM Computing Surveys, first released 2019.

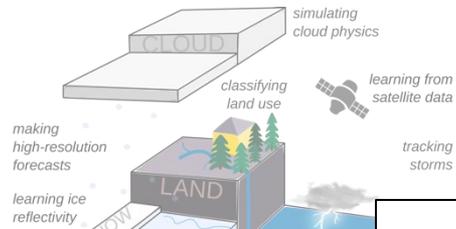


Societal adaptation

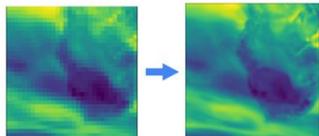
Land use

Electricity systems

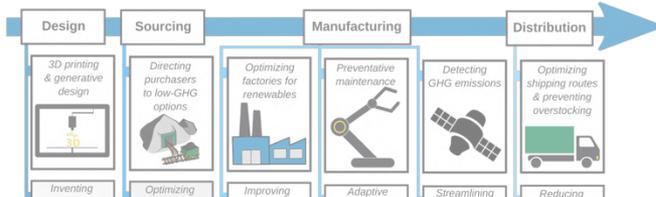
Climate prediction



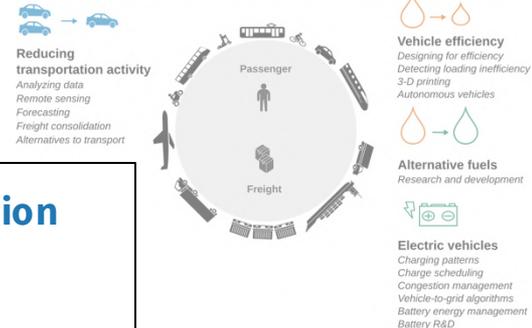
Downscaling FNO



Industry



Transportation

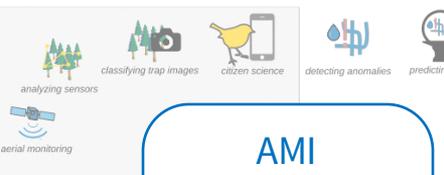


How machine learning can advance climate action

Distilling raw data into actionable information

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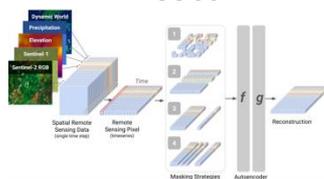
Rolnick, et al. Tackling Climate Change with Machine Learning, ACM Computing Surveys, first released 2019.



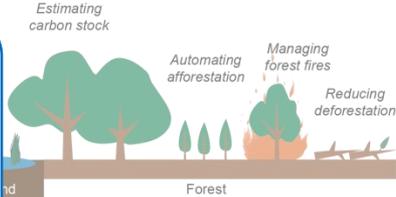
AMI



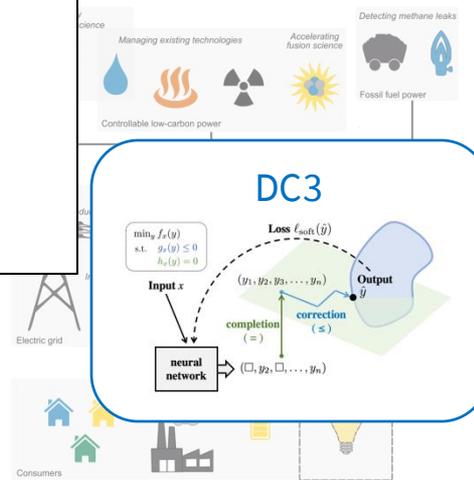
Presto



Land use



Electricity systems



Societal adaptation



Example of what not to do

ML continues to rely on benchmarks like ImageNet-1k to evaluate models and pre-train for applied settings.

Such benchmarks are often derived from Internet data, chosen & labeled without relevant experts in the room.

Example: We worked with ecologists to analyze the 27% of ImageNet-1k that is wild animals.

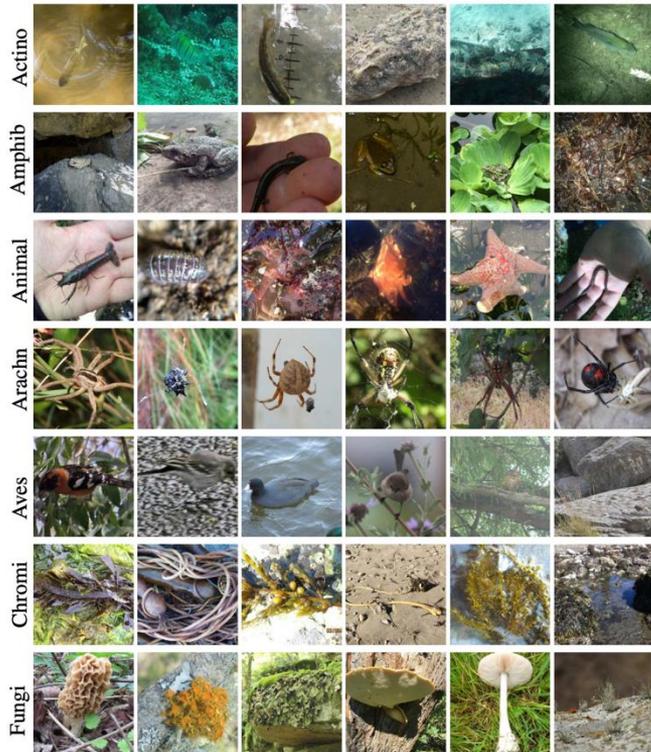
- 12.3% of the images are wrong, 11.9% of categories overlap with each other
- Species heavily biased towards United States.

Such datasets are used to pick “SoTA” algorithms as well as to (pre)train for real-world applications.



Alexandra Sasha Luccioni and David Rolnick,
Bugs in the Data: How ImageNet Misrepresents Biodiversity, AAAI 2023.

Better datasets



The screenshot shows the iNaturalist website interface. At the top, there is a search bar and navigation links: Explore, Your Observations, Community, Identify, and More. A notification icon shows 1 new message. Below the navigation is a message: "If you change your mind you can always edit your settings." The main heading is "Observations". Below this is a search bar for "Species" and "Location", with a "Go" button and a "Filters" button. The main content area displays a world map with a heatmap overlay showing observation density. The map is titled "The World" and shows a large red area in the North Atlantic and Europe. To the right of the map, there is a list of observations:

- Early Purple Orchid** (*Orchis mascula*)
Kent, UK • Yesterday
1 2h
- Common Spotted Orchid** (*Dactylorhiza fuchsii*)
Kent, UK • Yesterday
1 2h
- Insects** (Class Insecta)
Nantwich CW5 6BU... • Today
2 2h
- Spreading Phlox** (*Phlox diffusa*)
Jackson County, OR... • May 4, 2024
1 7h

Automated Monitoring of Insects (AMI)

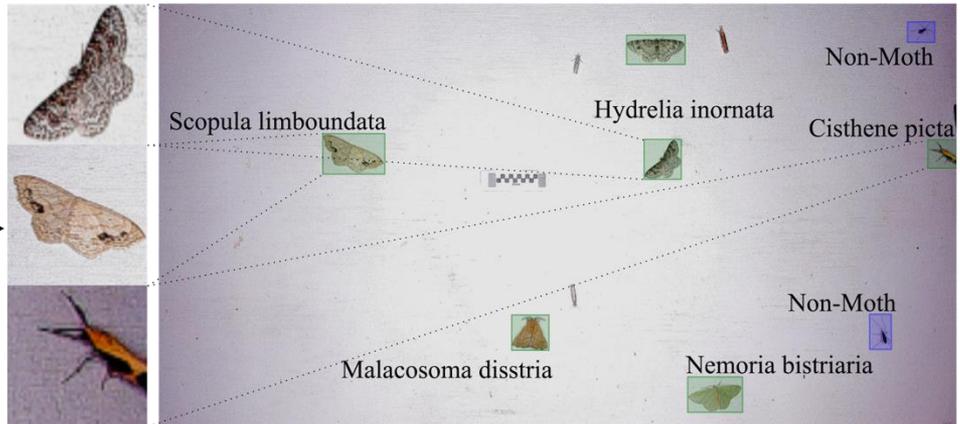


Automated Monitoring of Insects (AMI)

AMI-GBIF (Citizen Science + Museum Collections)



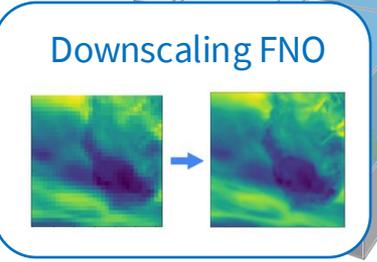
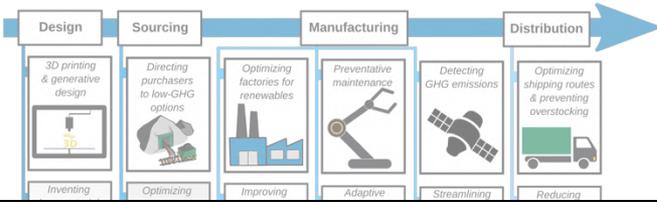
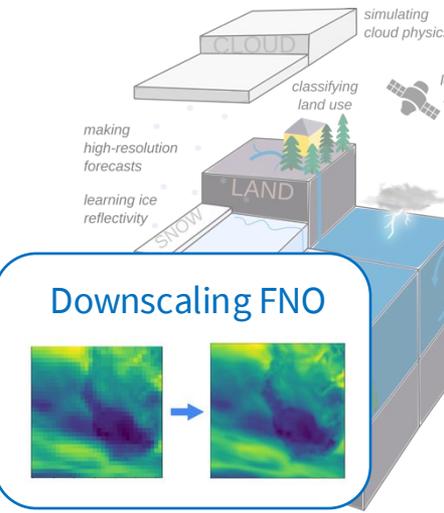
AMI-Traps (Insect Camera Traps)



Climate prediction

Industry

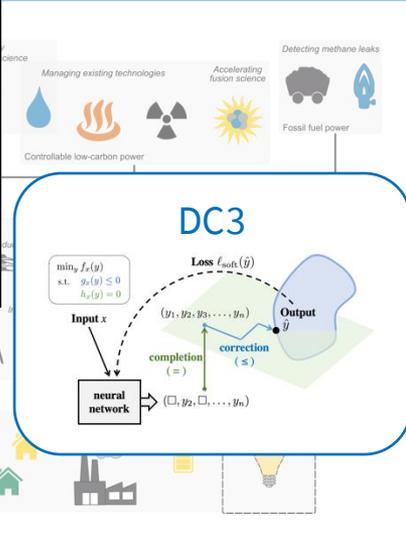
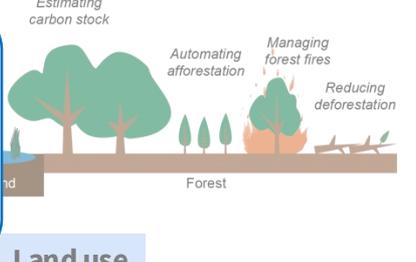
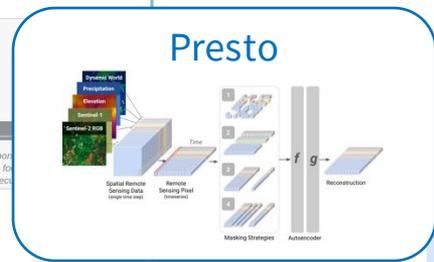
Transportation



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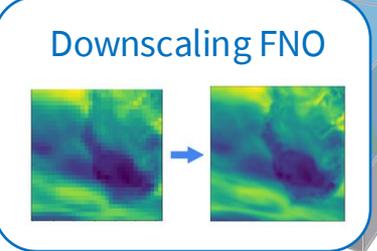
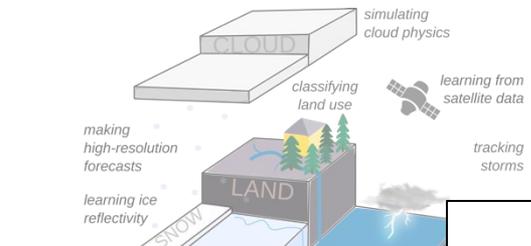


Societal adaptation

Land use

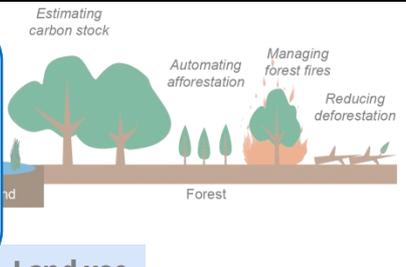
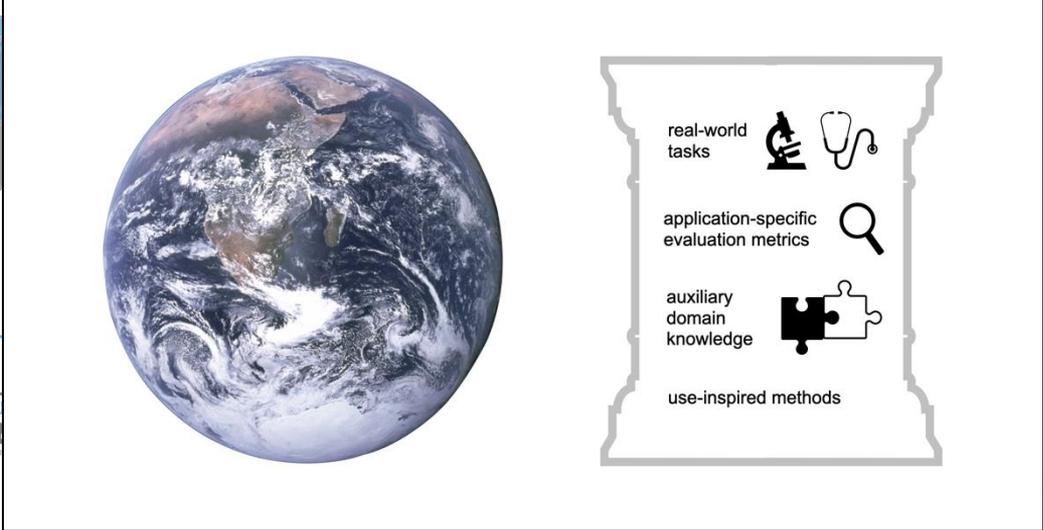
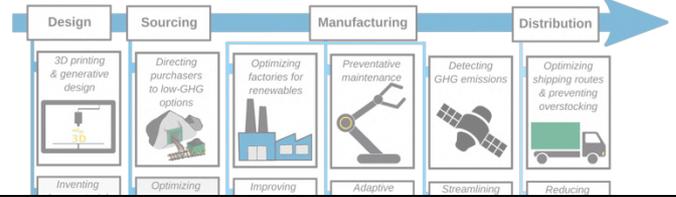
Electricity systems

Climate prediction



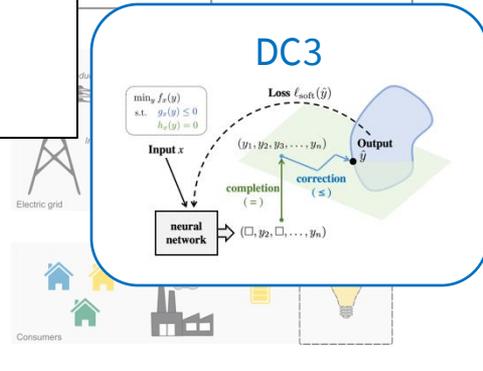
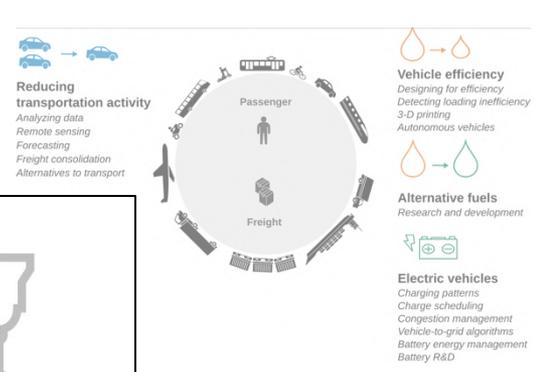
Societal adaptation

Industry



Land use

Transportation

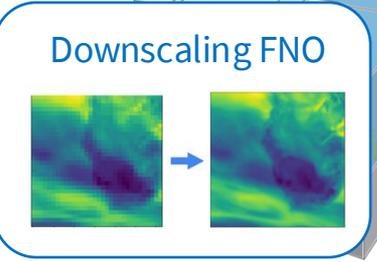
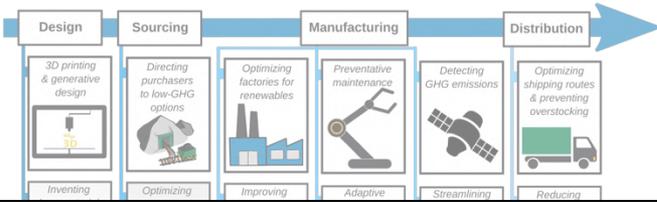
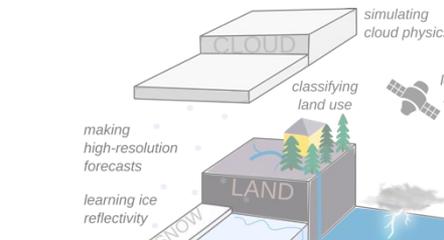


Electricity systems

Climate prediction

Industry

Transportation



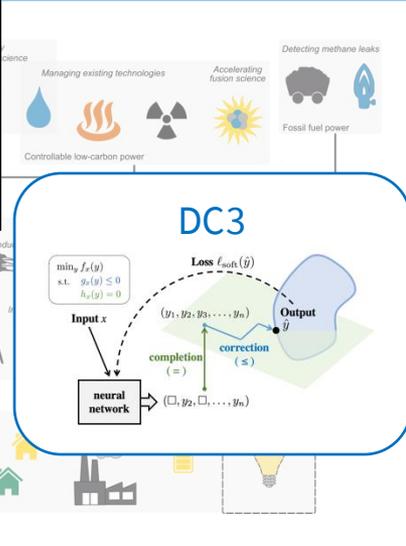
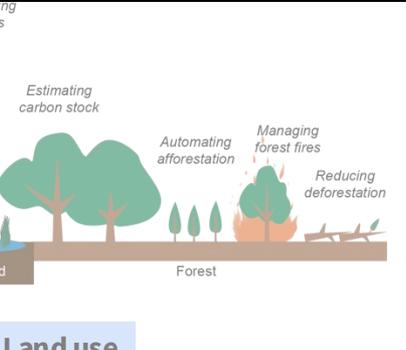
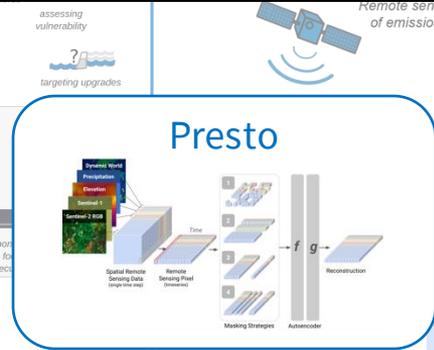
Key considerations

ML is not a silver bullet and is only relevant sometimes

High-impact applications are not always flashy

Interdisciplinary collaboration

- ▶ Scoping the right problems
- ▶ Incorporating relevant domain information
- ▶ Shaping pathways to impact



Societal adaptation

Land use

Electricity systems

ML can also negatively impact the climate

Computation-related impacts

- ▶ Energy from computation
- ▶ Embodied emissions from hardware
- ▶ Low for many algorithms, high for some

*“AI for Good” doesn’t only mean adding new “good” applications of AI. It means **shaping all applications of AI to be better for society.***

Application-related impacts

- ▶ ML use in fossil fuel exploration/extraction (5% production boost)
- ▶ ML-enabled advertising systems that increase consumption (e.g. fast fashion)
- ▶ Autonomous vehicles: Pos. / neg. impacts depending on how tech is developed

Kaack, Donti, Strubell, Kamiya, Creutzig, Rolnick, “Aligning AI with Climate Change Mitigation,” Nature Climate Change 2022.

Ways to get involved

Consider becoming a bridge between ML and another field, such as energy, agriculture, or Earth sciences

Many job opportunities exist in this space, incl. mainstream CS research, focused institutes, startups, major tech companies, public sector initiatives

Working explicitly on climate problems isn't the only way to help - consider how to better **align other ML projects** w/ climate goals

Every application of ML affects the climate, often in multiple ways

And of course ML is not the only way to work on climate change...



Climate Change AI

Catalyzing impactful work at the intersection of climate change & ML

Digital resources

Reports with opportunities for researchers, practitioners, and policymakers

Paper Section ML Keywords Thematic Keywords

Electricity Systems

- + Forecasting supply and demand High Leverage
- + Improving scheduling and flexible demand

Conferences & events

Workshop series

- ▶ Upcoming at NeurIPS 2024
- ▶ View past papers at: www.climatechange.ai/papers

Summer school



Learn more & join in:

www.climatechange.ai

[Twitter](#) [Facebook](#) [LinkedIn](#) [@ClimateChangeAI](#)

Funding programs

Global research funding for impactful projects

Climate Change AI **Innovation Grants**

Announcing a **\$1.8M grants program** for projects at the intersection of AI and climate change

- Funding of up to **\$150K** for **year-long** research projects
- Supporting projects involving AI or machine learning that address problems in climate change mitigation, adaptation, or climate science

Newsletter, blog, & community



Welcome to the Climate Change AI community!

We are excited to have you here!

This is a place to connect, share and discuss all things related to climate change & machine learning.

If this is your first time here, you might want to head over to the [Climate Change AI](#) and introduce yourself.

- Calls for Submissions
- Funding
- Projects & Courses
- Readings
- Jobs

Other relevant resources

Selected communities & events

- ▶ **Energy:** ACM e-Energy, IEEE Power & Energy, PSCC, BuildSys, AI.EPRI
- ▶ **Land use:** GRSS-IEEE, Int'l Soc. of Precision Ag, Restor, Global Forest Watch
- ▶ **Climate & Earth science:** Climate Informatics, AGU/EGU, Phi-Week
- ▶ **Biodiversity:** AI for Conservation slack, WILDLABS, GEO BON
- ▶ **General:** CompSustNet (community & doctoral consortium)

Publication venues: Ongoing JMLR special track on climate change, Environmental Data Science, ACM COMPASS, many domain-specific venues

More info in the [Climate Change AI monthly newsletter](#)

Datasets and challenges

Energy: CityLearn, OPFLearn, ARPA-E GO, PowerGridworld, L2RPN, BeoBench, Building Data Genome, bbd.labworks.org, COBS, BOPTTEST/ACTB, Open Catalyst

Land use: TorchGeo, Radiant MLHub, blutjens/awesome-forests, CropHarvest, LandCoverNet, Agriculture-Vision, chrieke/awesome-satellite-imagery-datasets,

Climate & Earth science: mldata.pangeo.io, ClimateLearn, ClimART, CauseMe

Adaptation: wandb/droughtwatch, Global Flood Database, FloodNet, ITU GEOAI

Biodiversity: iNat dataset, LifeCLEF, FGVC, iWildCam, Movebank

Roadmap for working in ML for climate action

Identify key areas that you may want to work in

Check out **datasets or challenges** to get hands-on practice

Explore and learn more, including how non-ML techniques are being used

Find collaborators with complementary domain expertise

Work together to **scope problems** and **data sources** (may not be ML-ready)

Design algorithms to **incorporate domain knowledge** where possible

Work with deployment partners & affected stakeholders to guide impact



Thank you!

