

A satellite image of Earth, showing the Middle East, North Africa, and parts of Europe and Asia. The image is dark, with the landmasses appearing in shades of brown, tan, and green, and the oceans in deep blue. Clouds are visible as white and light gray patterns over the land and sea.

Machine Learning and Climate Change

David Rolnick

McGill University

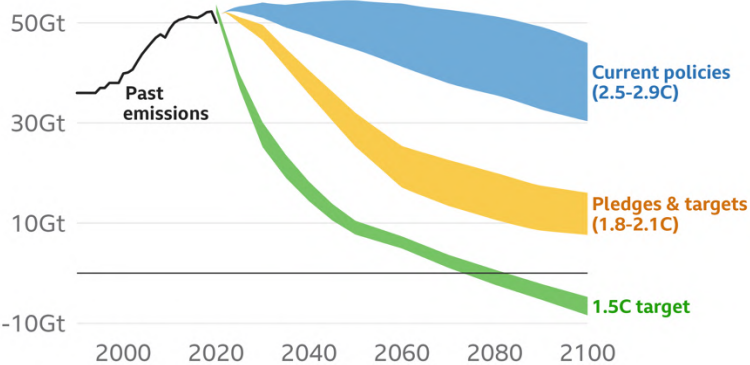
Mila – Quebec AI Institute

Climate Change AI



How close is the world to its 1.5C target?

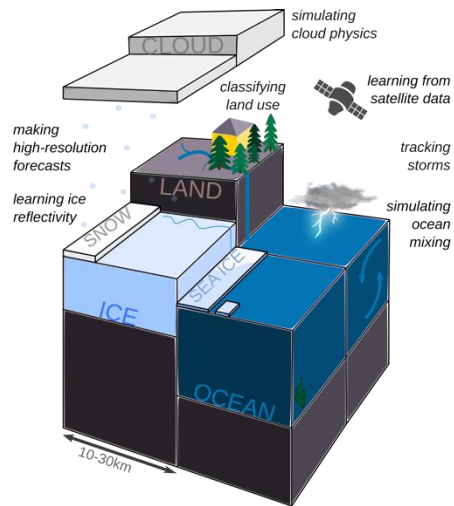
Projected greenhouse gas emissions and future warming levels vary by actions taken



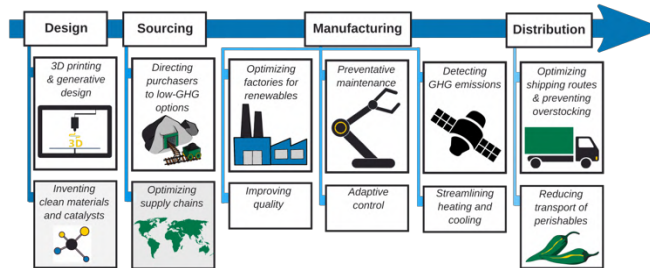
Emissions measured in gigatonnes of carbon dioxide equivalent

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

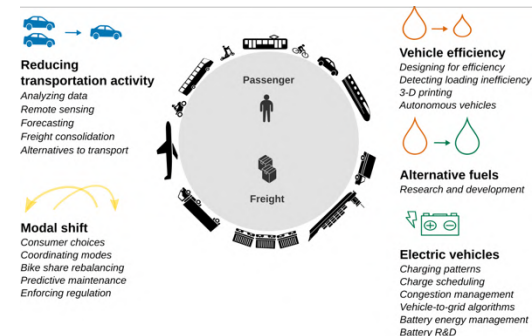
Climate prediction



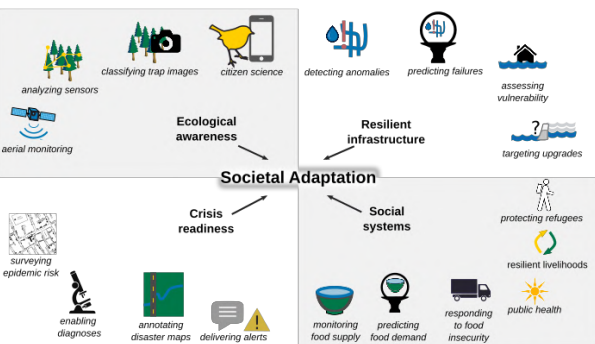
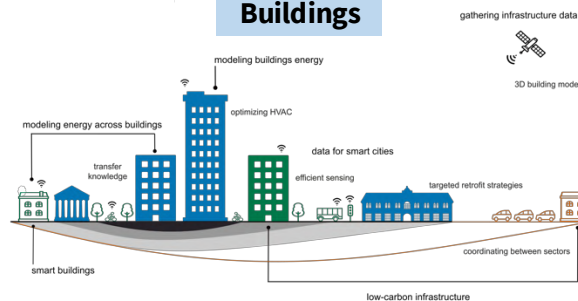
Industry



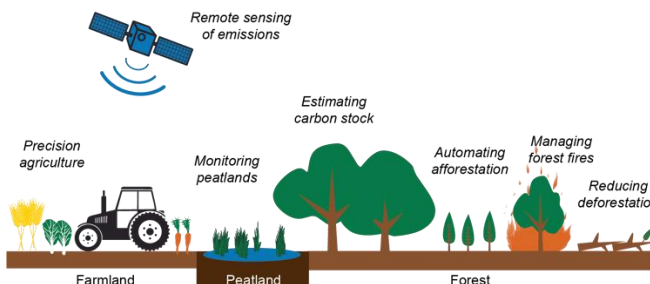
Transportation



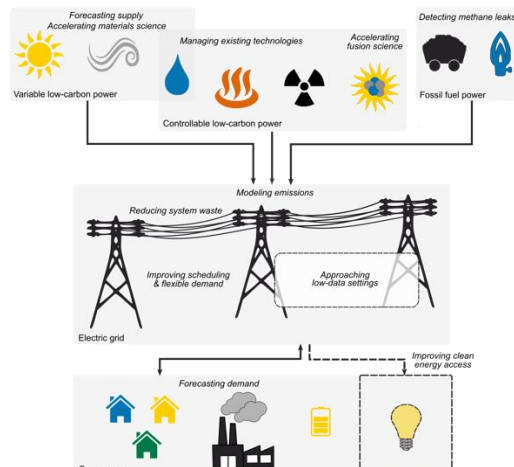
Buildings



Societal adaptation

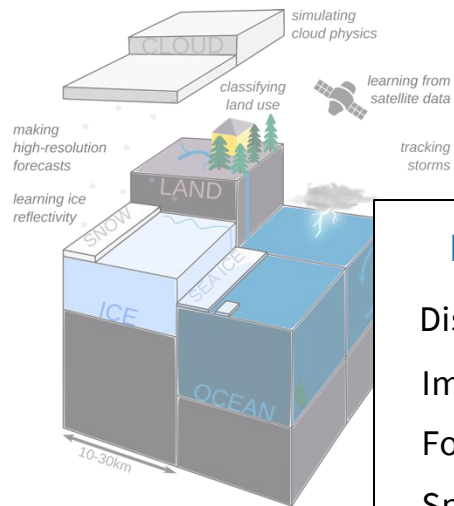


Land use

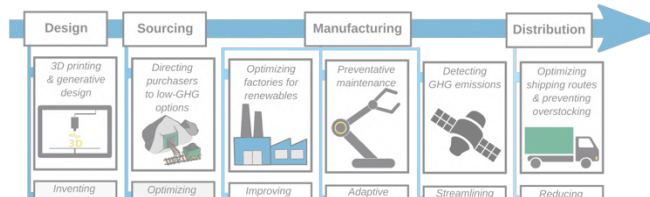


Electricity systems

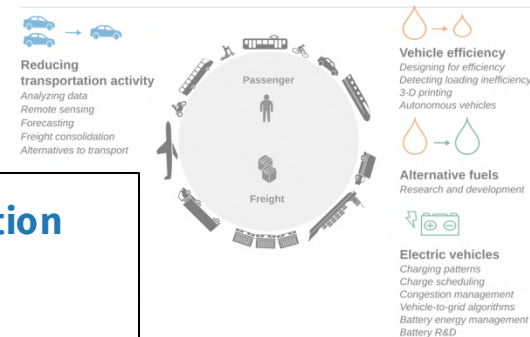
Climate prediction



Industry



Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

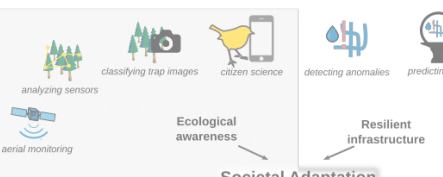
Improving operational efficiency

Forecasting

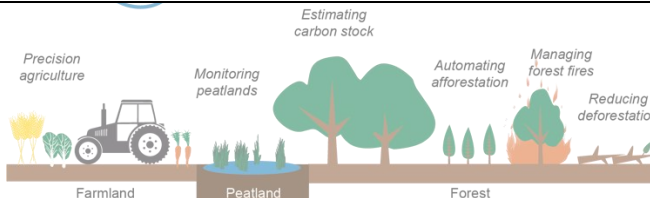
Speeding up time-intensive simulations

Accelerating scientific discovery

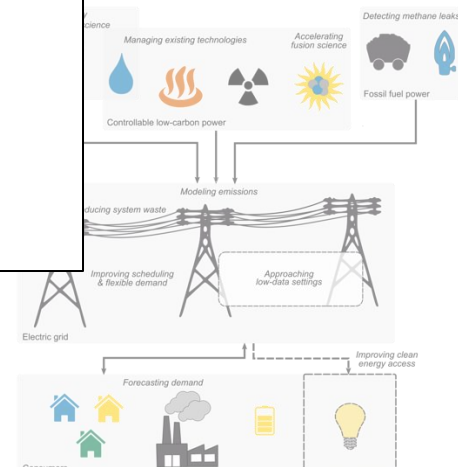
Rolnick, et al. Tackling Climate Change with Machine Learning, ACM Computing Surveys, first released 2019.



Societal adaptation



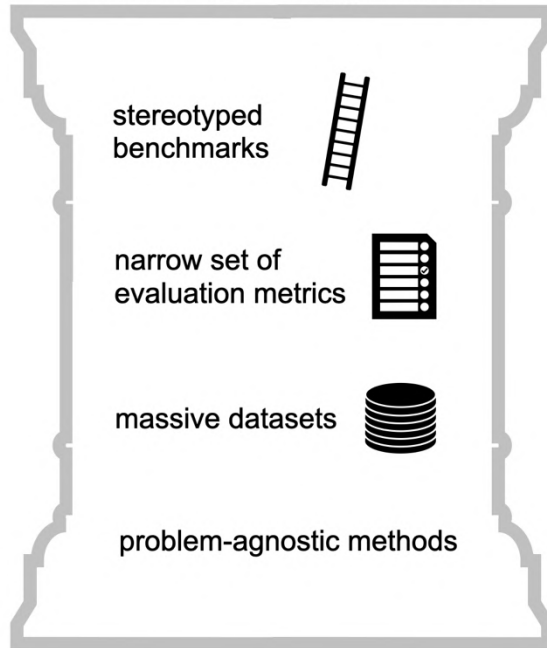
Land use



Electricity systems

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.

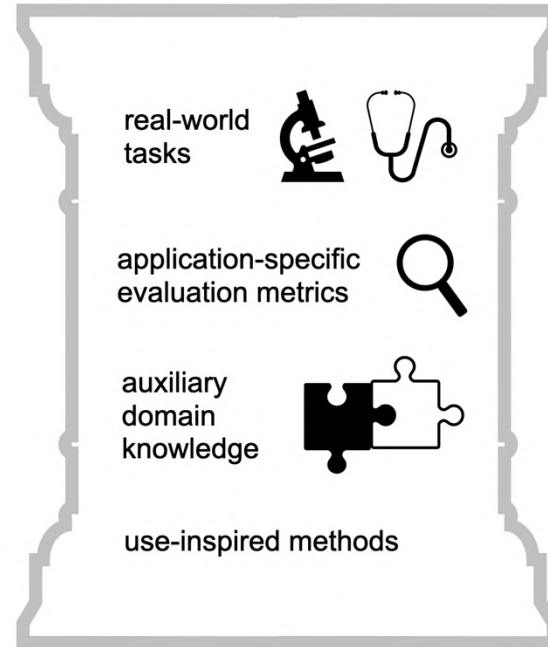
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Application-Driven ML

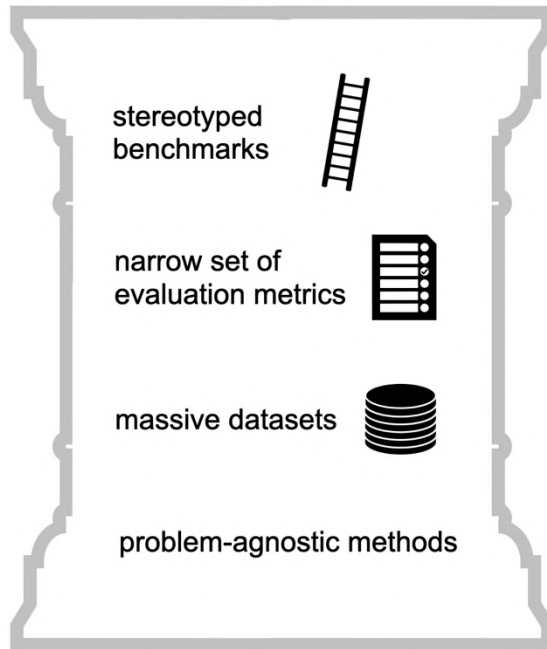
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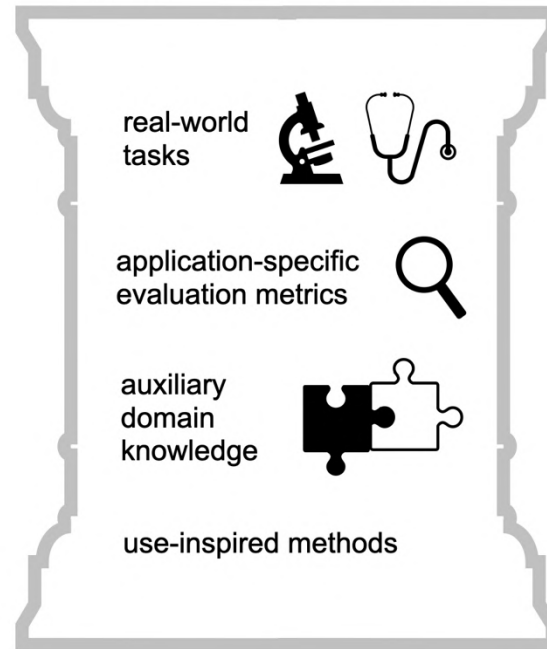
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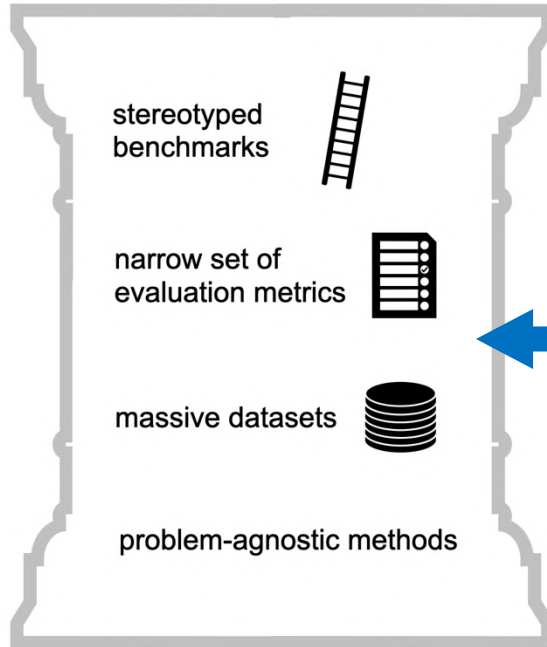
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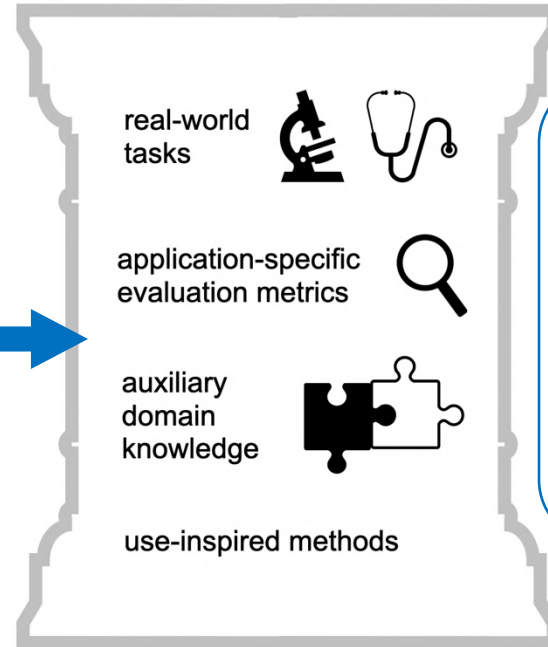
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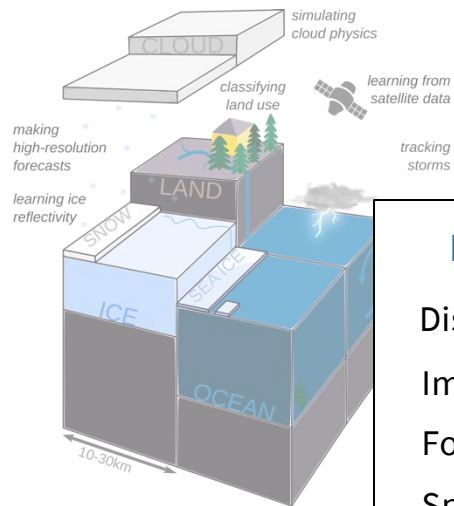
Challenges for ML

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

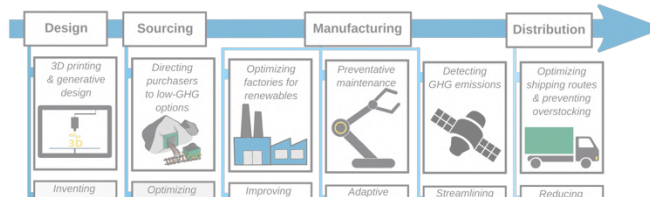
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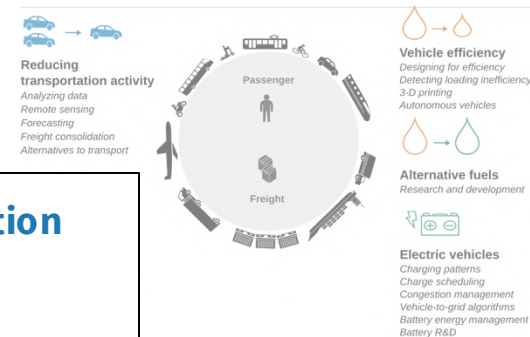
Climate prediction



Industry



Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

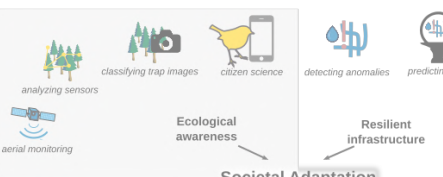
Improving operational efficiency

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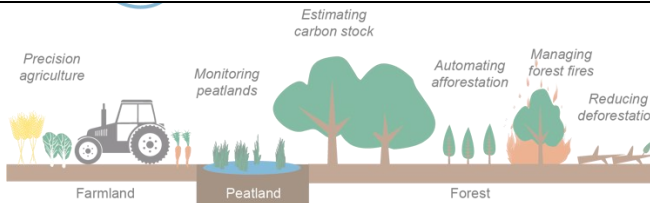
Speeding up time-intensive simulations

Accelerating scientific discovery

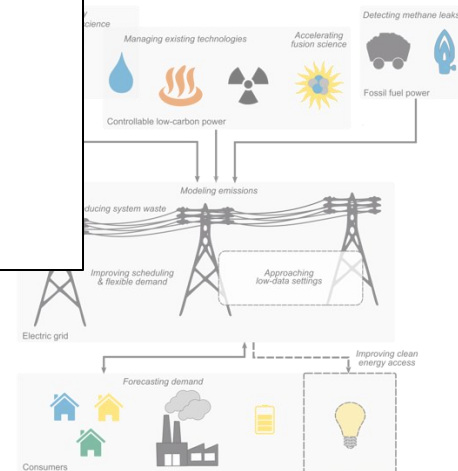
Rolnick, et al. Tackling Climate Change with Machine Learning, ACM Computing Surveys, first released 2019.



Societal adaptation

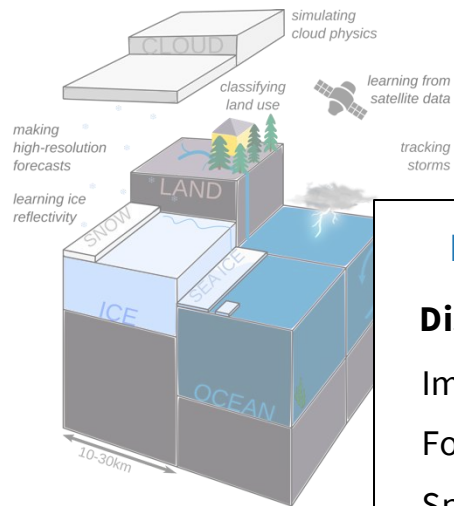


Land use

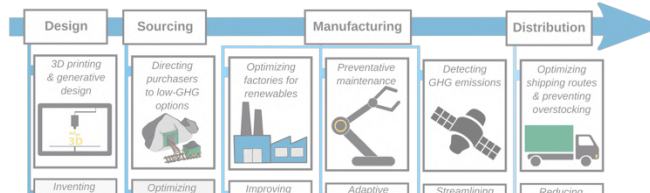


Electricity systems

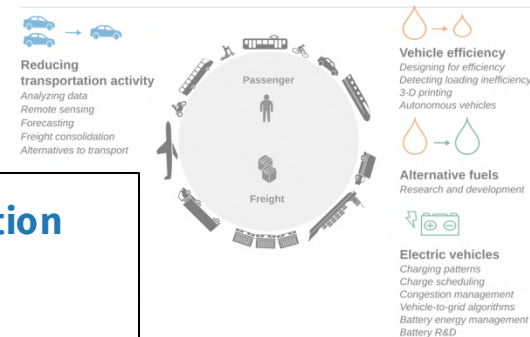
Climate prediction



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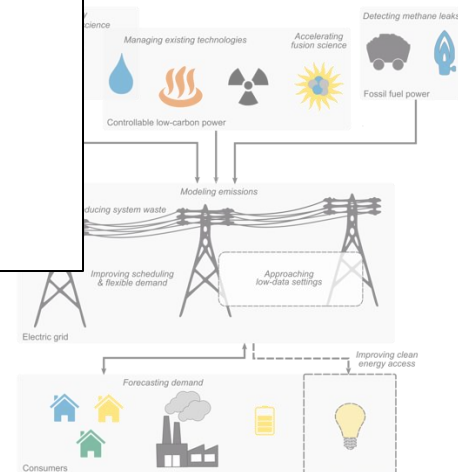
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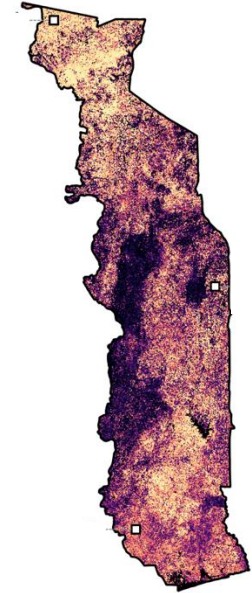


Electricity systems

ML for agricultural remote sensing



CropHarvest dataset, Togo



Crop Probability
0 1

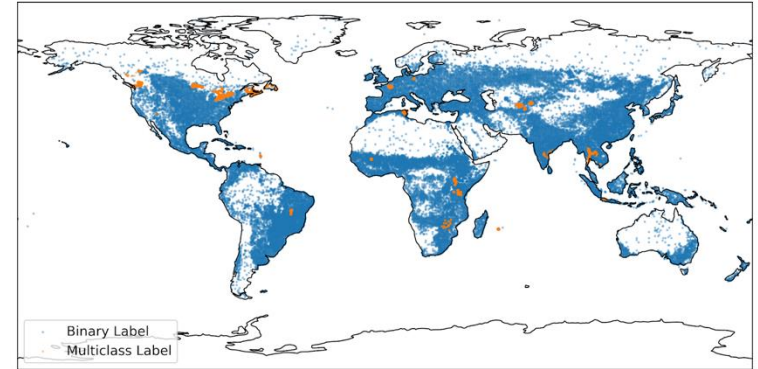
Kerner et al. (2020)



ML for agricultural remote sensing

Key challenges

Sparse labeled data



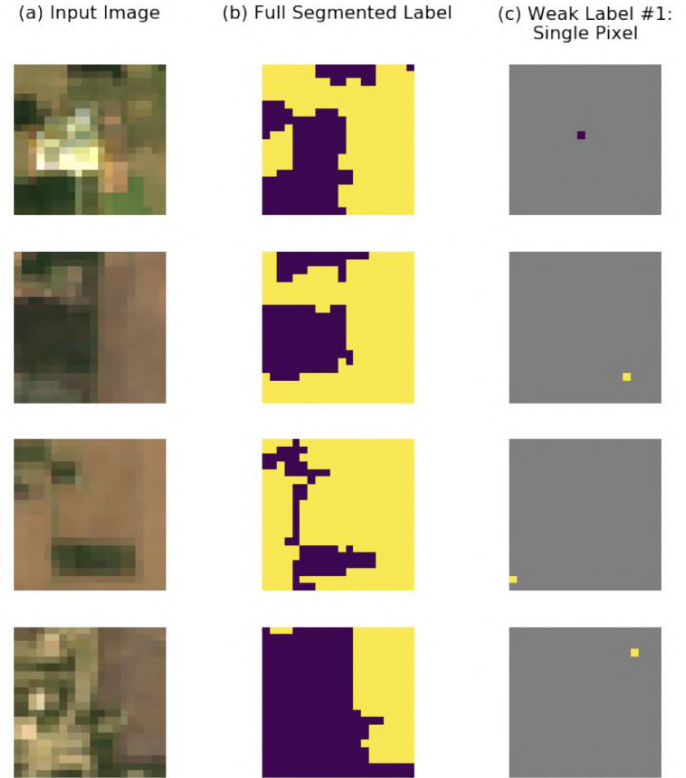
CropHarvest dataset

ML for agricultural remote sensing

Key challenges

Sparse labeled data

Irregularly shaped data



Wang et al. (2020)

ML for agricultural remote sensing

Key challenges

Sparse labeled data

Irregularly shaped data

Limited computational budget



ML for agricultural remote sensing

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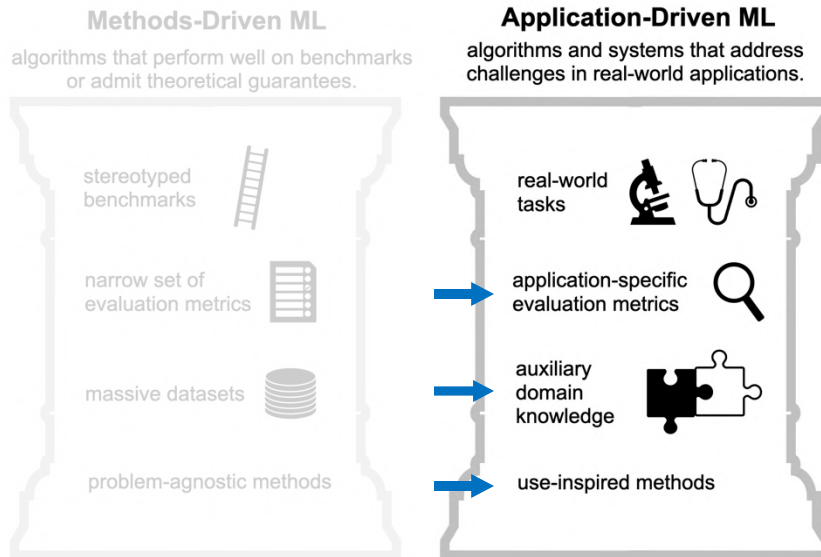
→ Limited computational budget

Problem-relevant information

Geographic structure

Large amount of unlabeled data

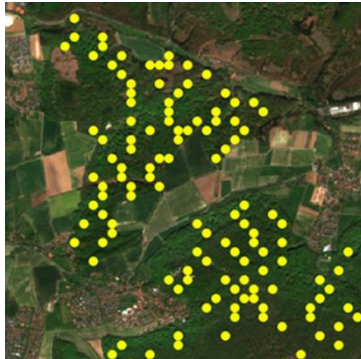
Diversity of input sensors/features



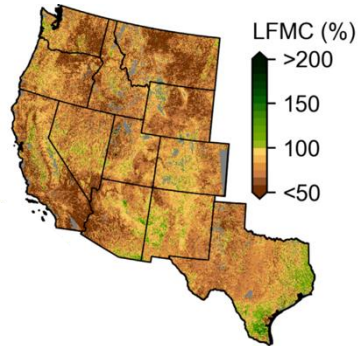
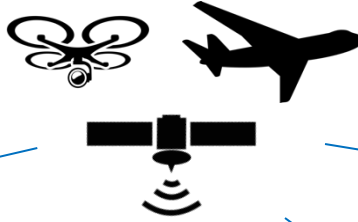
Many related problems



CropHarvest dataset



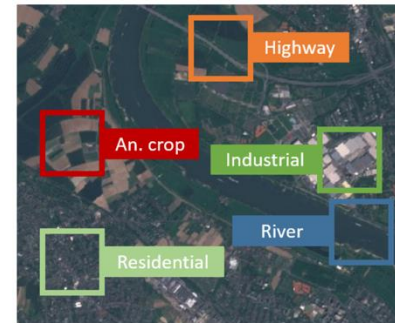
TreeSatAI dataset



Fuel moisture content
(Rao et al. 2020)



“Tick tick bloom”: Algae



EuroSat dataset

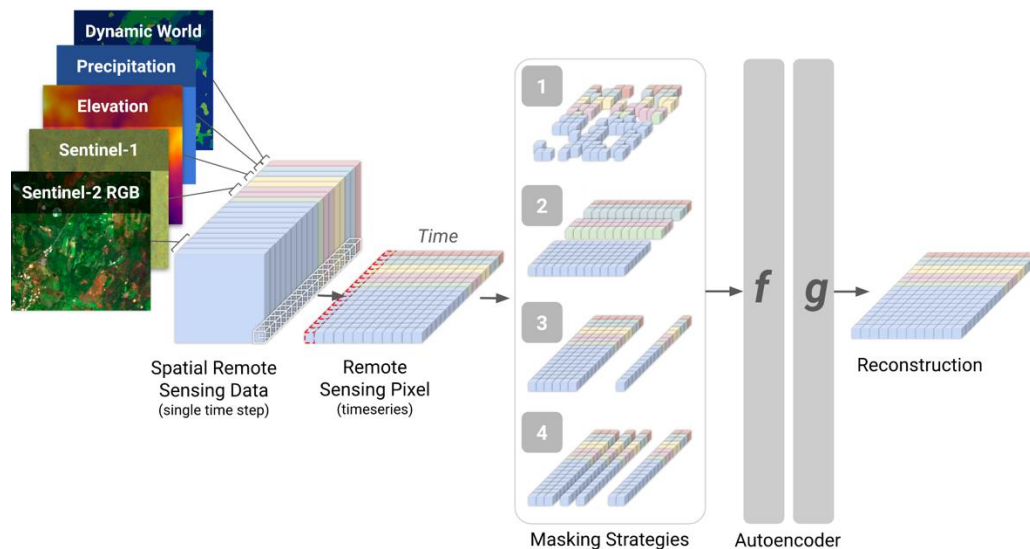
Presto algorithm – self-supervised learning

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.

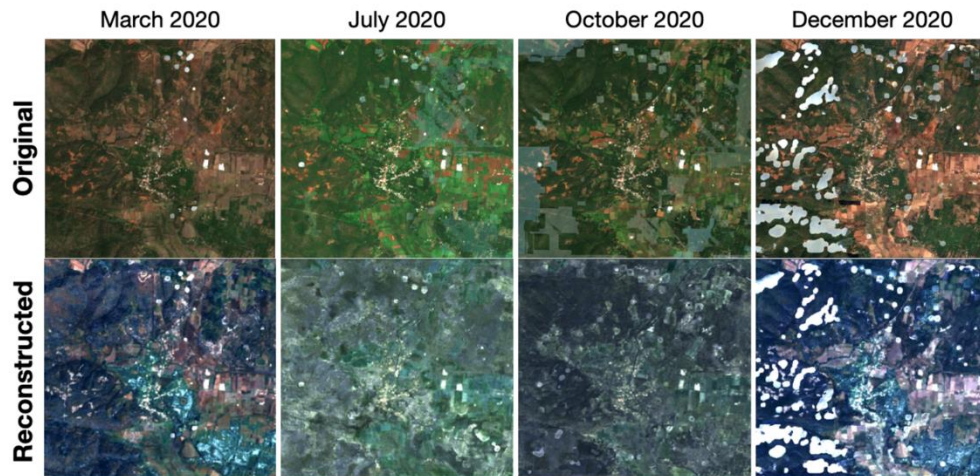
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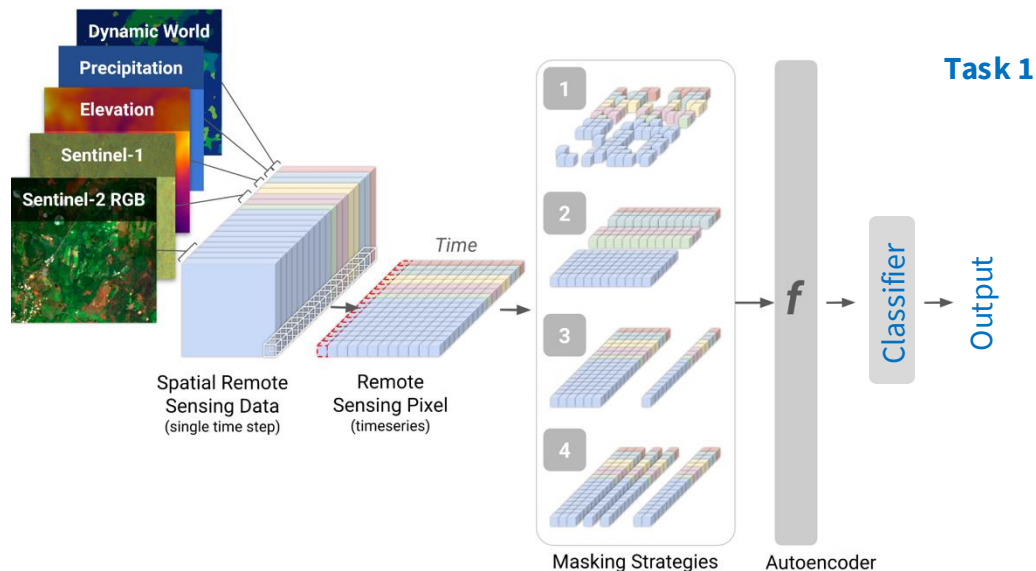


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Presto algorithm – use case

Learned encodings can then be used in solving downstream task

With limited labeled data, train a lightweight classifier (linear regression, random forest, kNN)

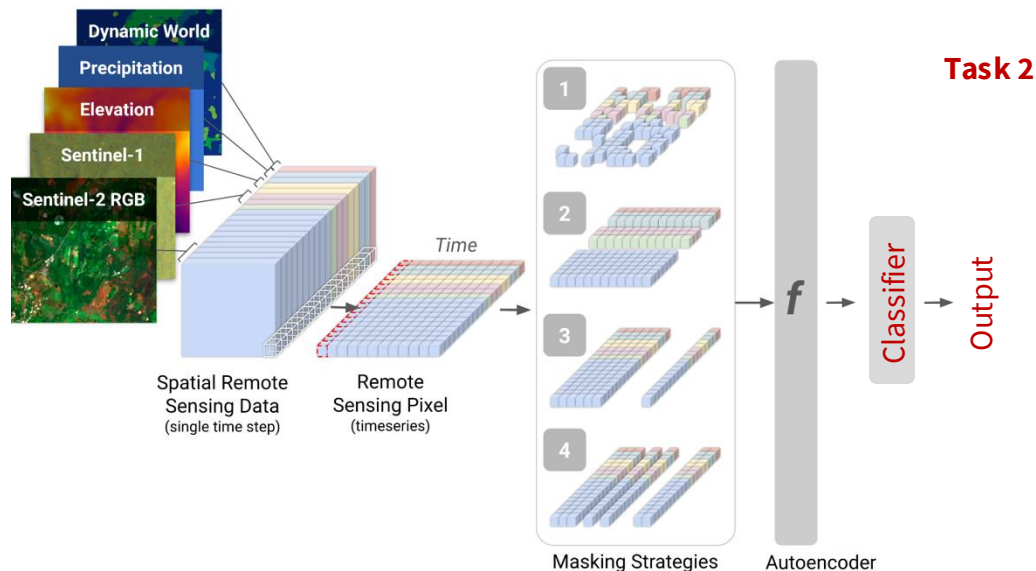


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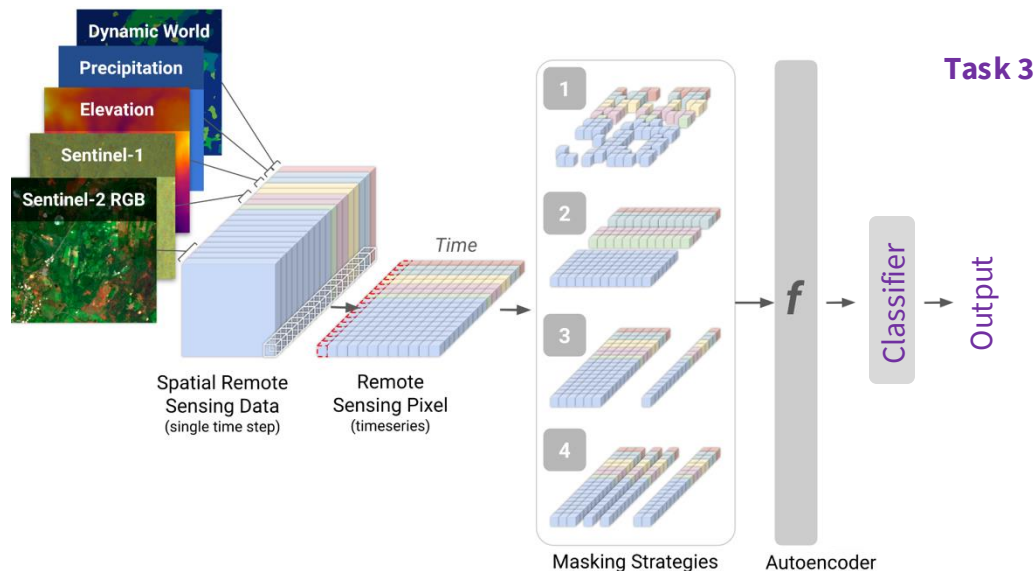


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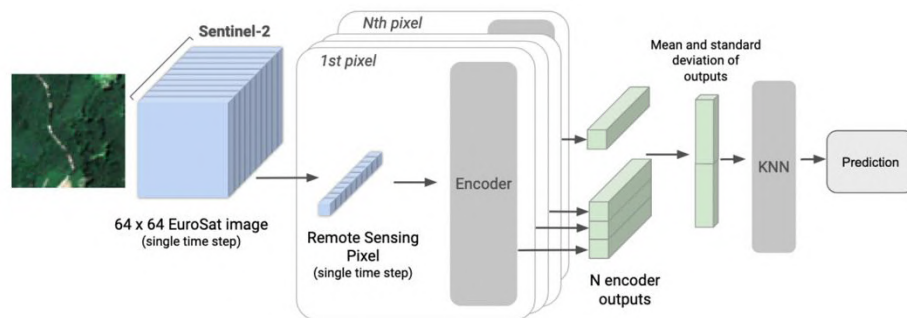
Tseng, Cartuyvels, Zvonkov, Purohit, Rolnick, Kerner, “Lightweight, pre-trained transformers for remote sensing timeseries”, preprint arXiv:2304.14065.

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
MOSAICS-1D _R	418K	8193	0.738
TIML	91K	91K	0.802
Presto _R no DW	402K	129	0.835 0.836

EuroSat

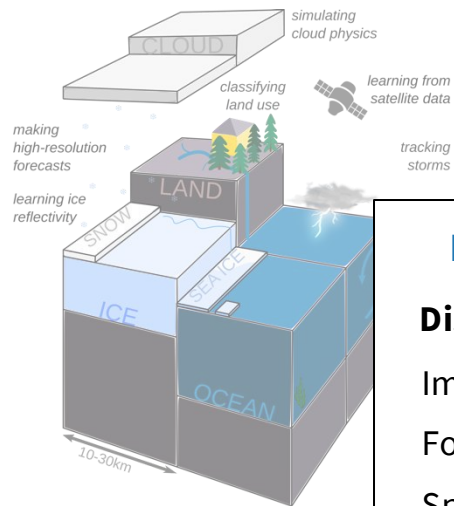
	Backbone	Inputs	Params (M)	Accuracy
GASSL	ResNet-18	RGB	11.69	0.895
SeCo	ResNet-18	RGB	11.69	0.931
SatMAE	ViT-Large	RGB	303.10	0.955
SatMAE	ViT-Large	MS	305.96	0.990
Random init.	Presto	RGB MS	0.40	0.745 0.924
Presto	Presto	RGB MS	0.40	0.849 0.953

TreeSatAI

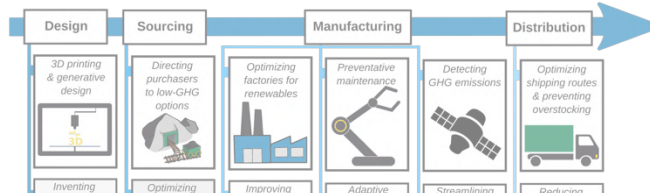
Model	Data	Weighted		Micro	
		F ₁	mAP	F ₁	mAP
MLP		10.09	29.42	12.82	33.09
LightGBM	S1	11.86	32.79	14.07	35.11
Presto _{RF}		38.34	35.45	40.79	38.64
MLP		51.97	64.19	54.59	65.83
LightGBM	S2	48.17	61.99	52.52	61.66
Presto _{RF}		55.29	61.53	58.29	63.31

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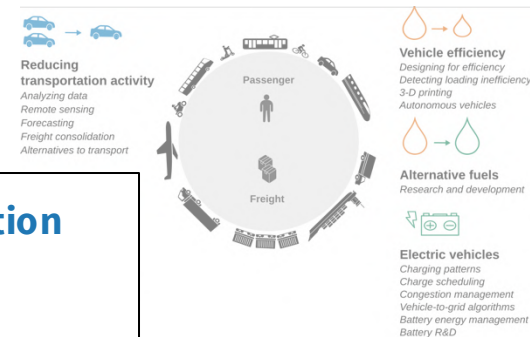
Climate prediction



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

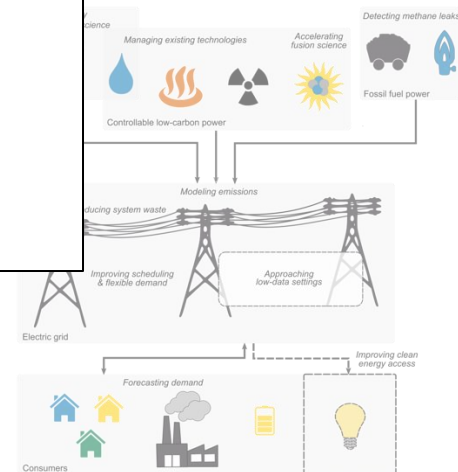
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Societal adaptation

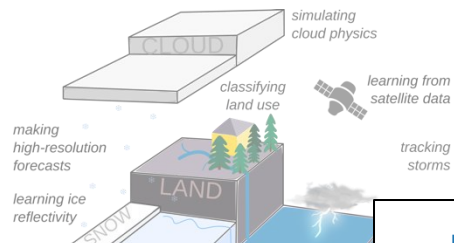


Land use

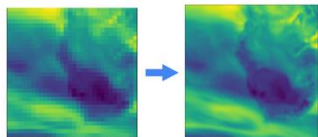


Electricity systems

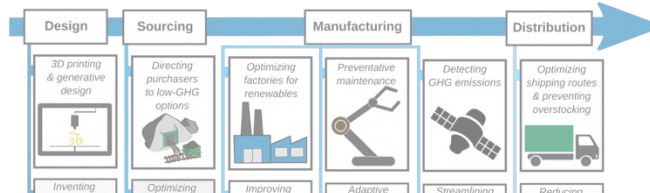
Climate prediction



Downscaling FNO

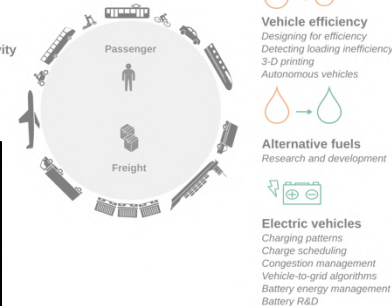


Industry



Transportation

Reducing transportation activity
Analyzing data
Remote sensing
Forecasting
Freight consolidation
Alternatives to transport



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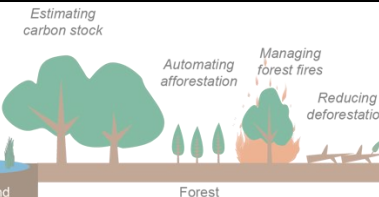
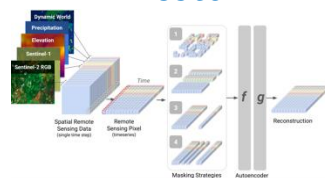
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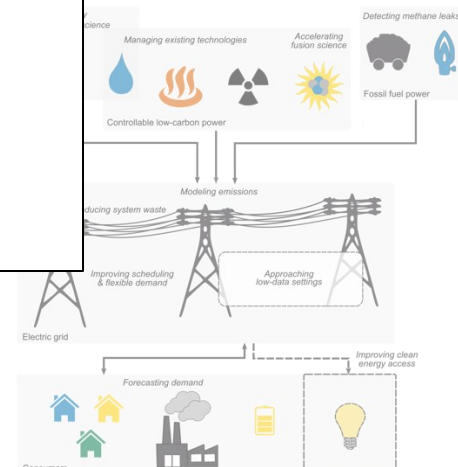


Societal adaptation

Presto

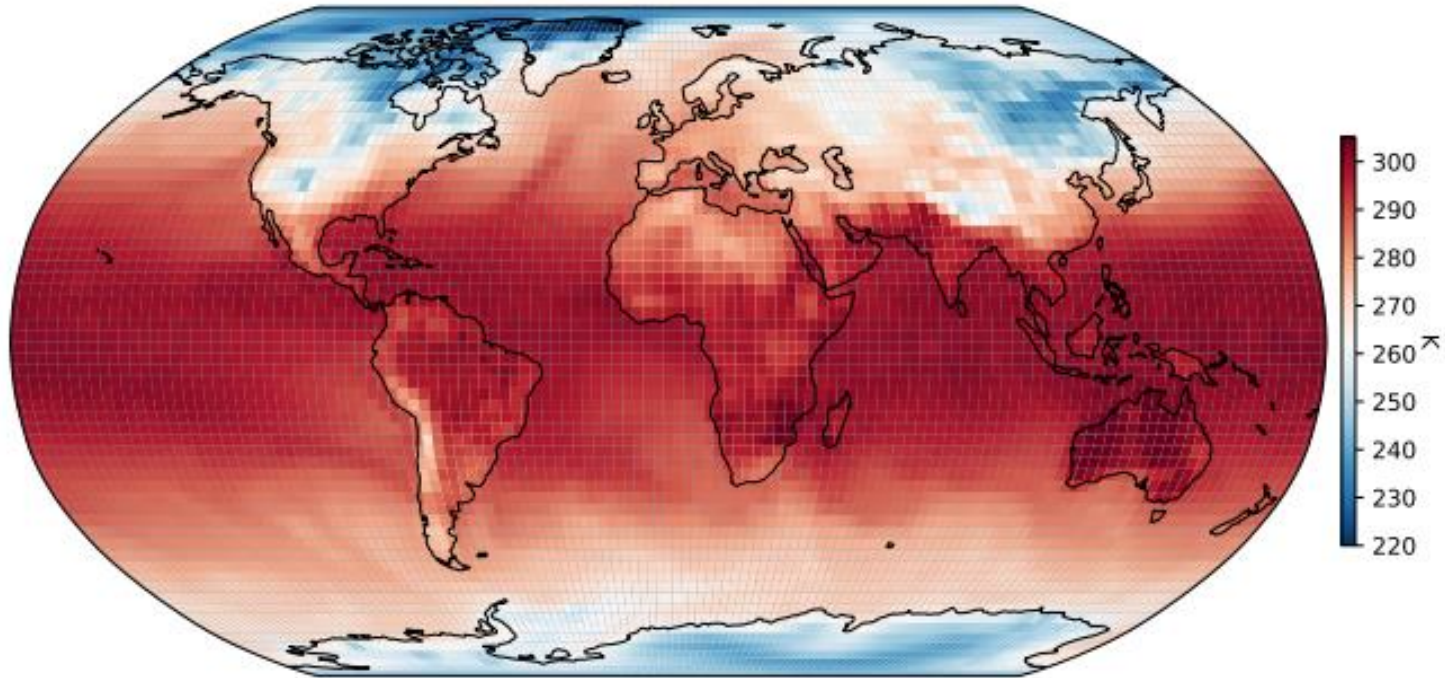


Land use



Electricity systems

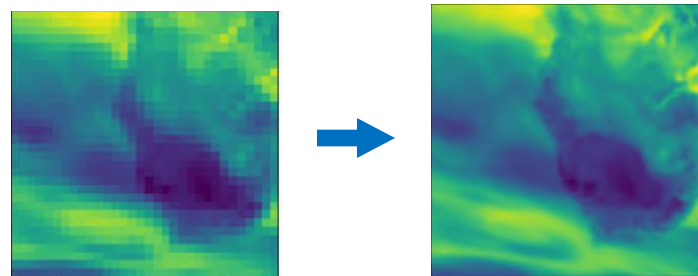
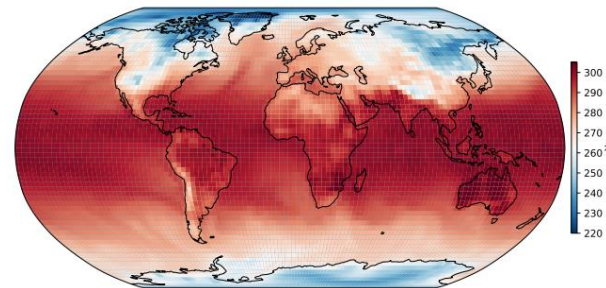
High-resolution climate data on demand



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

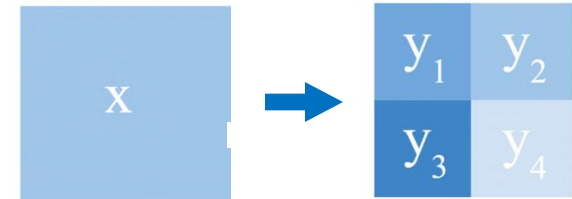
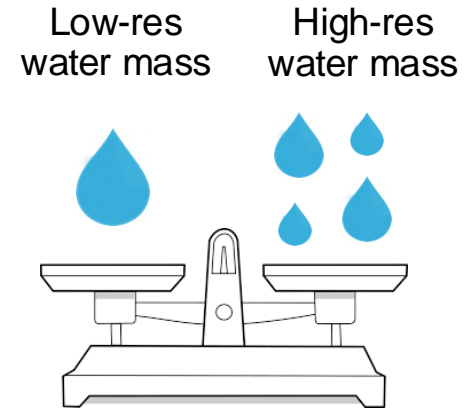
Machine learning for downscaling climate data

Standard ML super-resolution methods:

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

Key challenges:

- Physical constraints



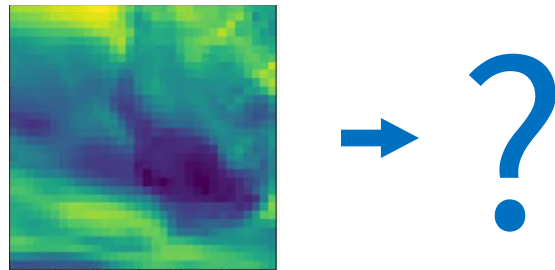
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Machine learning for downscaling climate data

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- Vision transformers

Key challenges:

- Physical constraints
- Lack of high-res training data
- Differences from “natural” images

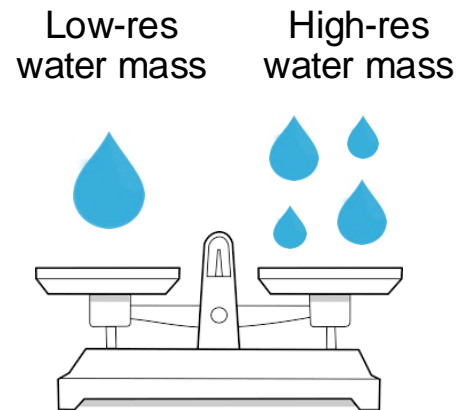
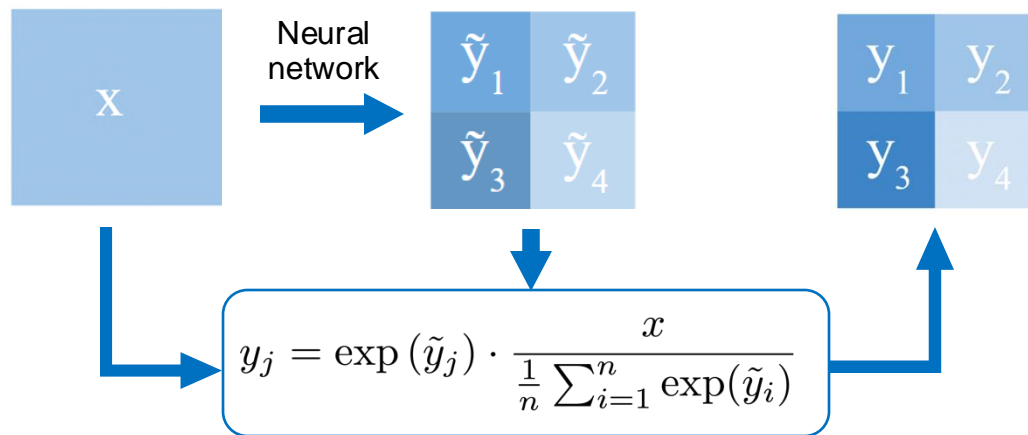


Part 1: physical constraints

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

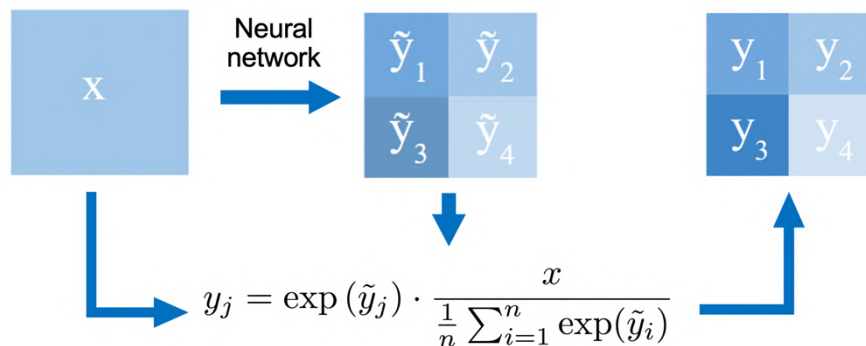
Typical ML approach: Try to learn from data, or add a loss penalty

Our approach: enforce via a hard constraint layer

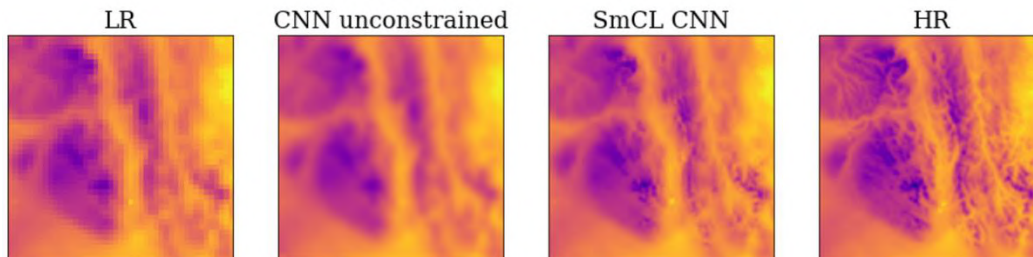


Harder, Yang, Ramesh, Sattigeri, Hernandez-Garcia, Watson, Szwarcman, Rolnick, "Generating physically-consistent high-resolution climate data with hard-constrained neural networks", Journal of Machine Learning Research (JMLR) 2023.

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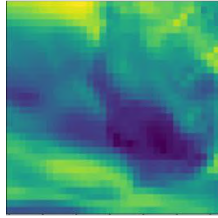


- ✓ Physical realism
- ✓ Accuracy
- ✓ Visual quality

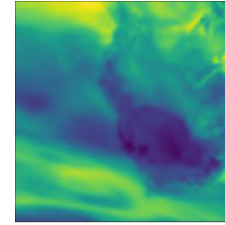


Harder, Yang, Ramesh, Sattigeri, Hernandez-Garcia, Watson, Szwarcman, Rolnick, “Generating physically-consistent high-resolution climate data with hard-constrained neural networks”, Journal of Machine Learning Research (JMLR) 2023.

Part 2: arbitrary resolution downscaling

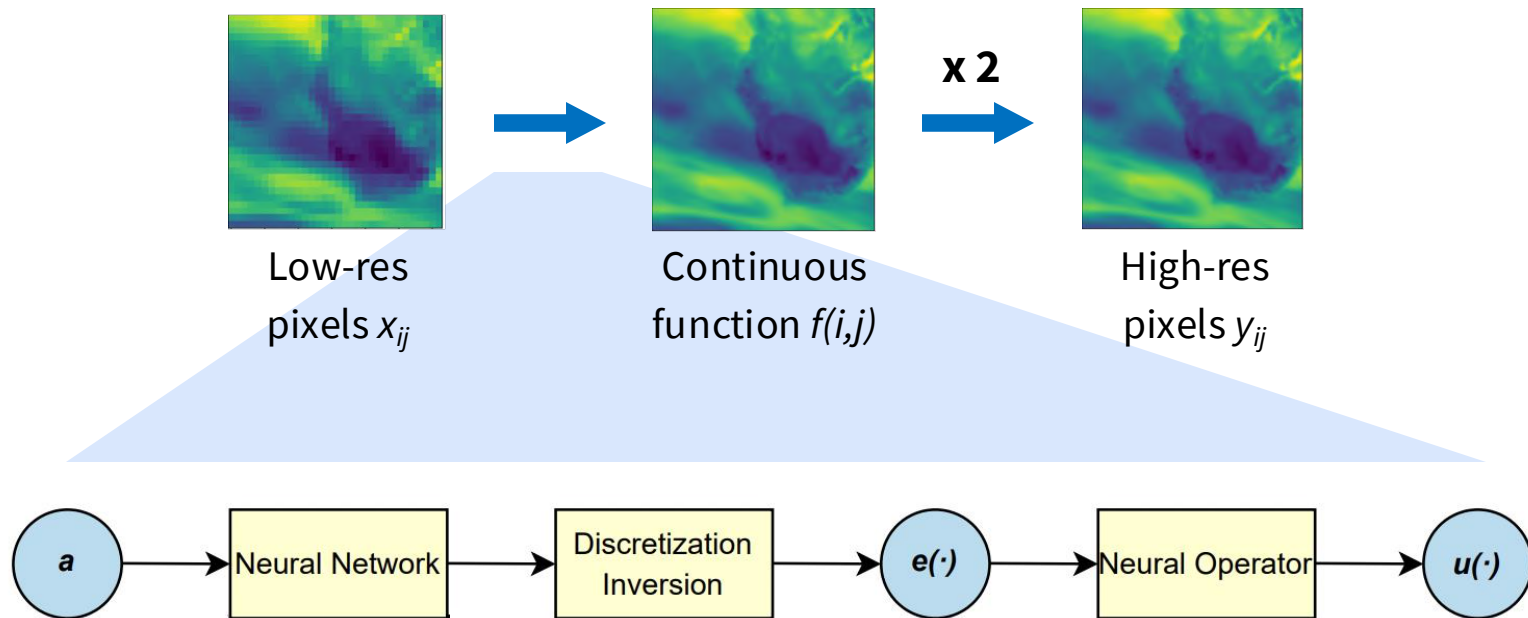


Low-res
pixels x_{ij}



High-res
pixels y_{ij}

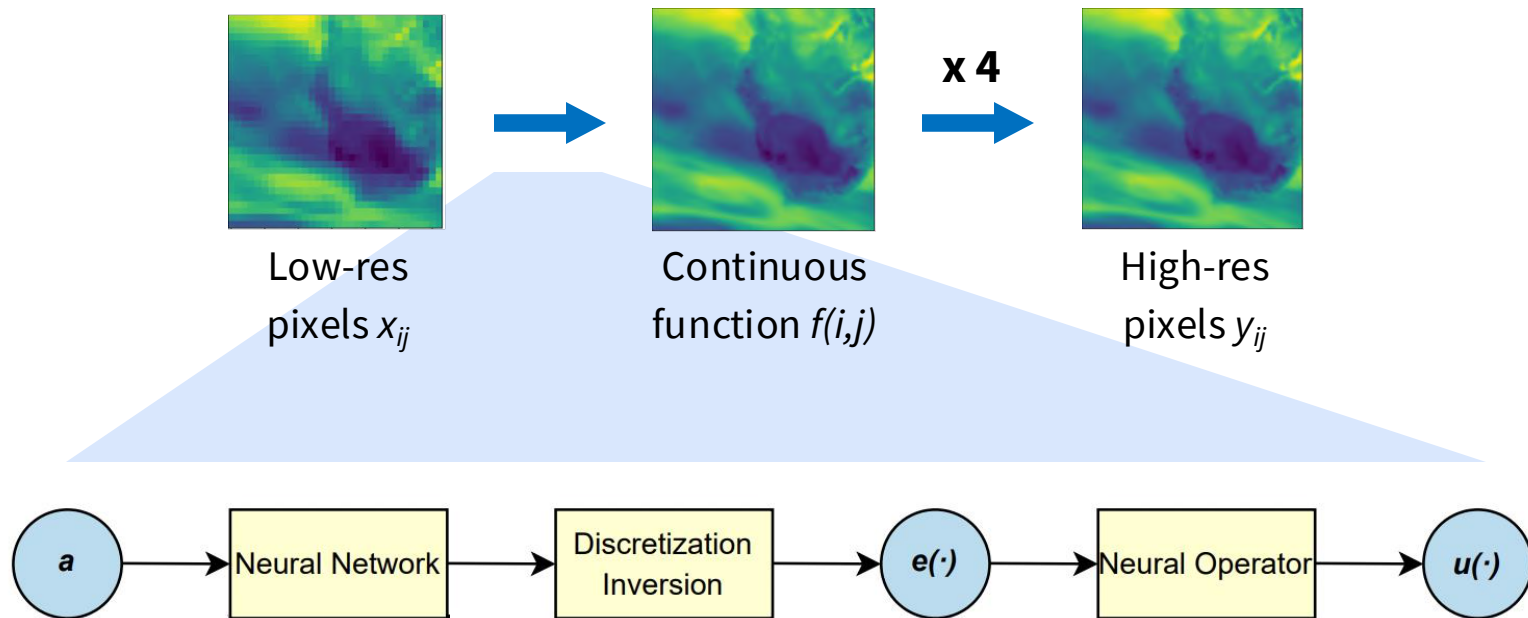
Part 2: arbitrary resolution downscaling



Yang, Hernandez-Garcia, Harder, Ramesh, Sattegeri, 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

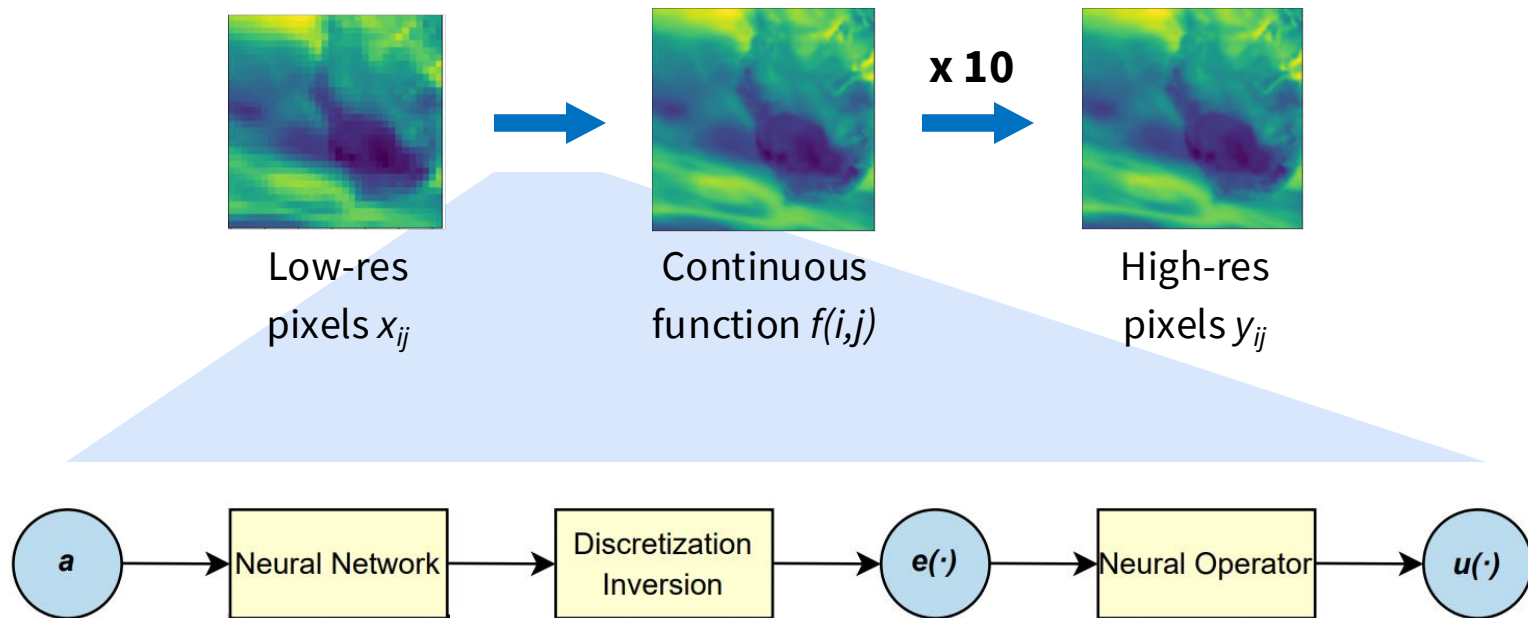
Part 2: arbitrary resolution downscaling



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Fourier neural operator parametrizes map between functions in Fourier domain

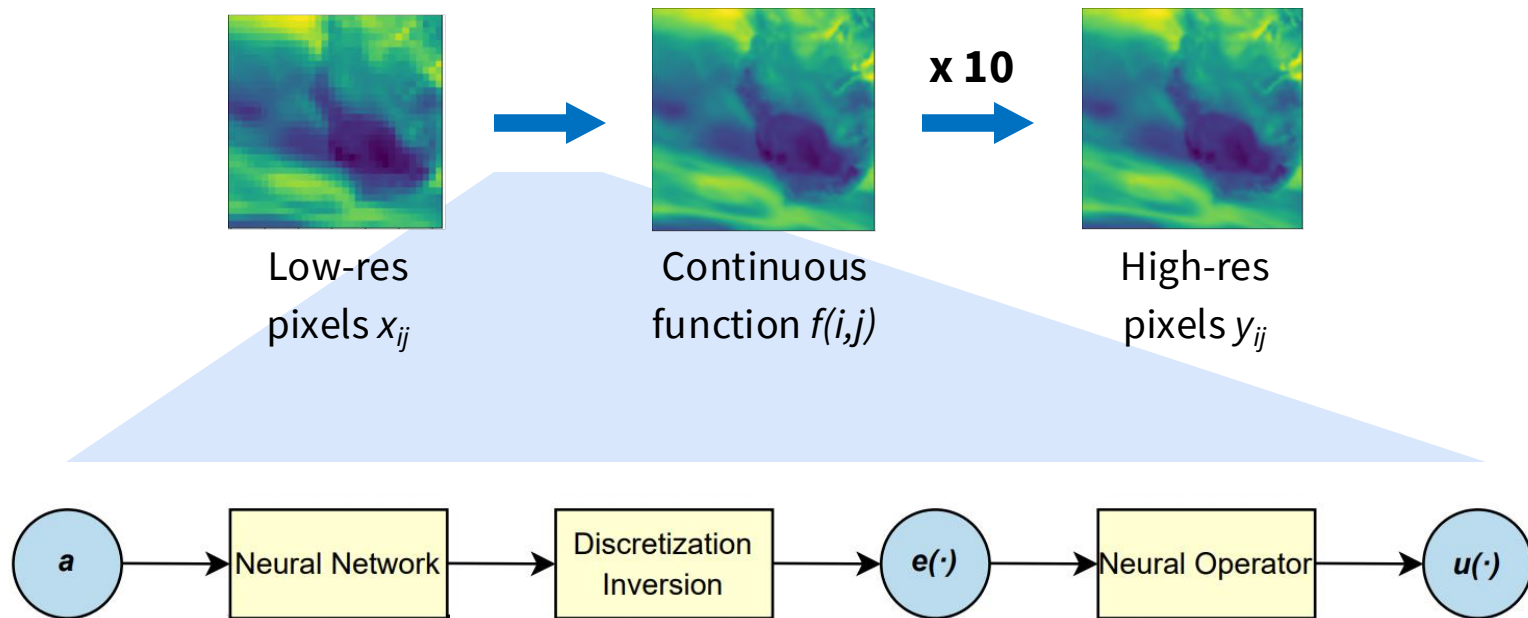
Part 2: arbitrary resolution downscaling



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



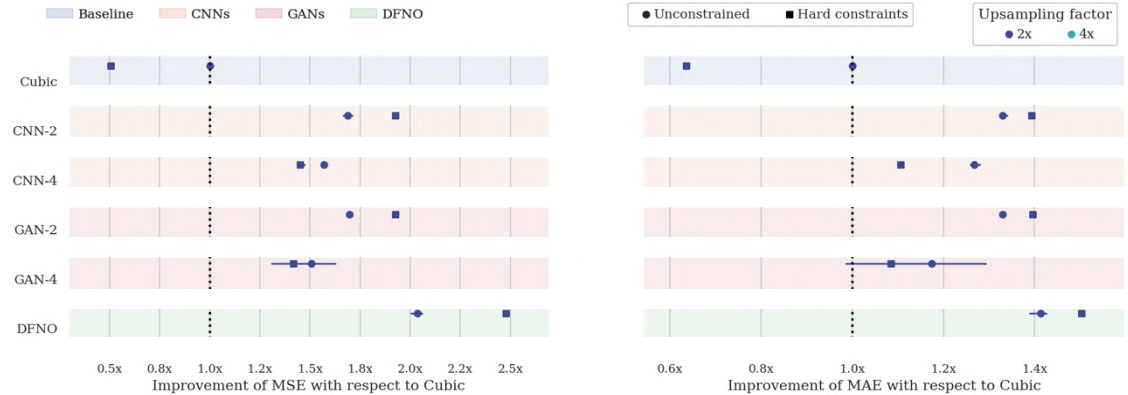
Generalizes without need for high-res data

Fourier domain well-matched to fluid dynamics

Fourier neural operator parametrizes map
between functions in Fourier domain

Experimental results

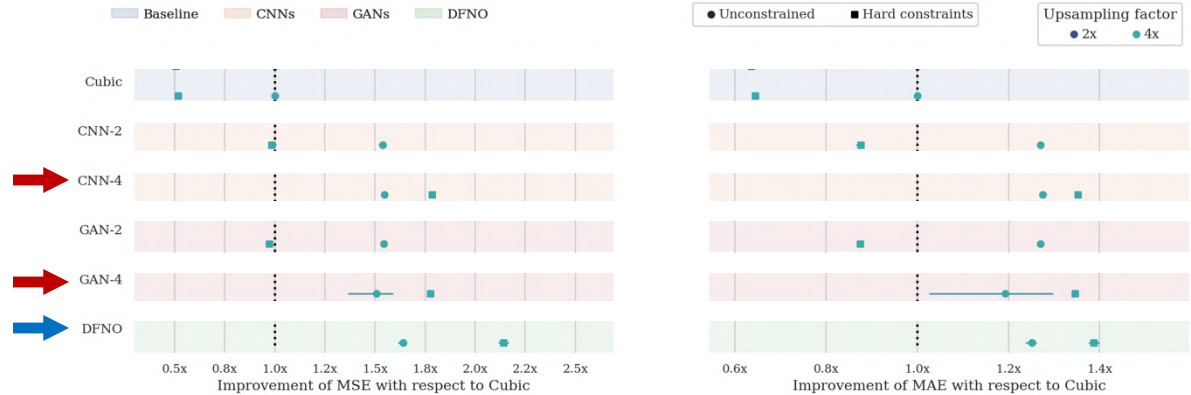
ERA5 reanalysis data
Total column water



Experimental results

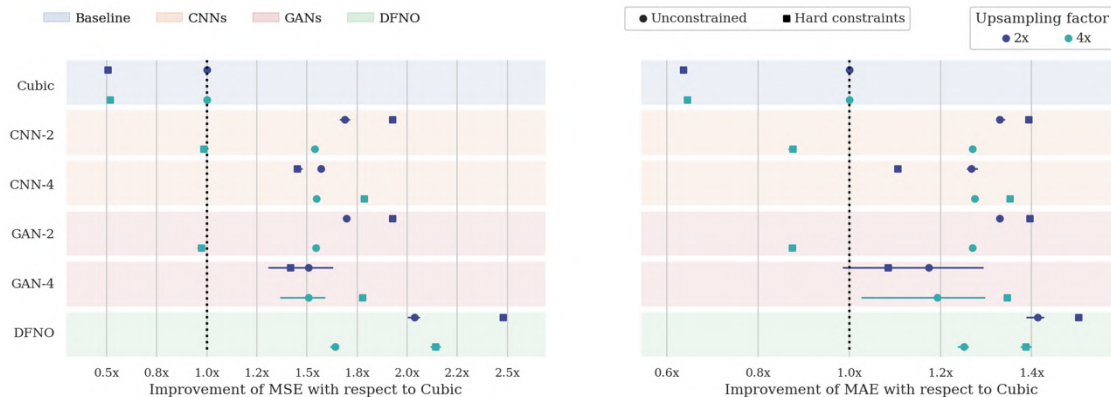
ERA5 reanalysis data
Total column water

Trained
specifically
on 4x task
→
Zero-shot
generalization
from 2x task
→

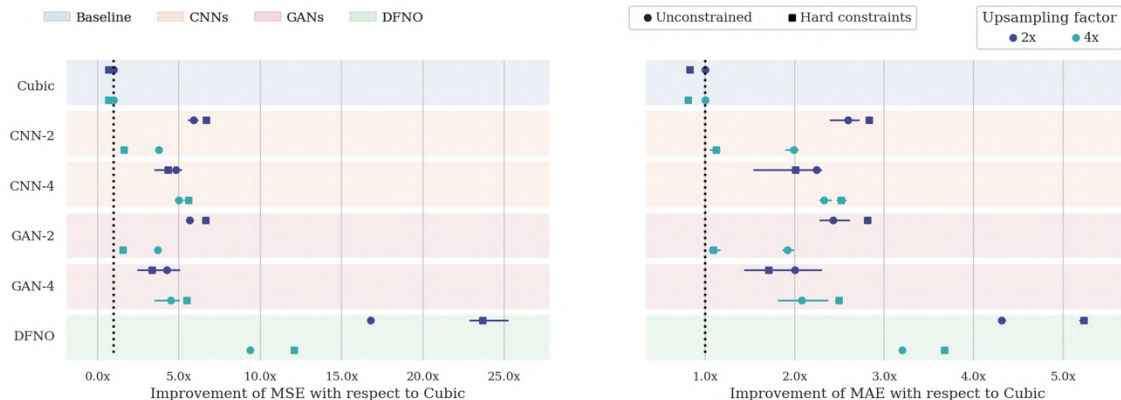


Experimental results

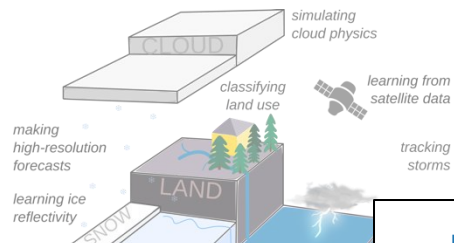
ERA5 reanalysis data
Total column water



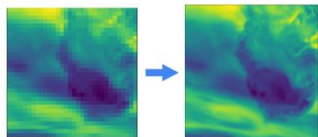
Navier-Stokes eqn.
viscous, incompressible
fluid in vorticity form
(original FNO problem)



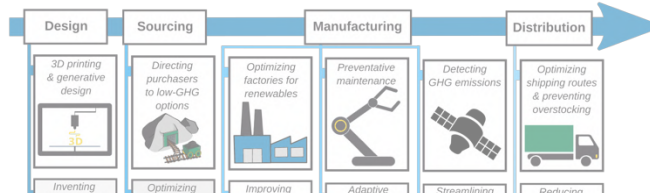
Climate prediction



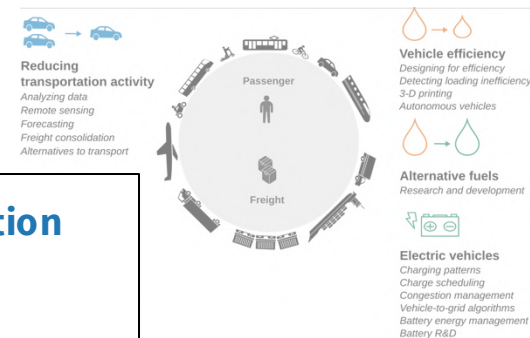
Downscaling FNO



Industry



Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

Improving operational efficiency

Forecasting

Speeding up time-intensive simulations

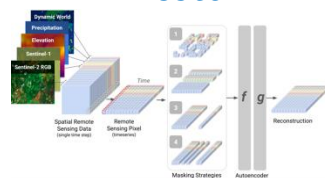
Accelerating scientific discovery

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

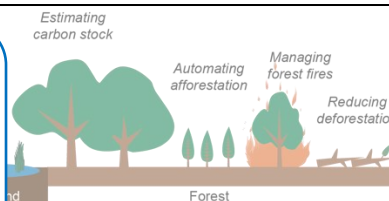


Societal adaptation

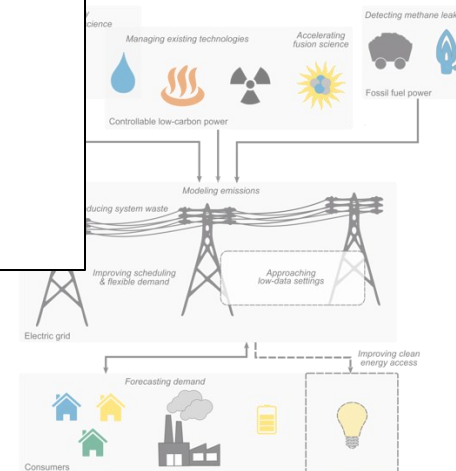
Presto



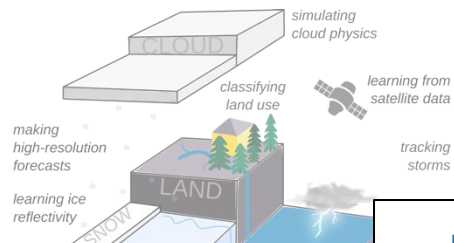
Land use



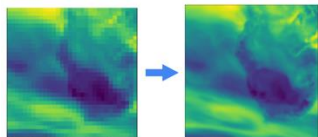
Electricity systems



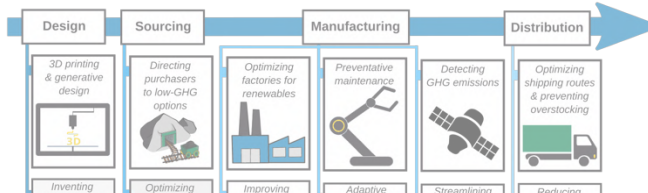
Climate prediction



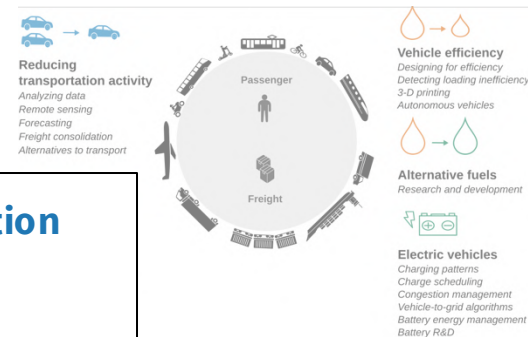
Downscaling FNO



Industry



Transportation



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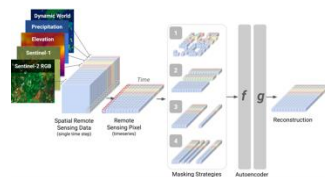
Accelerating scientific discovery

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

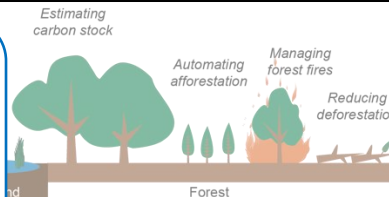


Societal adaptation

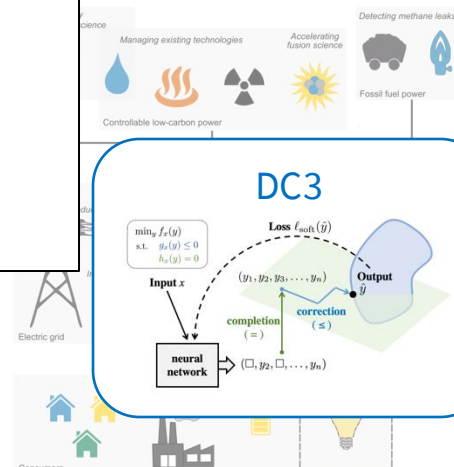
Presto



Land use



Electricity systems



Constrained deep learning for grid optimization

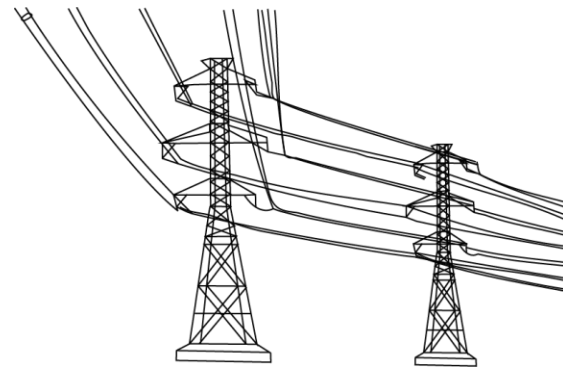
Balancing the electrical grid requires solving a nonconvex opt problem, AC Optimal Power Flow

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

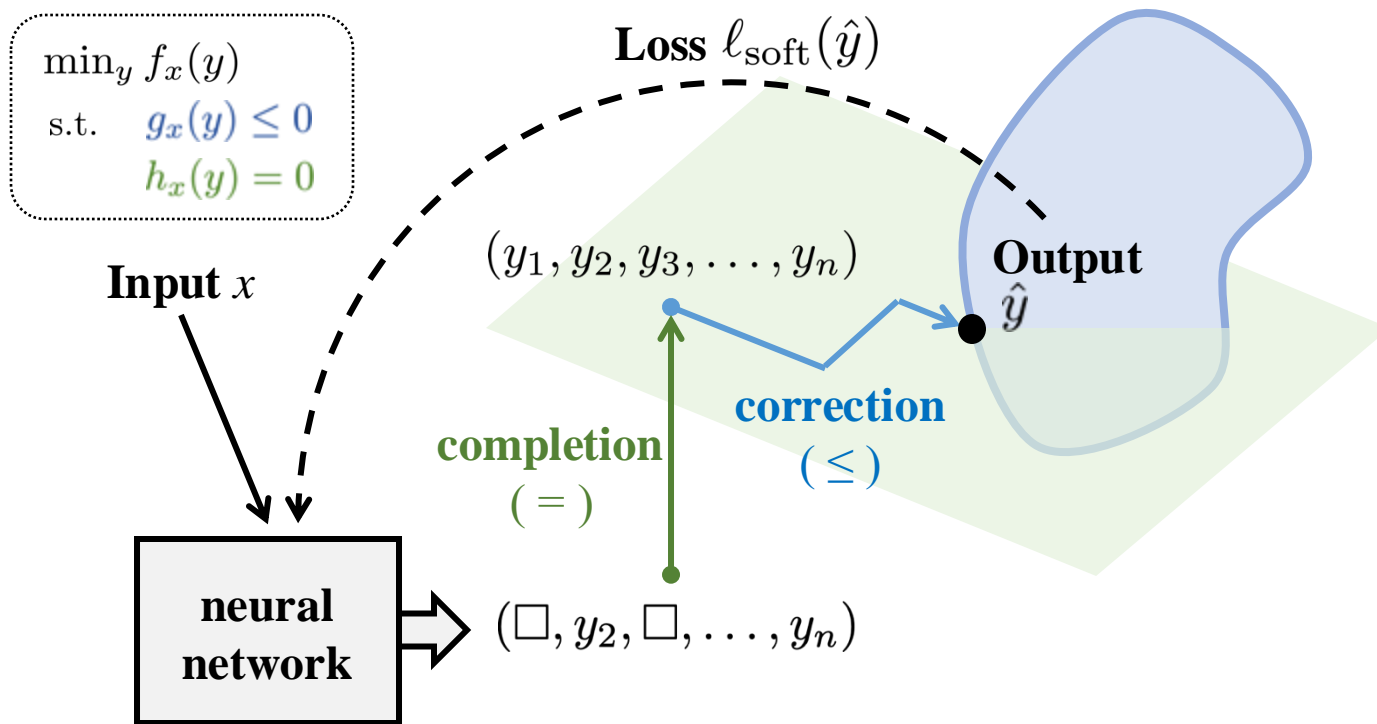
Goal: Approximate mapping from x to y , while satisfying constraints

$$\min_y f_x(y)$$

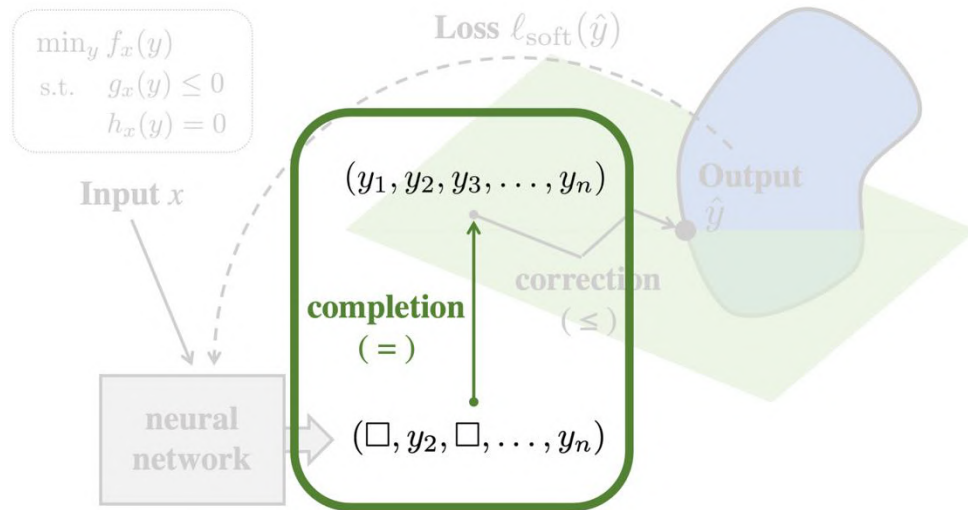
$$\text{s.t.} \quad g_x(y) \leq 0$$

$$h_x(y) = 0$$

DC3: Deep Constraint Completion & Correction



Equality completion



Output **subset of variables**

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

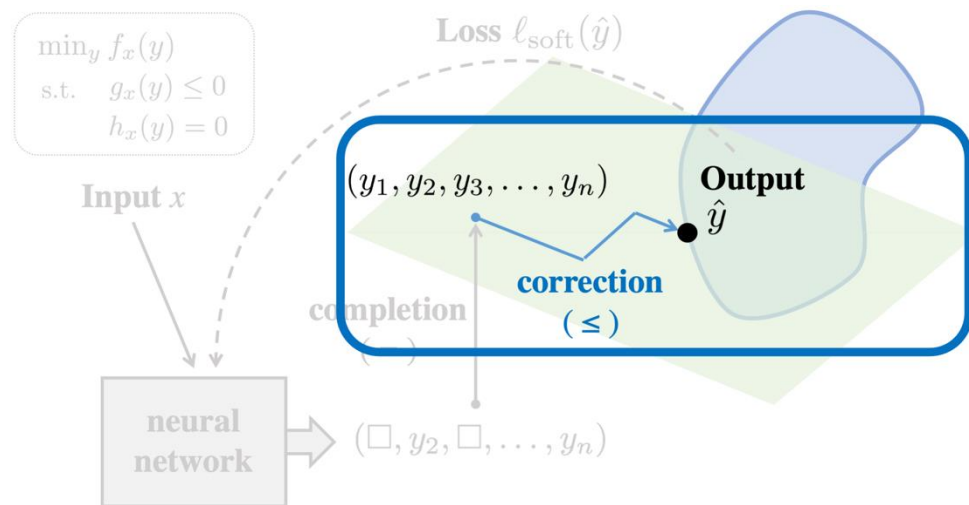
Then **solve for rest**: $\varphi_x(z)$

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



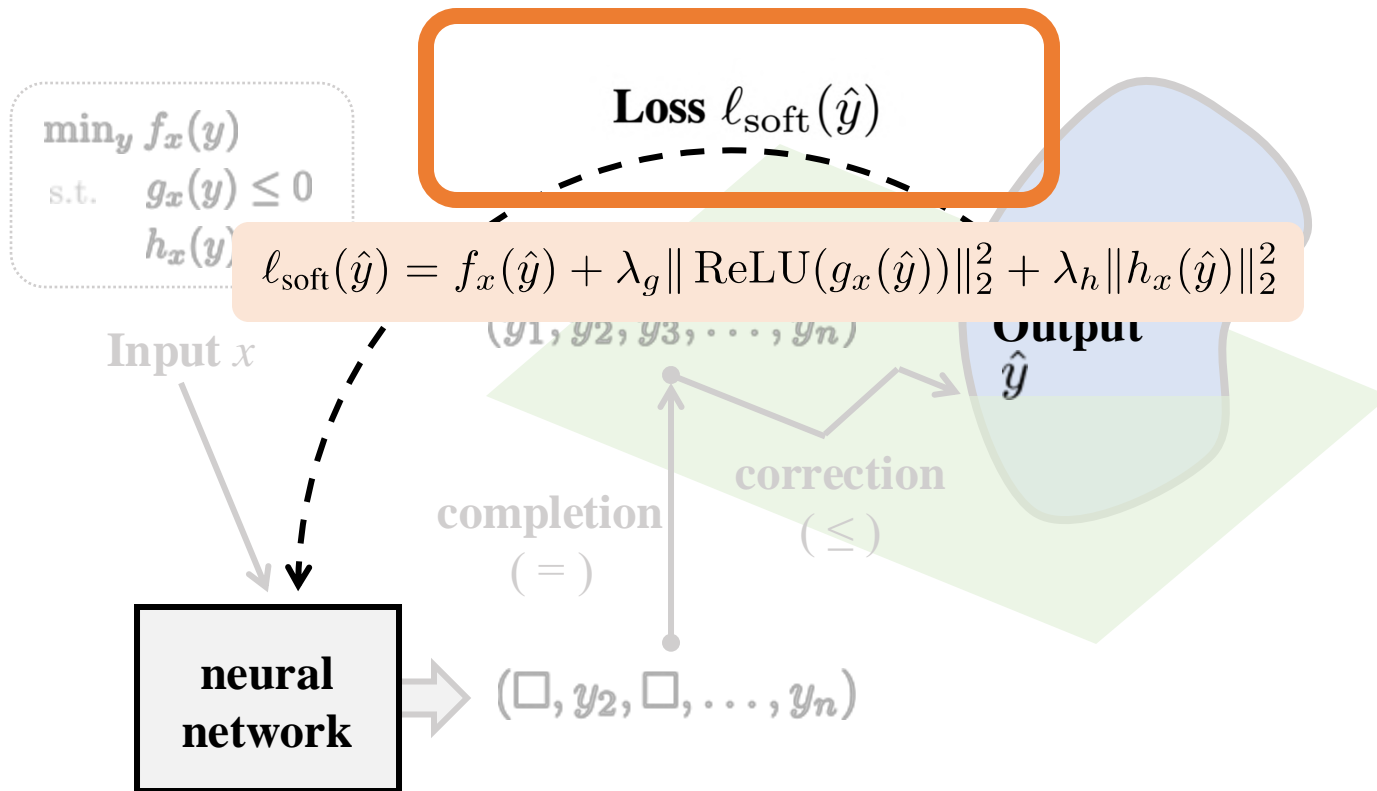
Gradient steps along manifold defined by equality constraints:

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

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

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

End-to-end training with soft loss

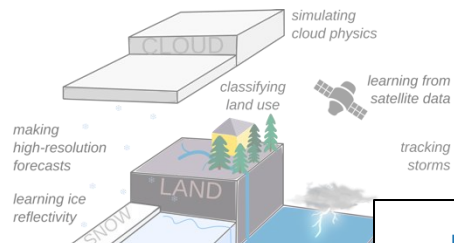


Performance on AC Optimal Power Flow

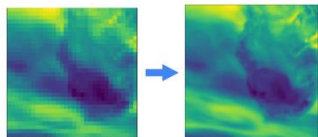
Satisfies all constraints (unlike other DL methods)
10x faster than optimizer, 0.22% optimality gap
and even faster in practice thanks to GPU parallelization

	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)

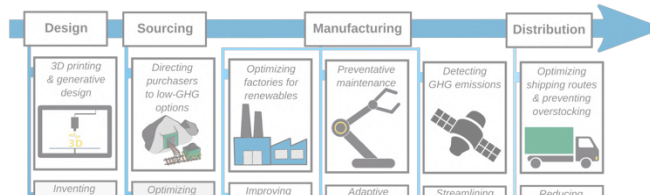
Climate prediction



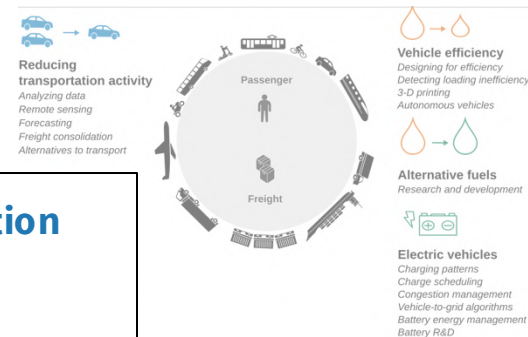
Downscaling FNO



Industry



Transportation



How machine learning can advance climate action

Distilling raw data into actionable information

Improving operational efficiency

Forecasting

Speeding up time-intensive simulations

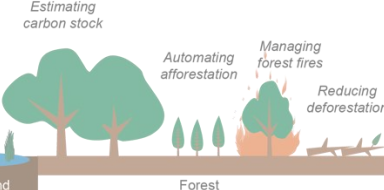
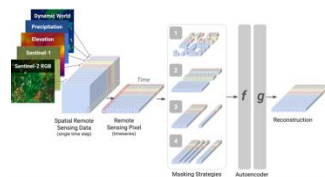
Accelerating scientific discovery

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

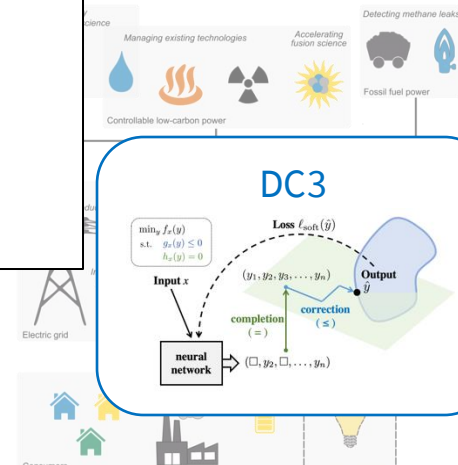


Societal adaptation

Presto

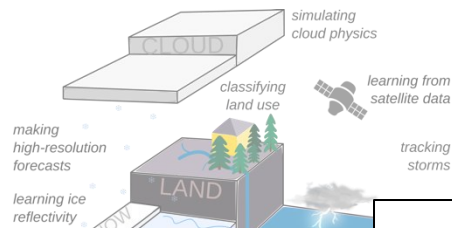


Land use

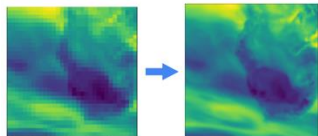


Electricity systems

Climate prediction



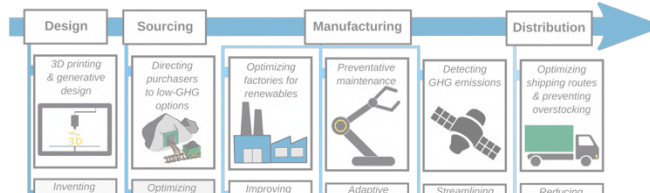
Downscaling FNO



AMI



Industry



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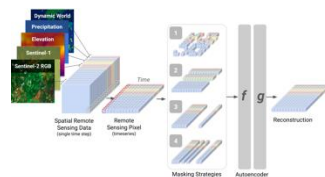
Forecasting

Speeding up time-intensive simulations

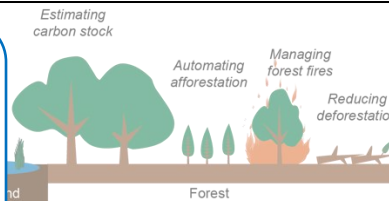
Accelerating scientific discovery

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

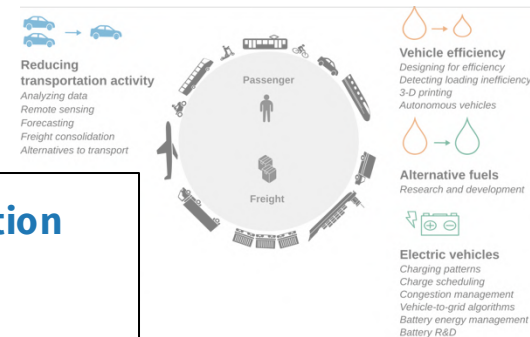
Presto



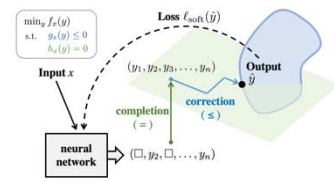
Land use



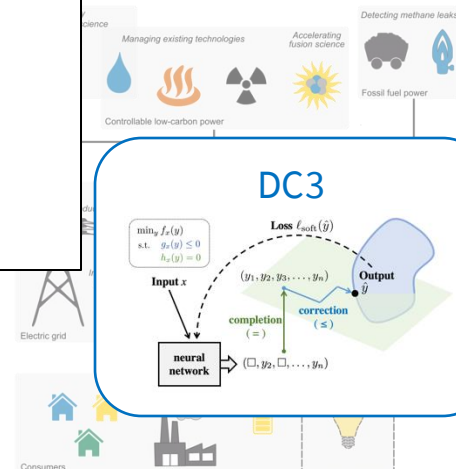
Transportation



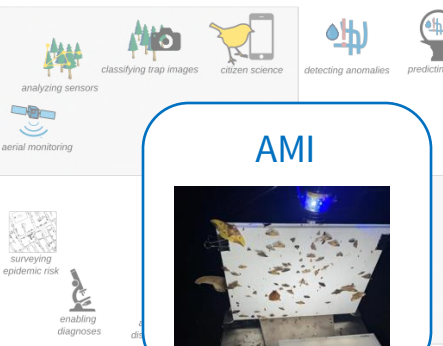
DC3



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.

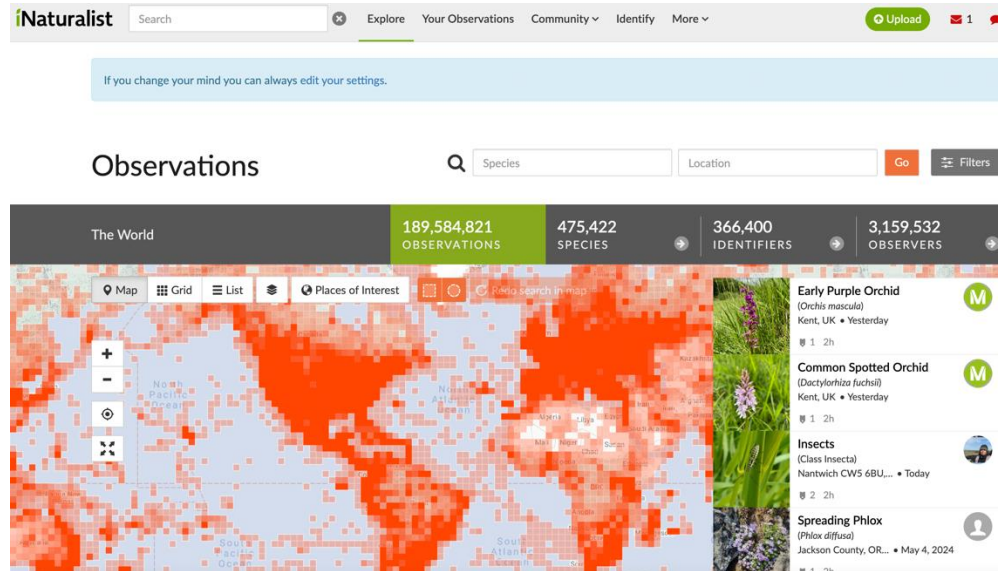
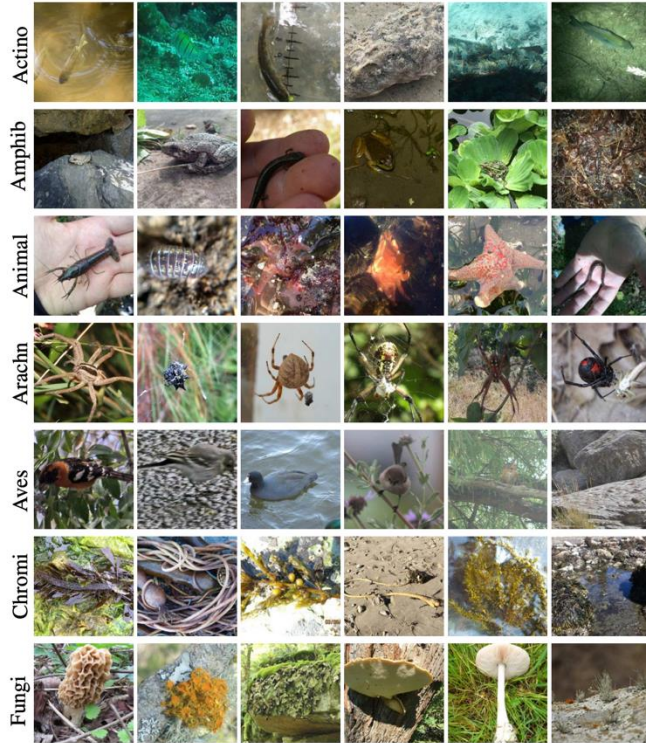
- 12.3% of the images are wrong, 11.9% of categories overlap with each other
- Species heavily biased towards United States.

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



Automated Monitoring of Insects (AMI)

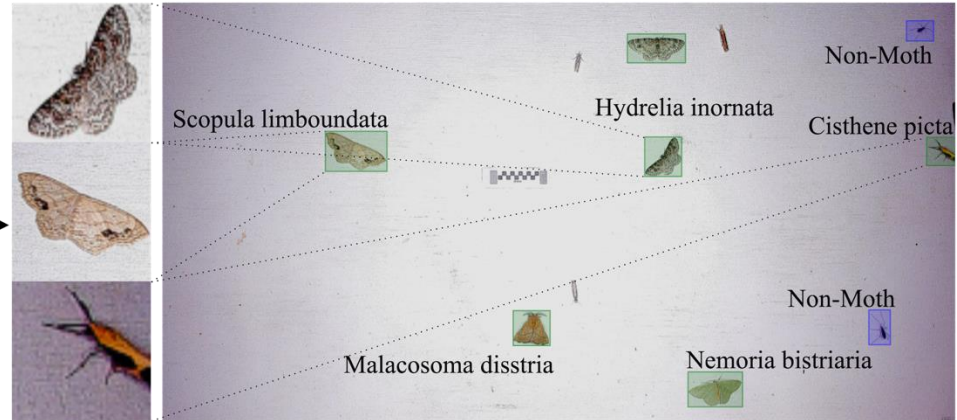


Automated Monitoring of Insects (AMI)

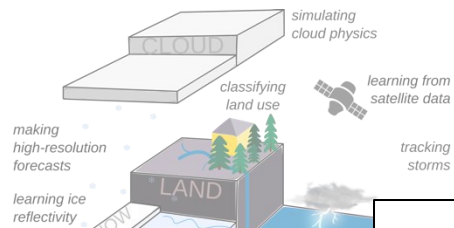
AMI-GBIF (Citizen Science + Museum Collections)



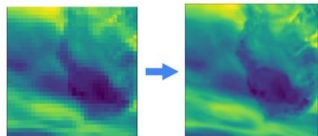
AMI-Traps (Insect Camera Traps)



Climate prediction



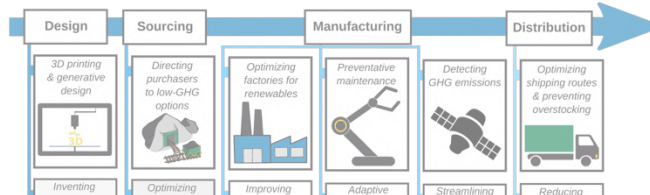
Downscaling FNO



AMI



Industry



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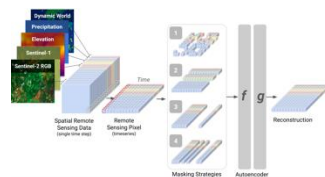
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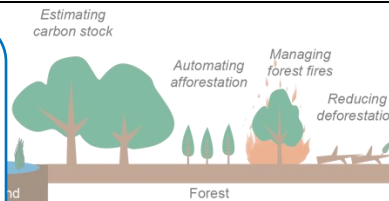
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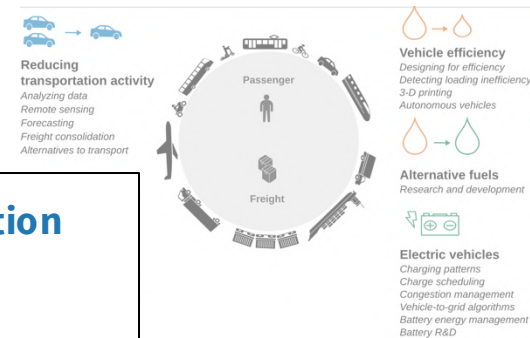
Presto



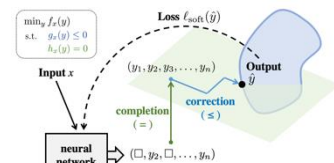
Land use



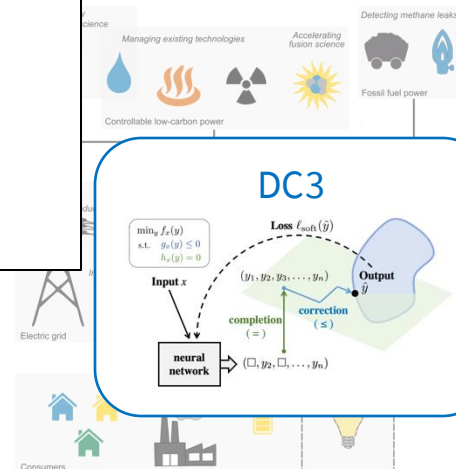
Transportation



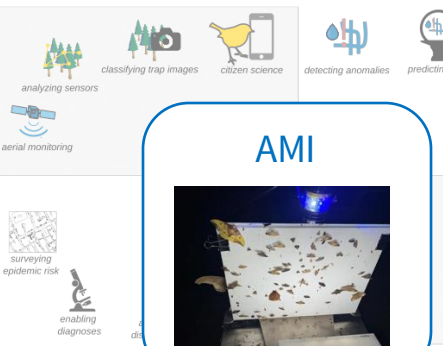
DC3



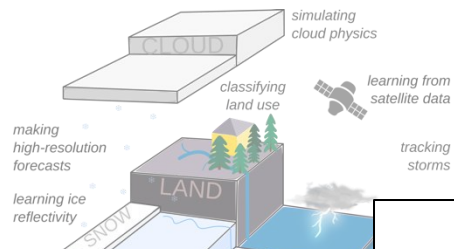
Electricity systems



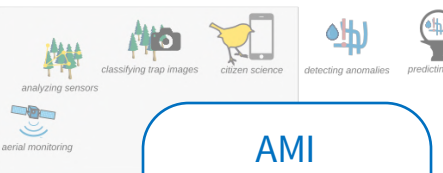
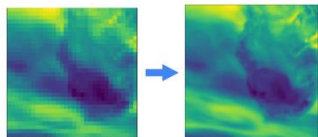
Societal adaptation



Climate prediction



Downscaling FNO

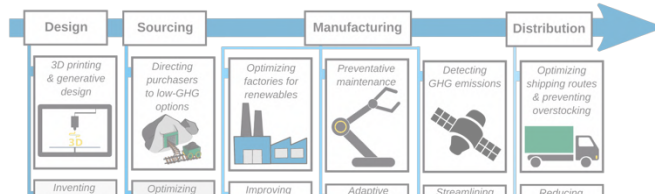


AMI



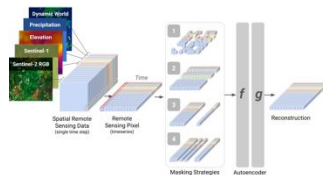
Societal adaptation

Industry



methods

Presto



Estimating carbon stock

Automating

Managing forest fires

Reducing prestation

Forest

Land use

Transportation



Reducing transportation activity


- Analyzing data
- Remote sensing
- Forecasting
- Freight consolidation
- Alternatives to transport



Vehicle efficiency
Designing for efficiency
Detecting loading inefficiency
 3-D printing
 Autonomous vehicles



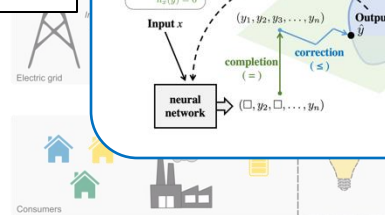
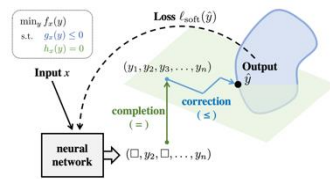
Alternative fuels
Research and development



Electric vehicles
 Charging patterns
 Charge scheduling
 Congestion management
 Vehicle-to-grid algorithms
 Battery energy management
 Battery R&D

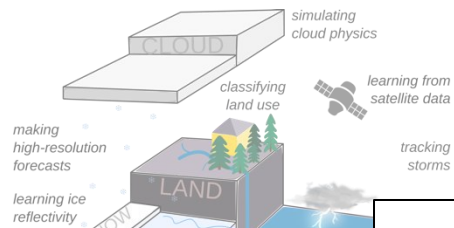


DC3

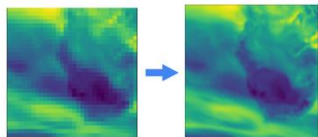


Electricity systems

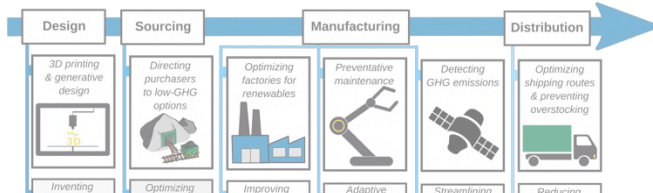
Climate prediction



Downscaling FNO



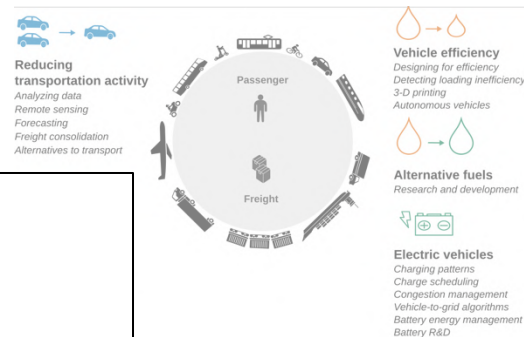
Industry



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

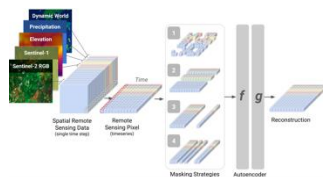
Transportation



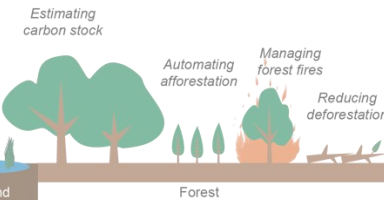
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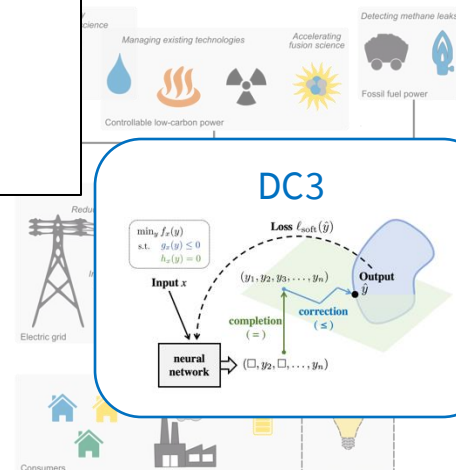
Presto



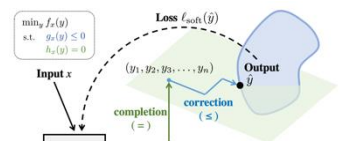
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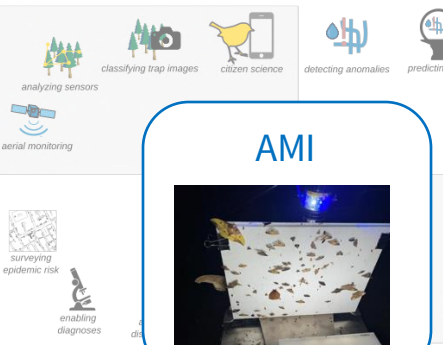
Electricity systems



DC3



Societal adaptation



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
- + 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



- 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

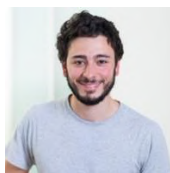
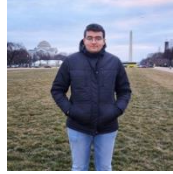
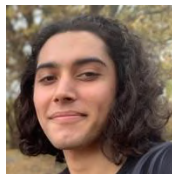
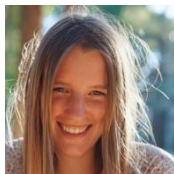
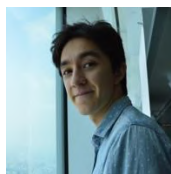
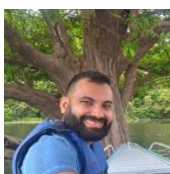
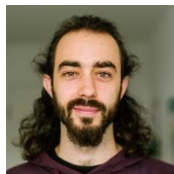
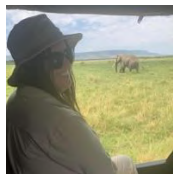


McGill
UNIVERSITY



Mila

Thank you!



Smithsonian
Tropical Research Institute



UK Centre for
Ecology & Hydrology