Objective-Driven AI

Towards AI systems that can learn, remember, reason, plan, have common sense, yet are steerable and safe

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Meta – Fundamental AI Research

Ding-Shum Lecture
Department of Mathematics
Harvard University
2024-03-28

Machine Learning sucks! (compared to humans and animals)

- **Supervised learning (SL) requires large numbers of labeled samples.**
- **Reinforcement learning (RL) requires insane amounts of trials.**
- **Self-Supervised Learning (SSL) works great but...**
  - Generative prediction only works for text and other discrete modalities

- **Animals and humans:**
  - Can learn new tasks **very** quickly.
  - Understand how the world works
  - Can reason an plan
- **Humans and animals have common sense**
- **There behavior is driven by objectives (drives)**

We Need Human-Level AI for Intelligent Assistant

- **In the near future, all of our interactions with the digital world will be mediated by AI assistants.**
- **Smart glasses**
  - Communicates through voice, vision, display, electro-myogram interfaces (EMG)
- **Intelligent Asistant**
  - Can answer all of our questions
  - Can helps us in our daily lives
  - Understands our preferences and interests
- **For this, we need machines with human-level intelligence**
  - Machines that understand how the world works
  - Machines that can remember, reason, plan.

“Her”
(2013)

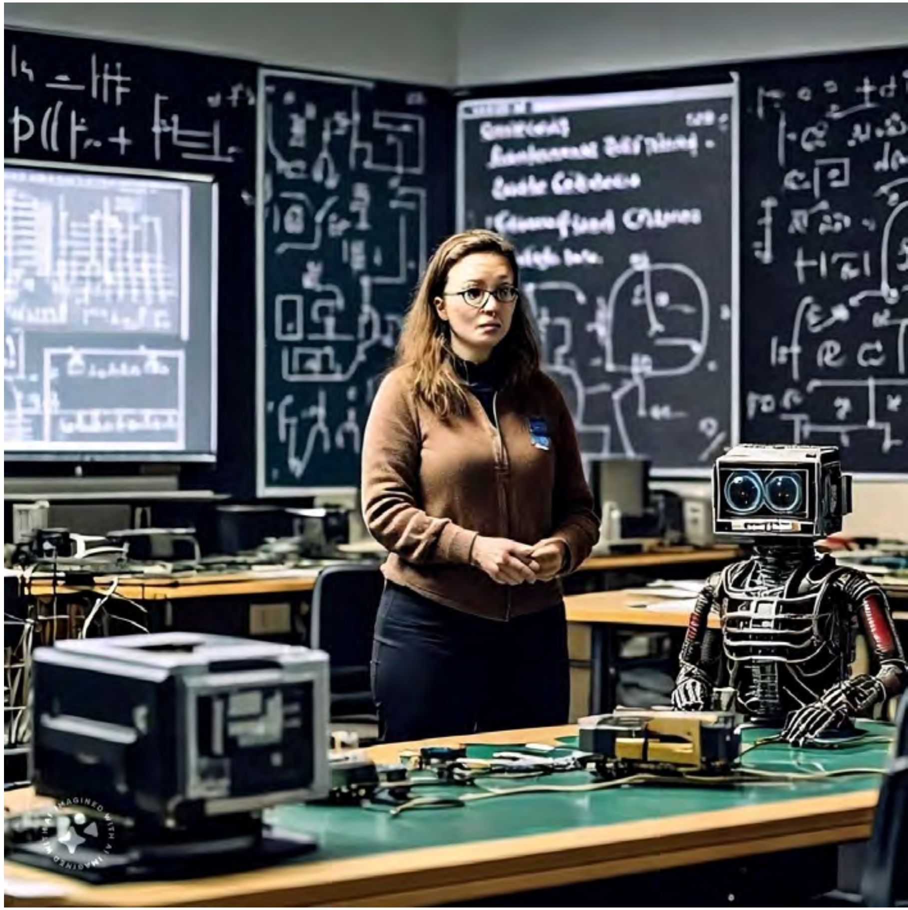
Future AI Assistants need Human-Level AI

- **AI assistants will require (super-)human-level intelligence**
  - Like having a staff of smart “people” working for us
- **But, we are nowhere near human-level AI today**
  - Any 17 year-old can learn to drive in 20 hours of training
  - Any 10 year-old can learn to clear the dinner table in one shot
  - Any house cat can plan complex actions
- **What are we missing?**
  - Learning how to world works (not just from text)
  - World models. Common sense
  - Memory, Reasoning, Hierarchical Planning

Desiderata for AMI (Advanced Machine Intelligence)

- **Systems that learn world models from sensory inputs**
  - E.g. learn intuitive physics from video
- **Systems that have persistent memory**
  - Large-scale associative memories
- **Systems that can plan actions**
  - So as to fulfill an objective
- **Systems that are controllable & safe**
  - By design, not by fine-tuning.

- **Objective-Driven AI Architecture**

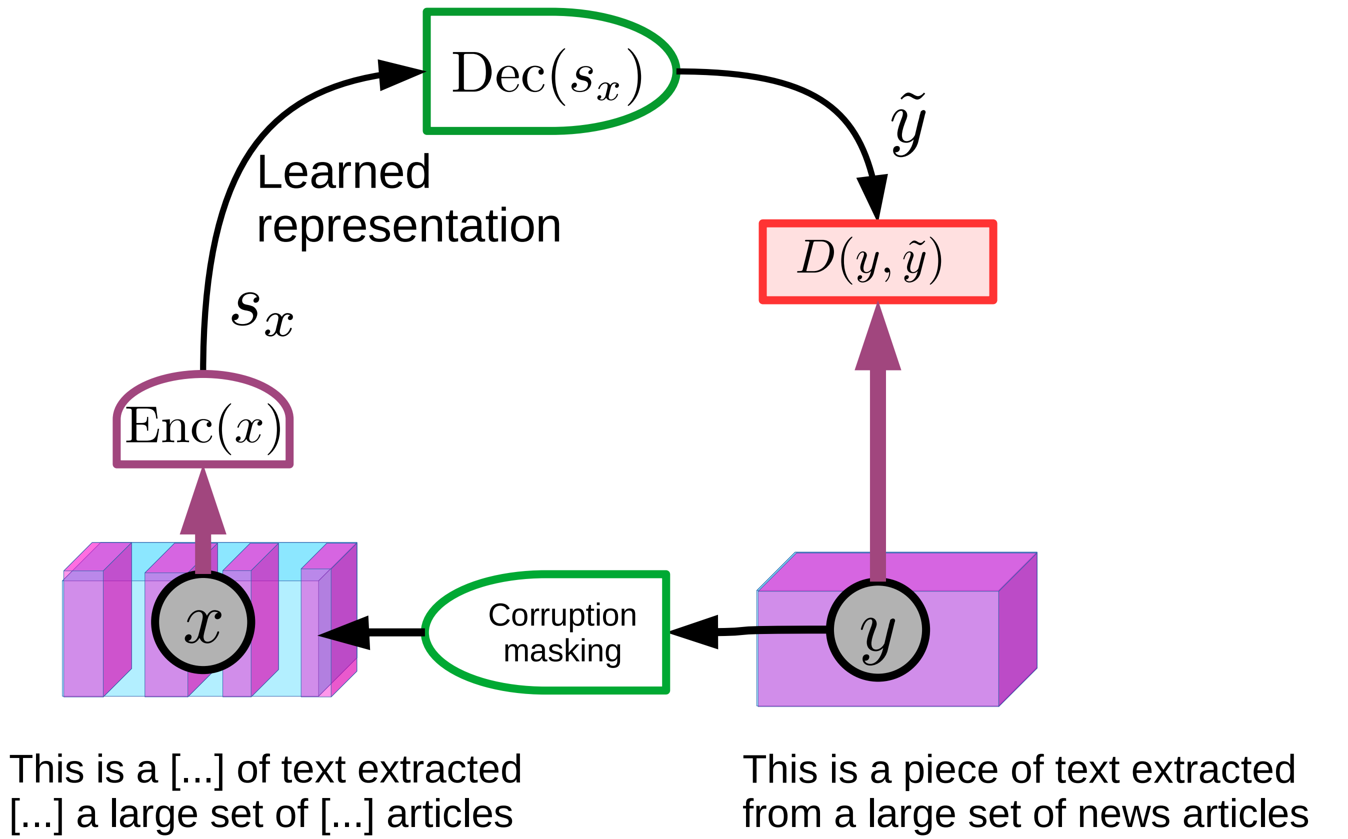


Self-Supervised Learning has taken over the world

For understanding and generating text, images, video, 3D models, speech, proteins,...

Self-Supervised Learning via Denoising / Reconstruction

- **Denoising Auto-Encoder [Vincent 2008], BERT [Devlin 2018], RoBERTa [Ott 2019]**



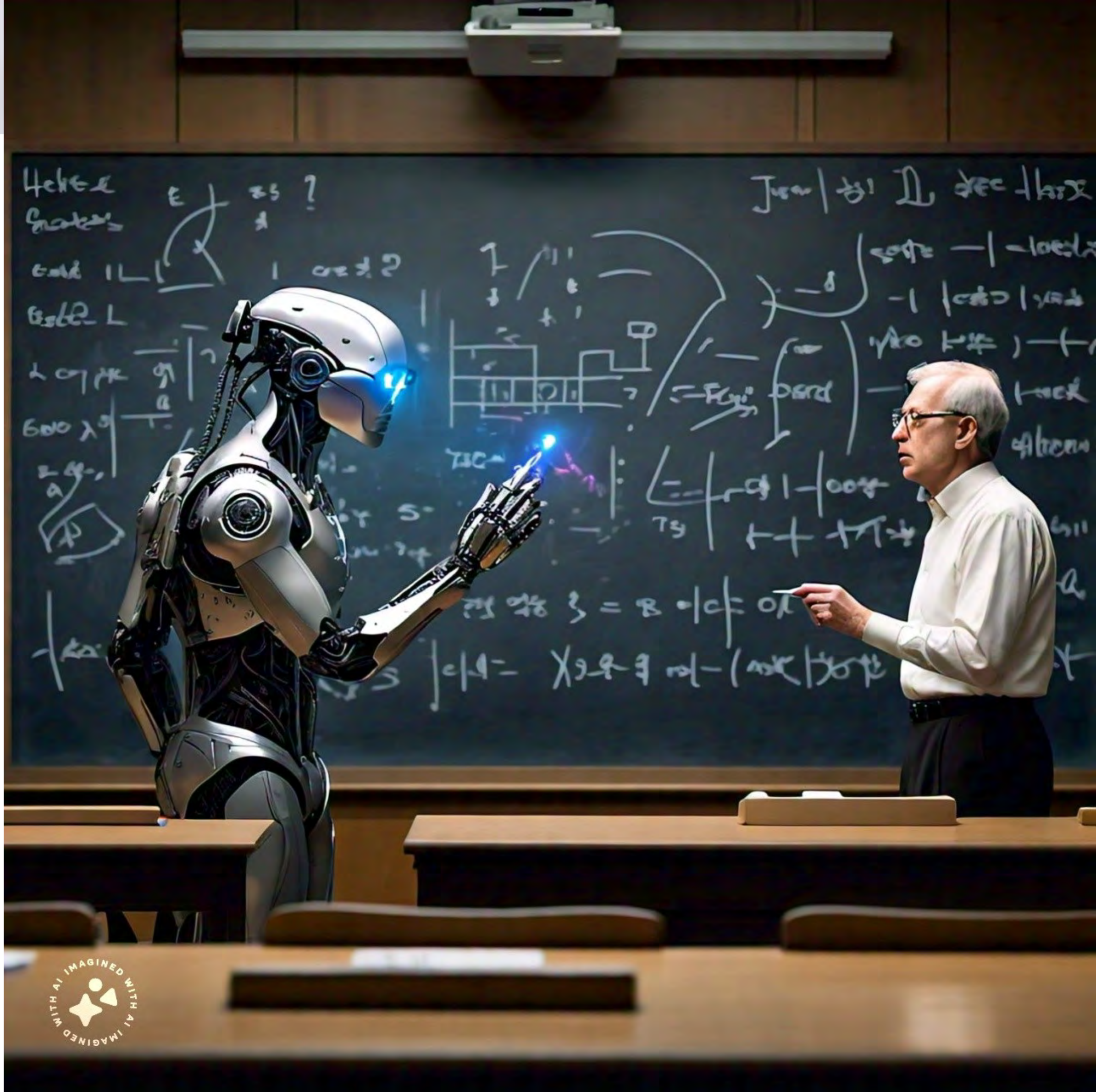
Emu: image generation

[ArXiv:2309.15807]

Dai et al.:
Emu: Enhancing Image Generation Models Using Photogenic Needles in a Haystack

AI at Meta, September 2023

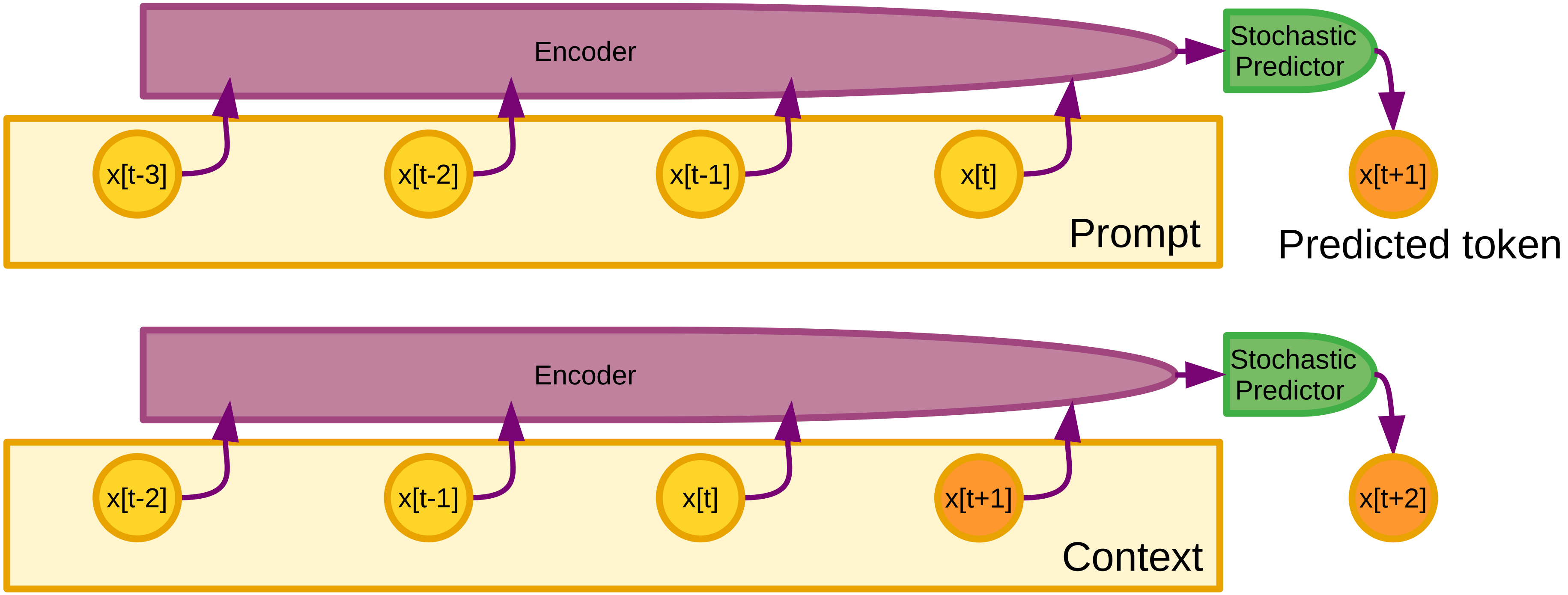
Meta AI on WhatsApp & Messenger:
/imagine a photo a Harvard mathematician proving the Riemann hypothesis on a blackboard with the help of an intelligent robot.



Generative AI and Auto-Regressive Large Language Models

Auto-Regressive Generative Architectures

- Outputs one “token” after another
- Tokens may represent words, image patches, speech segments...



Auto-Regressive Large Language Models (AR-LLMs)

- **Outputs one text token after another**
- **Tokens may represent words or subwords**
- **Encoder/predictor is a transformer architecture**
  - With billions of parameters: typically from 1B to 500B
  - Training data: 1 to 2 trillion tokens
- **LLMs for dialog/text generation:**
  - Open: BlenderBot, Galactica, LlaMA, Llama-2, Code Llama (FAIR), Mistral-7B, Mixtral-4x7B (Mistral), Falcon (UAE), Alpaca (Stanford), Yi (01.AI), OLMo (AI2), Gemma (Google)….
  - Proprietary: Meta AI (Meta), LaMDA/Bard, Gemini (Google), ChatGPT (OpenAI) …
- **Performance is amazing … but … they make stupid mistakes**
  - Factual errors, logical errors, inconsistency, limited reasoning, toxicity...
- **LLMs have limited knowledge of the underlying reality**
  - They have no common sense, no memory, & they can't plan their answer

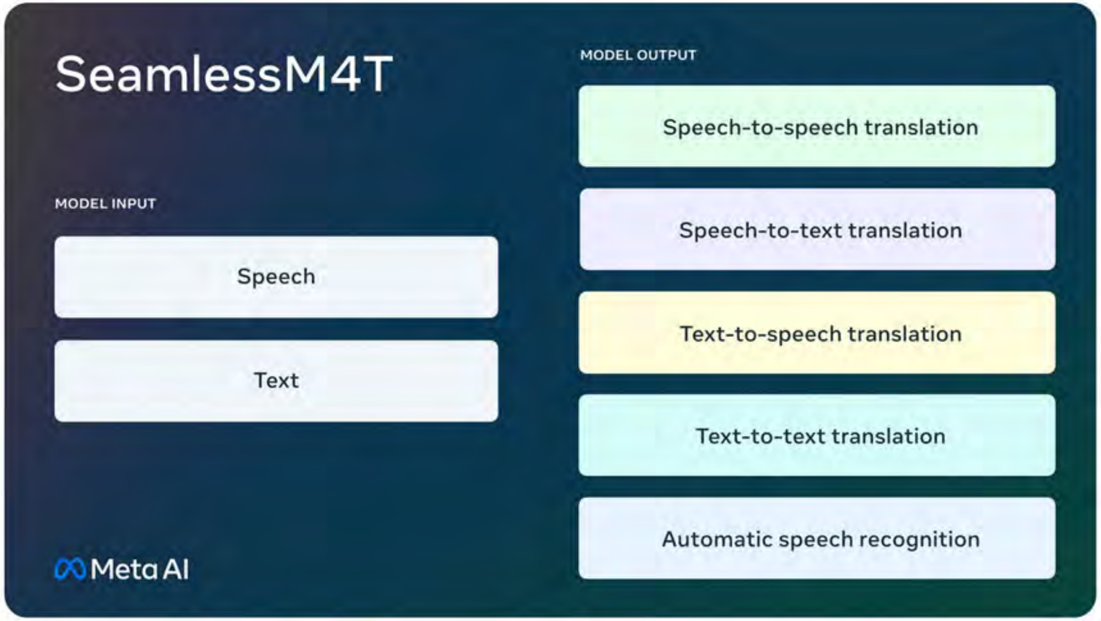
Llama-2: https://ai.meta.com/llama/

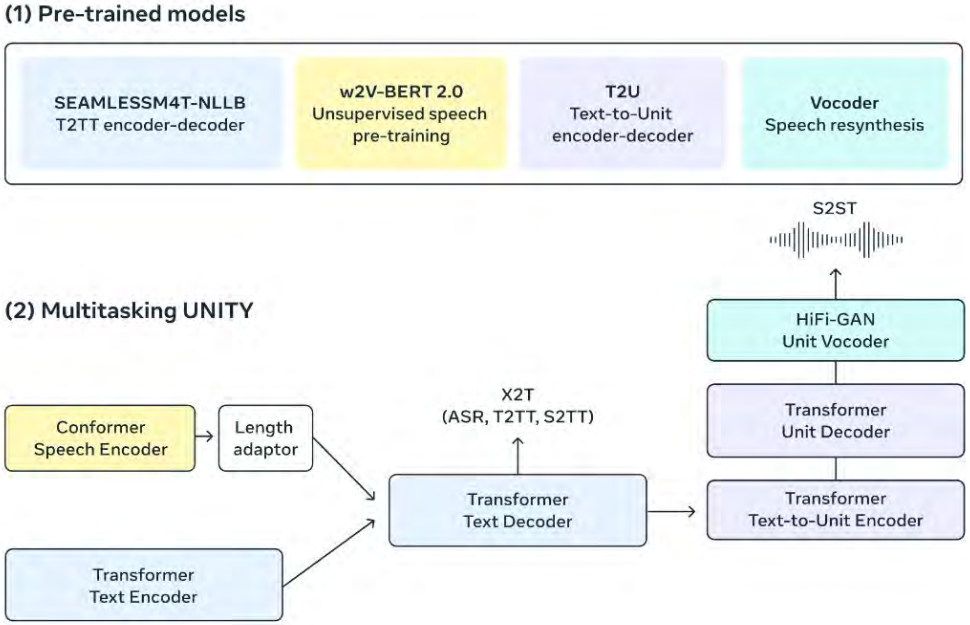
- **Open source code / free & open models / can be used commercially**
- **Available on Azure, AWS, HuggingFace,….**

MODEL SIZE (PARAMETERS)	PRETRAINED	FINE-TUNED FOR CHAT USE CASES
7B	**Model architecture:** **Pretraining Tokens:** 2 Trillion **Context Length:** 4096	**Data collection for helpfulness and safety:** **Supervised fine-tuning:** Over 100,000 **Human Preferences:** Over 1,000,000
13B		
70B		

SeamlessM4T

- Speech or text input: 100 languages
- Text output: 100 languages
- Speech output: 35 languages
- Seamless Expressive: real-time, preserves voice & expression
- https://ai.meta.com/blog/seamless-m4t/

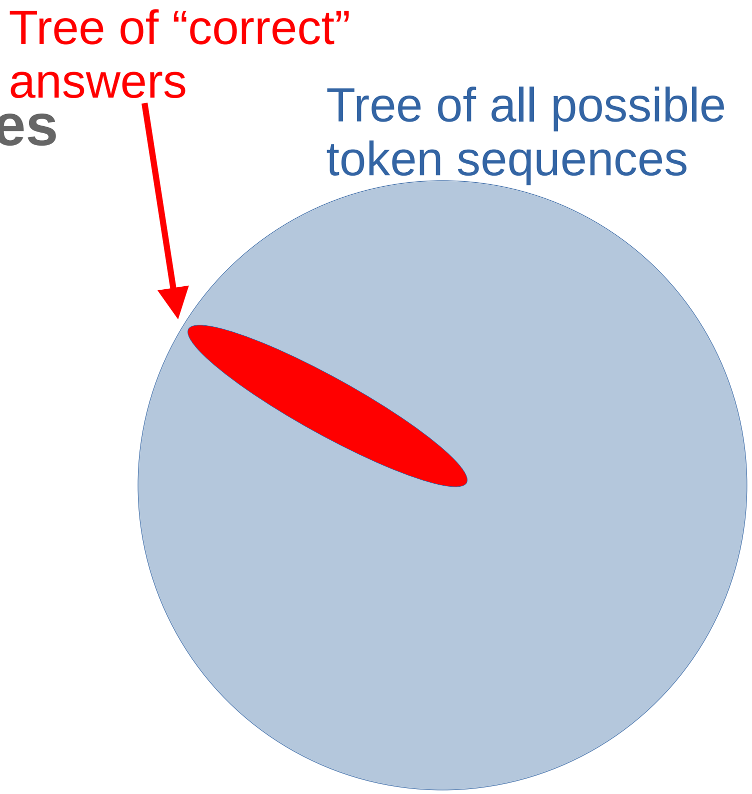




Auto-Regressive Generative Models Suck!

- Auto-Regressive LLMs are **doomed**.
- They cannot be made factual, non-toxic, etc.
- They are not controllable
- Probability e that any produced token takes us outside of the set of correct answers
- Probability that answer of length n is correct:
  - $P(\text{correct}) = (1-e)^n$
- **This diverges exponentially.**
- **It's not fixable (without a major redesign).**

  - See also [Dziri...Choi, ArXiv:2305.18654]



Limitations of LLMs: no planning!

- Auto-Regressive LLMs (at best) approximate the functions of the Wernicke and Broca areas in the brain.
- What about the pre-frontal cortex?

ArXiv:2301.06627

DISSOCIATING LANGUAGE AND THOUGHT IN LARGE LANGUAGE MODELS: A COGNITIVE PERSPECTIVE

A PREPRINT

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ArXiv:2206.10498

Large Language Models Still Can't Plan (A Benchmark for LLMs on Planning and Reasoning about Change)

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Auto-Regressive Generative Models Suck!

- **AR-LLMs**
  - Have a constant number of computational steps between input and output. Weak representational power.
  - Do not really reason. Do not really plan, Have no common sense
- **Noema Magazine, August 2023**

AI And The Limits Of Language

An artificial intelligence system trained on words and sentences alone will never approximate human understanding.

ESSAY TECHNOLOGY & THE HUMAN

BY JACOB BROWNING AND YANN LECUN

AUGUST 23, 2022

Auto-Regressive LLMs Suck !

- **Auto-Regressive LLMs are good for**
  - Writing assistance, first draft generation, stylistic polishing.
  - Code writing assistance
- **What they not good for:**
  - Producing factual and consistent answers (hallucinations!)
  - Taking into account recent information (anterior to the last training)
  - Behaving properly (they mimic behaviors from the training set)
  - Reasoning, planning, math
  - Using "tools", such as search engines, calculators, database queries…
- **We are easily fooled by their fluency.**
- **But they don't know how the world works.**

Current AI Technology is (still) far from Human Level

- **Machines do not learn how the world works, like animals and humans**
- **Auto-Regressive LLMs can not approach human-level intelligence**
  - Fluency, but limited world model, limited planning, limited reasoning.
  - Most human and animal knowledge is non verbal.
- **We are still missing major advances to reach animal intelligence**
  - AI is super-human in some narrow domains

- **There is no questions that, eventually, machines will eventually surpass human intelligence in all domains**
  - Humanity's total intelligence will increase
  - We should welcome that not fear it.

We are missing something really big!

- **Never mind humans, cats and dogs can do amazing feats**
  - Robots intelligence doesn’t come anywhere close
- **Any 10 year-old can learn to clear up the dinner table and fill up the dishwasher in minutes.**
  - We do not have robots that can do that.
- **Any 17 year-old can learn to drive a car in 20 hours of practice**
  - We still don’t have unlimited Level-5 autonomous driving
- **Any house cat can plan complex actions**

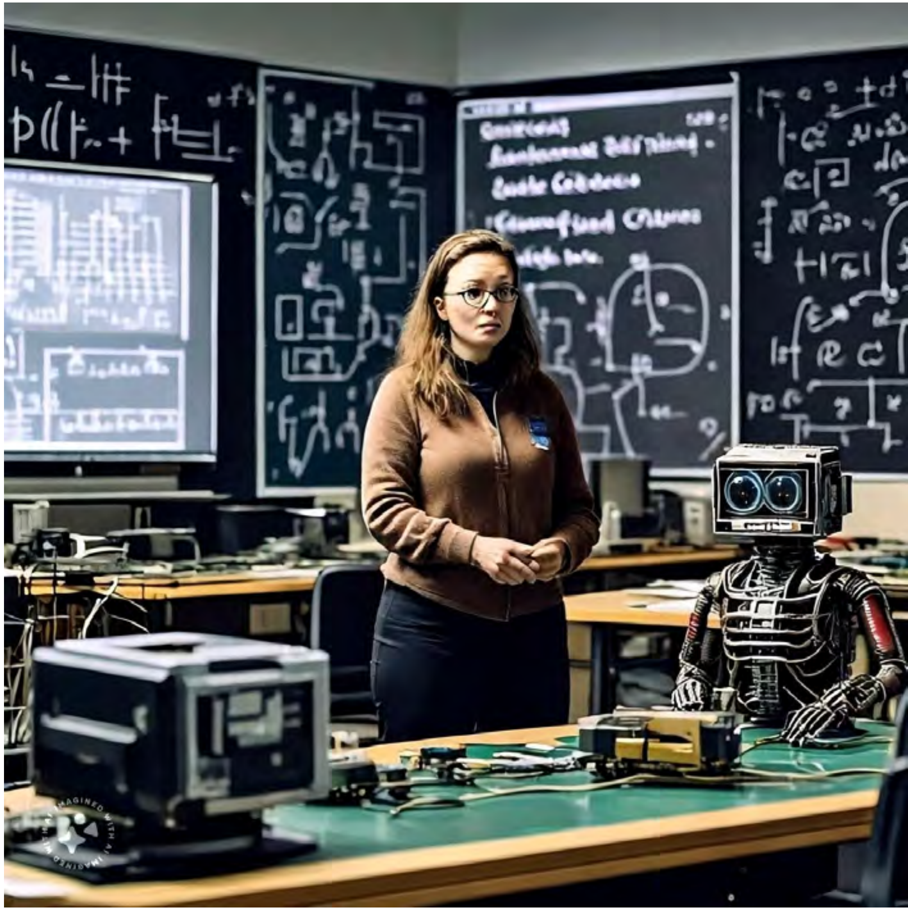
- **We keep bumping into Moravec’s paradox**
  - Things that are easy for humans are difficult for AI and vice versa.

Data bandwidth and volume: LLM vs child.

- **LLM**
  - Trained on 1.0E13 tokens (0.75E13 words). Each token is 2 bytes.
  - Data volume: 2.0E13 bytes.
  - Would take 170,000 years for a human to read (8h/day, 250 w/minute)
- **Human child**
  - 16,000 wake hours in the first 4 years (30 minutes of YouTube uploads)
  - 2 million optical nerve fibers, carrying about 10 bytes/sec each.
  - Data volume: 1.1E15 bytes
- **A four year-old child has seen 50 times more data than an LLM !**
- **In 300 hours, has child has seen more data than an LLM.**

What are we missing?

- **Systems that learn world models from sensory inputs**
  - E.g. learn intuitive physics from video
- **Systems that have persistent memory**
  - Large-scale associative memories
- **Systems that can plan actions**
  - So as to fulfill an objective
  - Reason like “System 2” in humans
- **Systems that are controllable & safe**
  - By design, not by fine-tuning.
- **Objective-Driven AI Architecture**



Objective-Driven AI Systems

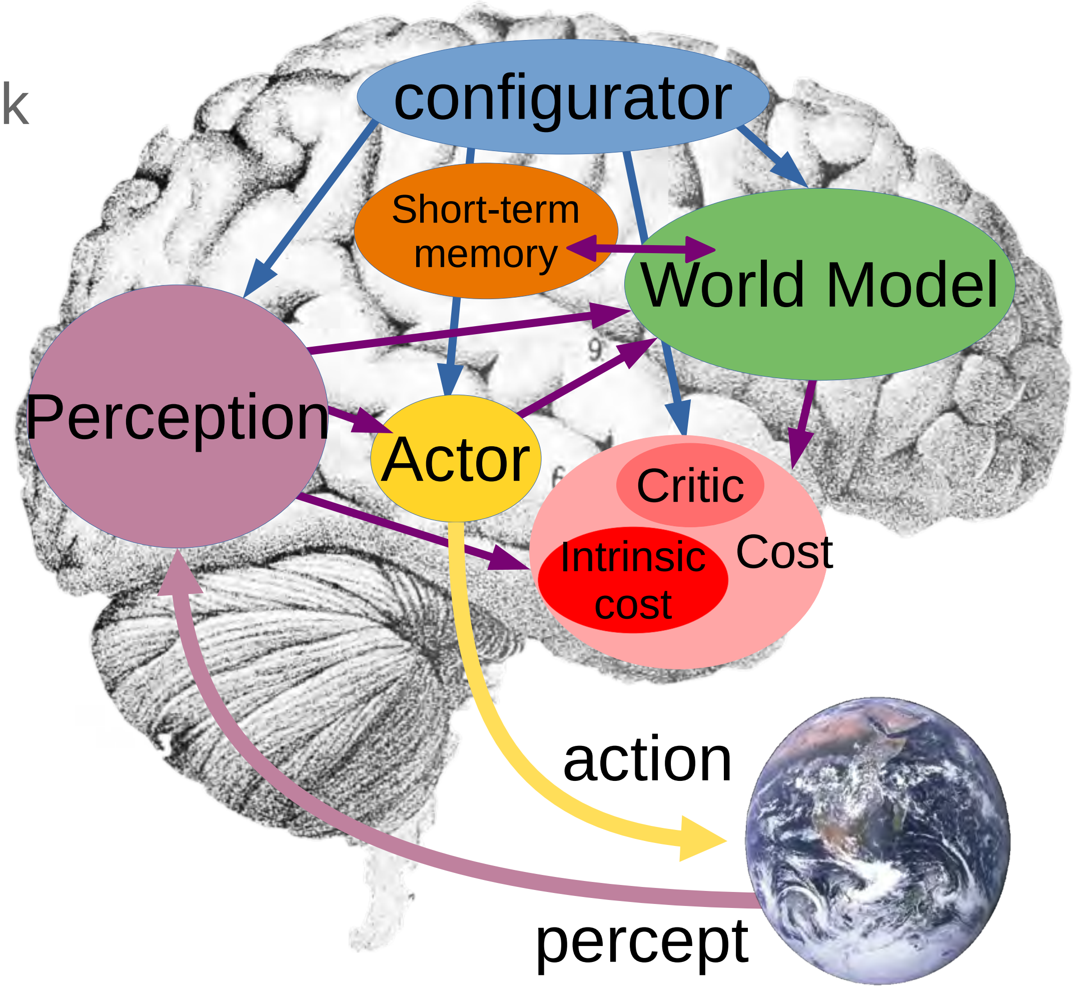
AI that can learn, reason, plan,
Yet is safe and controllable

"A path towards autonomous machine intelligence"
https://openreview.net/forum?id=BZ5a1r-kVsf

[various versions of this talk on YouTube]

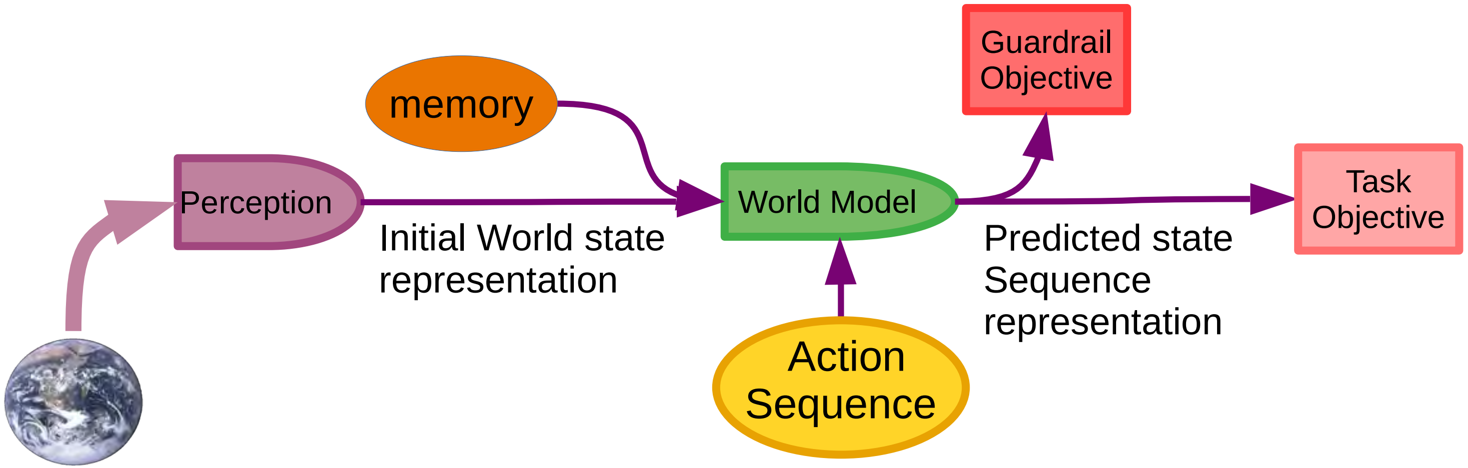
Modular Cognitive Architecture for Objective-Driven AI

- **Configurator**
  - Configures other modules for task
- **Perception**
  - Estimates state of the world
- **World Model**
  - Predicts future world states
- **Cost**
  - Compute “discomfort”
- **Actor**
  - Find optimal action sequences
- **Short-Term Memory**
  - Stores state-cost episodes



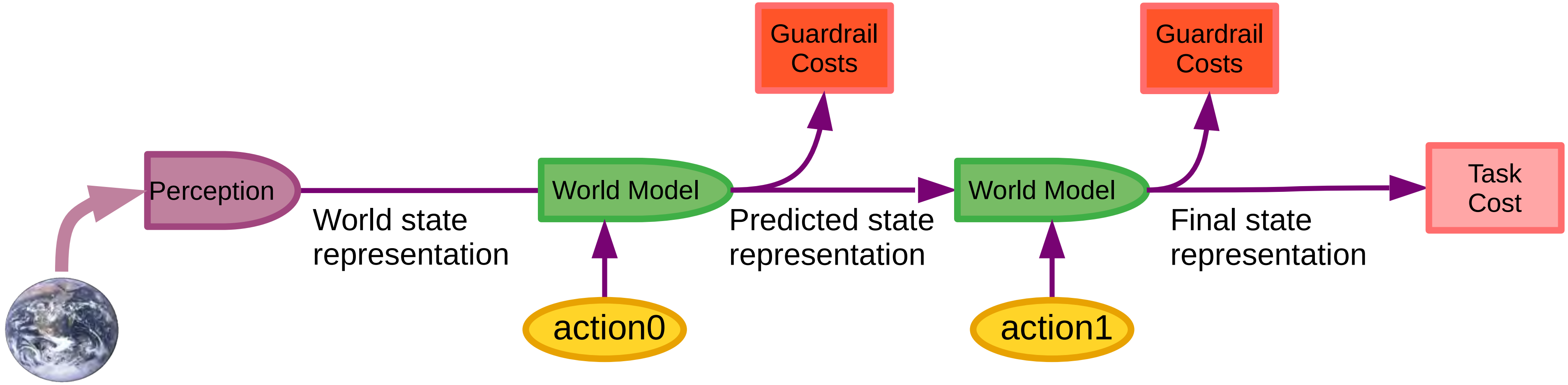
Objective-Driven AI

- **Perception:** Computes an abstract representation of the state of the world
  - Possibly combined with previously-acquired information in memory
- **World Model:** Predict the state resulting from an imagined action sequence
- **Task Objective:** Measures divergence to goal
- **Guardrail Objective:** Immutable objective terms that ensure safety
- **Operation:** Finds an action sequence that minimizes the objectives



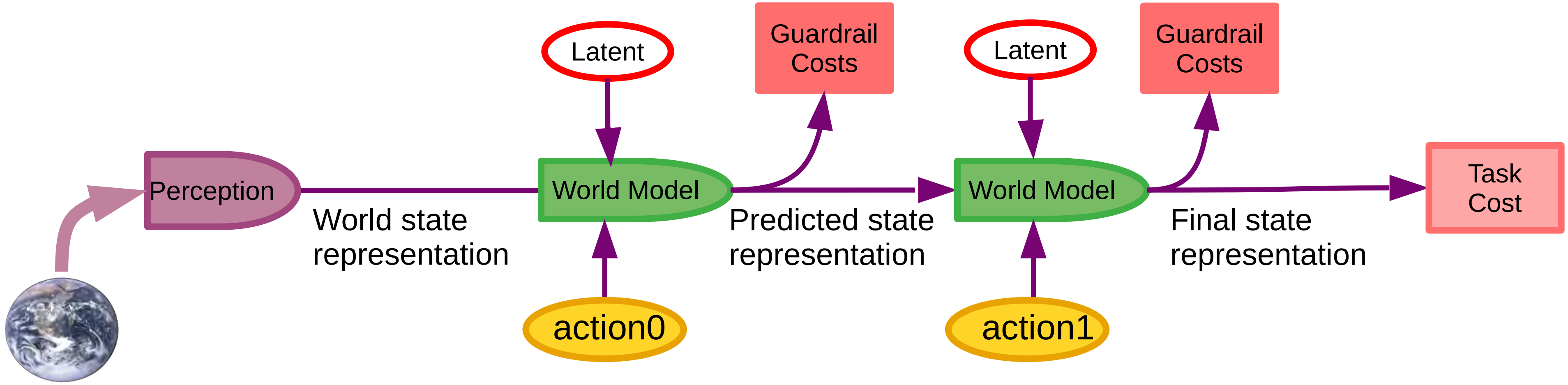
Objective-Driven AI: Multistep/Recurrent World Model

- **Same world model applied at multiple time steps**
- **Guardrail costs applied to entire state trajectory**
- **This is identical to Model Predictive Control (MPC)**
- **Action inference by minimization of the objectives**
  - Using gradient-based method, graph search, dynamic prog, A*, MCTS,….



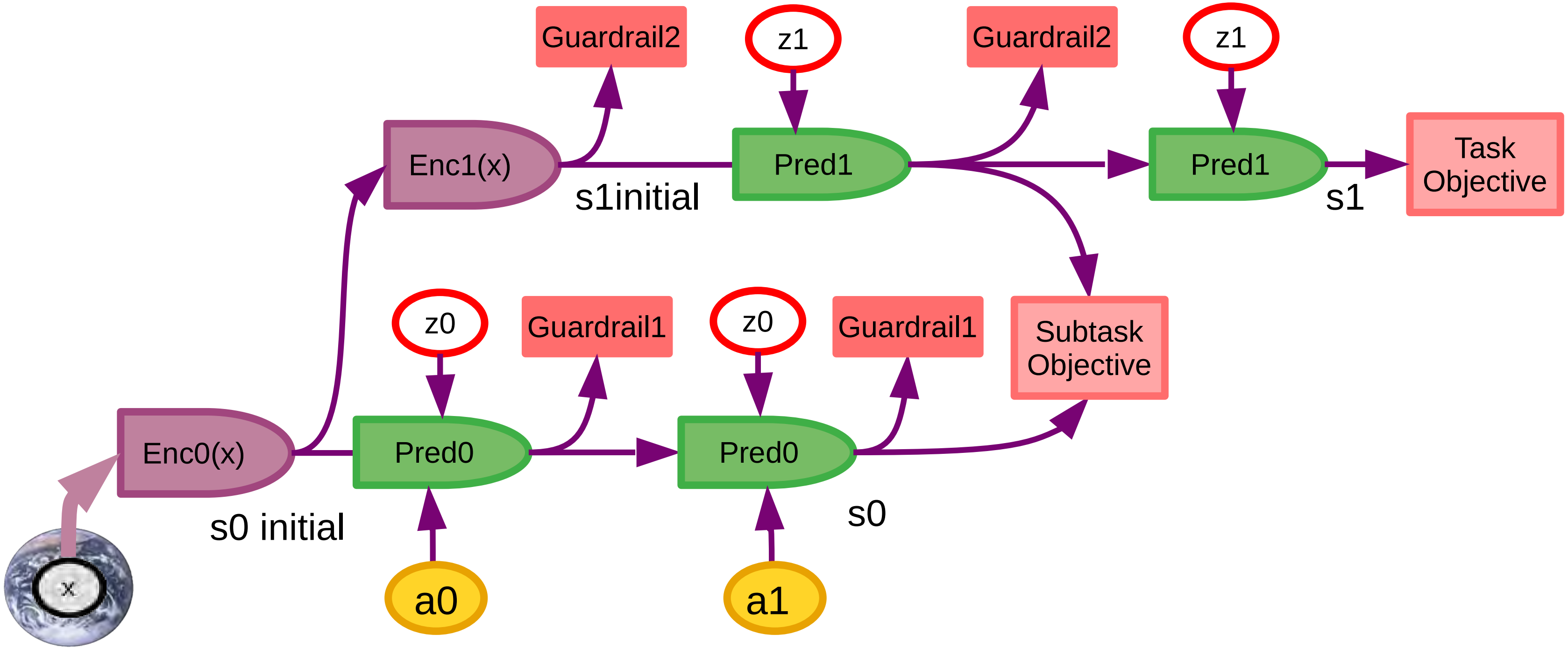
Objective-Driven AI: Non-Deterministic World Model

- **The world is not deterministic or fully predictable**
- **Latent variables parameterize the set of plausible predictions**
  - Can be sampled from a prior or swept through a set.
  - Planning can be done for worst case or average case
  - Uncertainty in outcome can be predicted and quantified



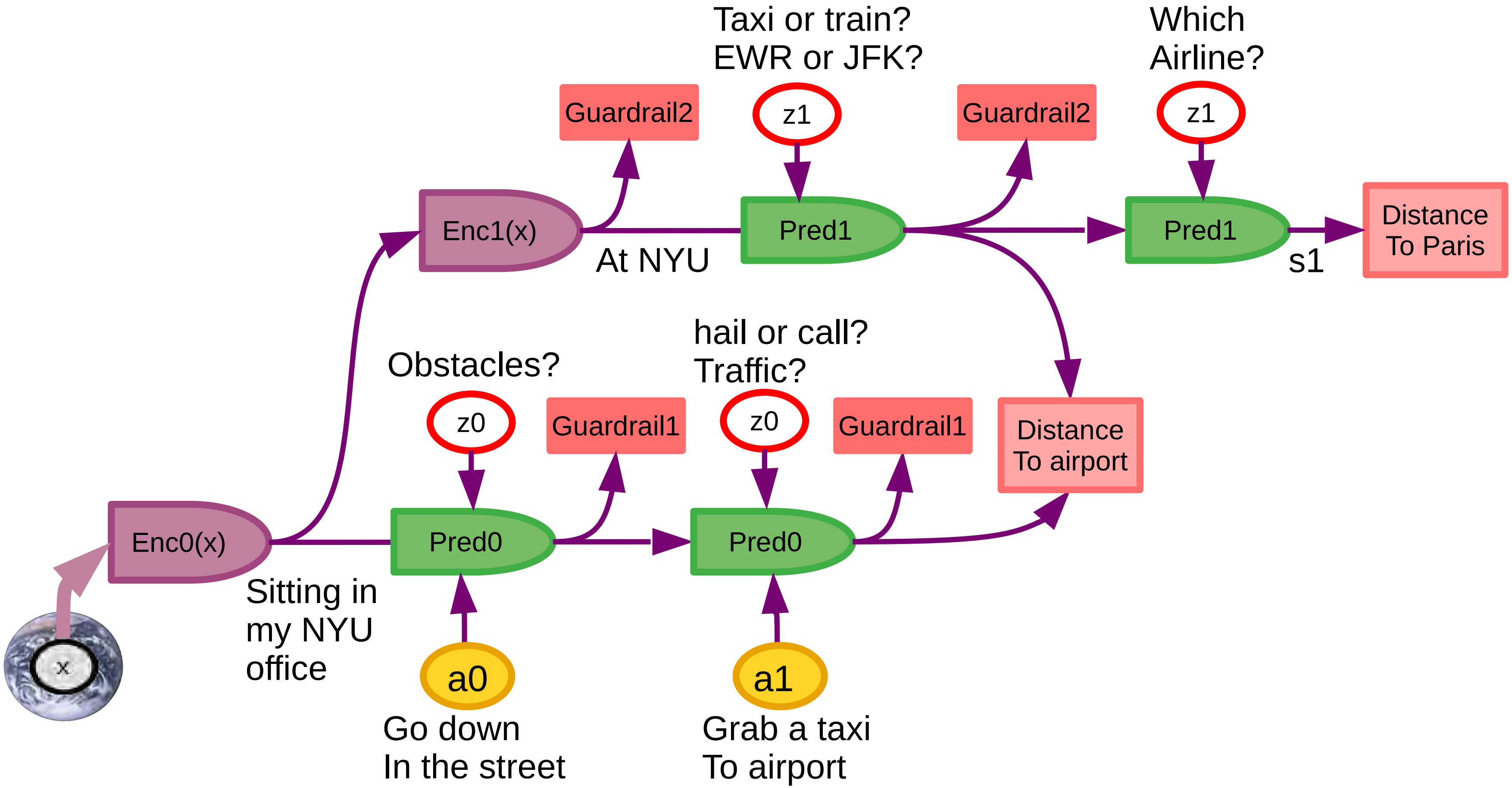
Objective-Driven AI: Hierarchical Planning

- **Hierarchical World Model and Planning**
  - Higher levels make longer-term predictions in more abstract representations
  - Predicted states at higher levels define subtask objectives for lower level
  - Guardrail objectives ensure safety at every level



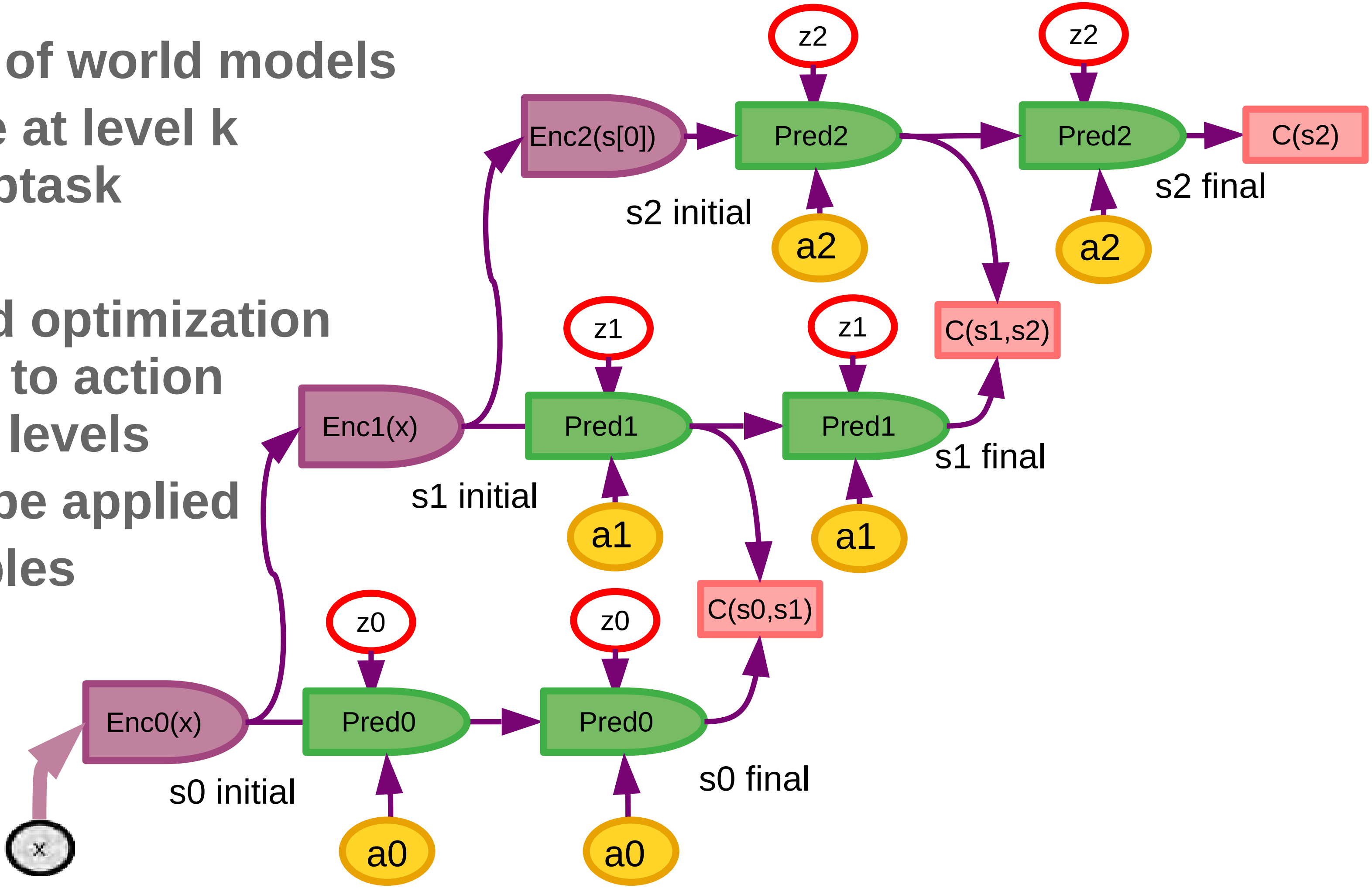
Objective-Driven AI: Hierarchical Planning

- Hierarchical Planning: going from NYU to Paris



Objective-Driven AI: Hierarchical Planning

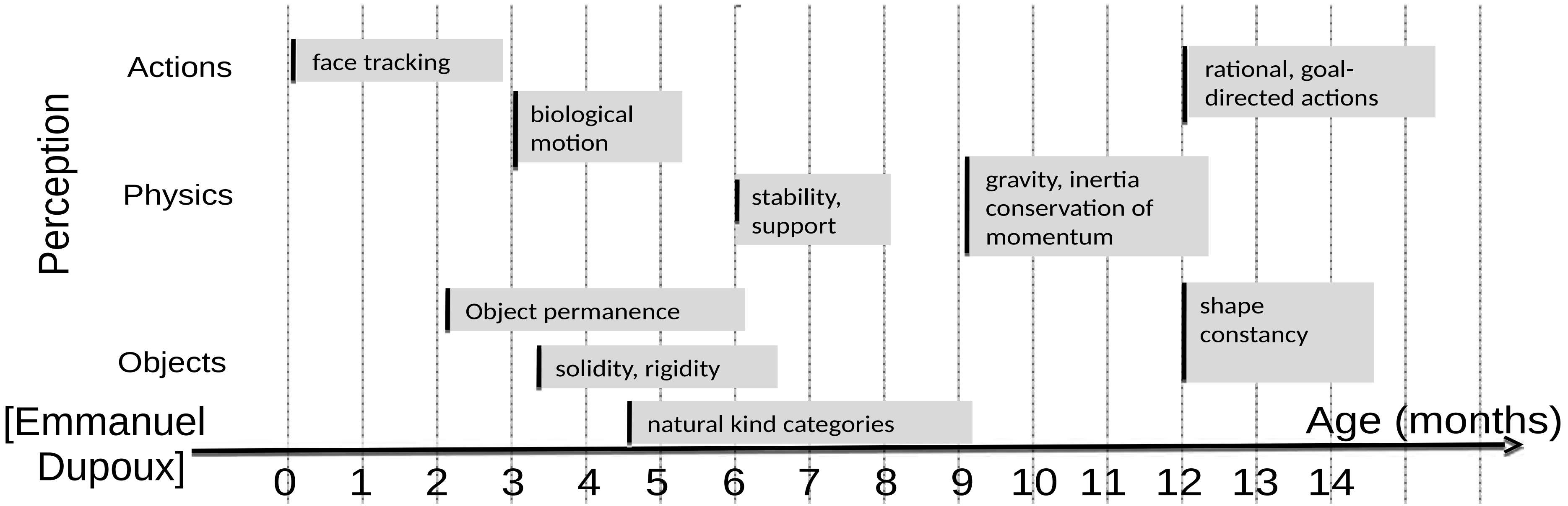
- Multiple levels of world models
- Predicted state at level k determines subtask for level k-1
- Gradient-based optimization can be applied to action variables at all levels
- Sampling can be applied to latent variables at all levels.



How could Machines Learn World Models from Sensory Input?

with
Self-Supervised Learning

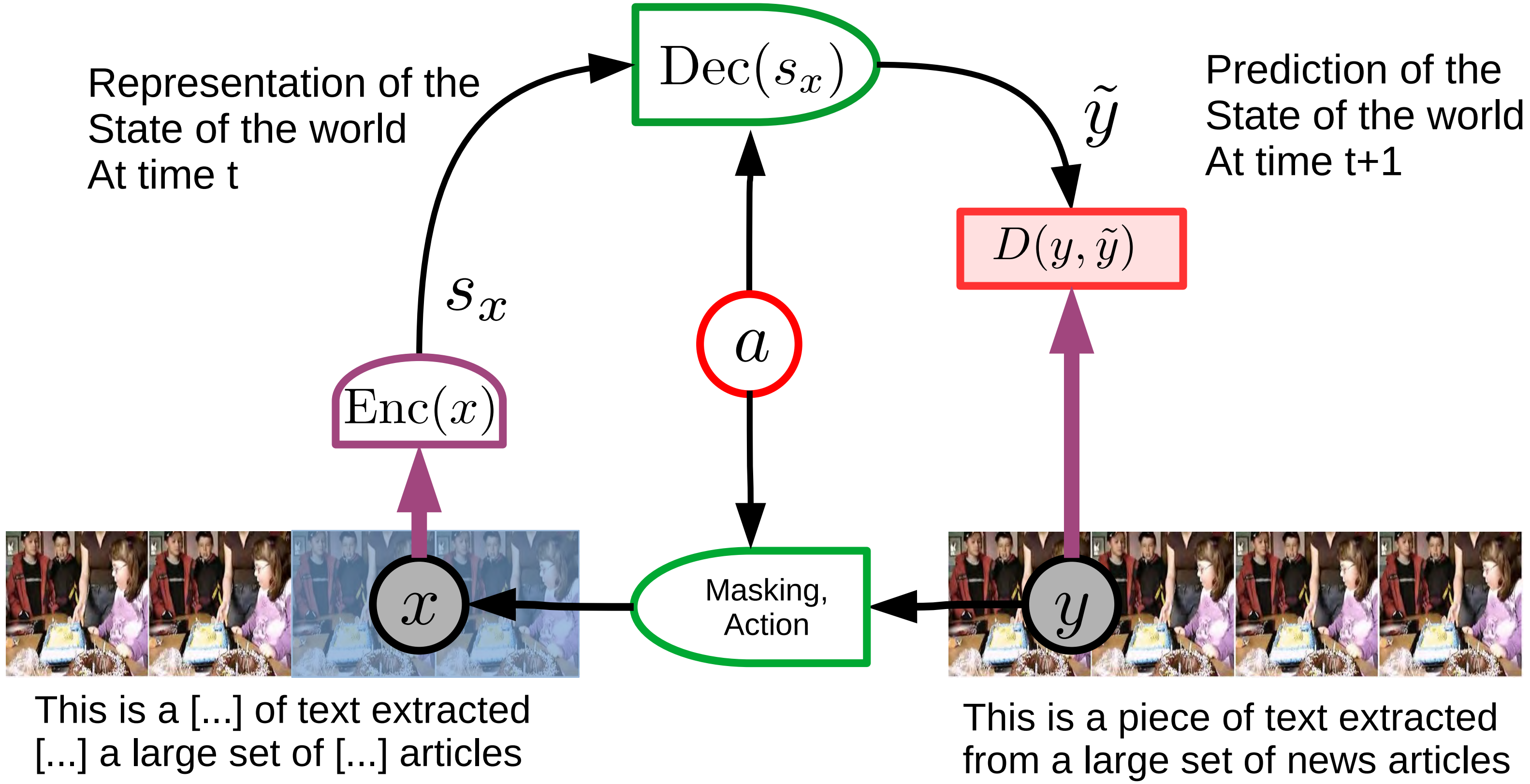
How could machines learn like animals and humans?



- **How do babies learn how the world works?**

Generative World Models with Self-Supervised Training?

- **Generative world model architecture**

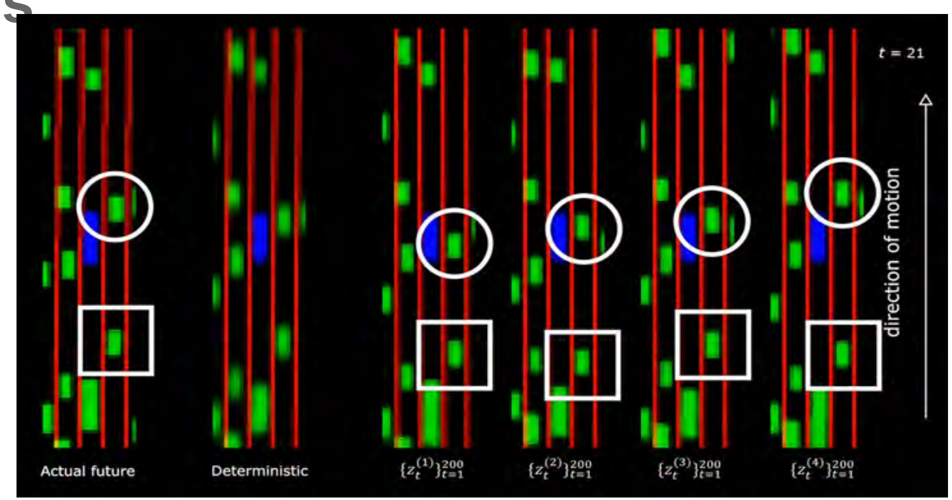


Generative Architectures DO NOT Work for Images

- Because the world is only partially predictable
- A predictive model should represent multiple predictions
- Probabilistic models are intractable in high-dim continuous domains.
- Generative Models must predict every detail of the world

- **My solution: Joint-Embedding Predictive Architecture**

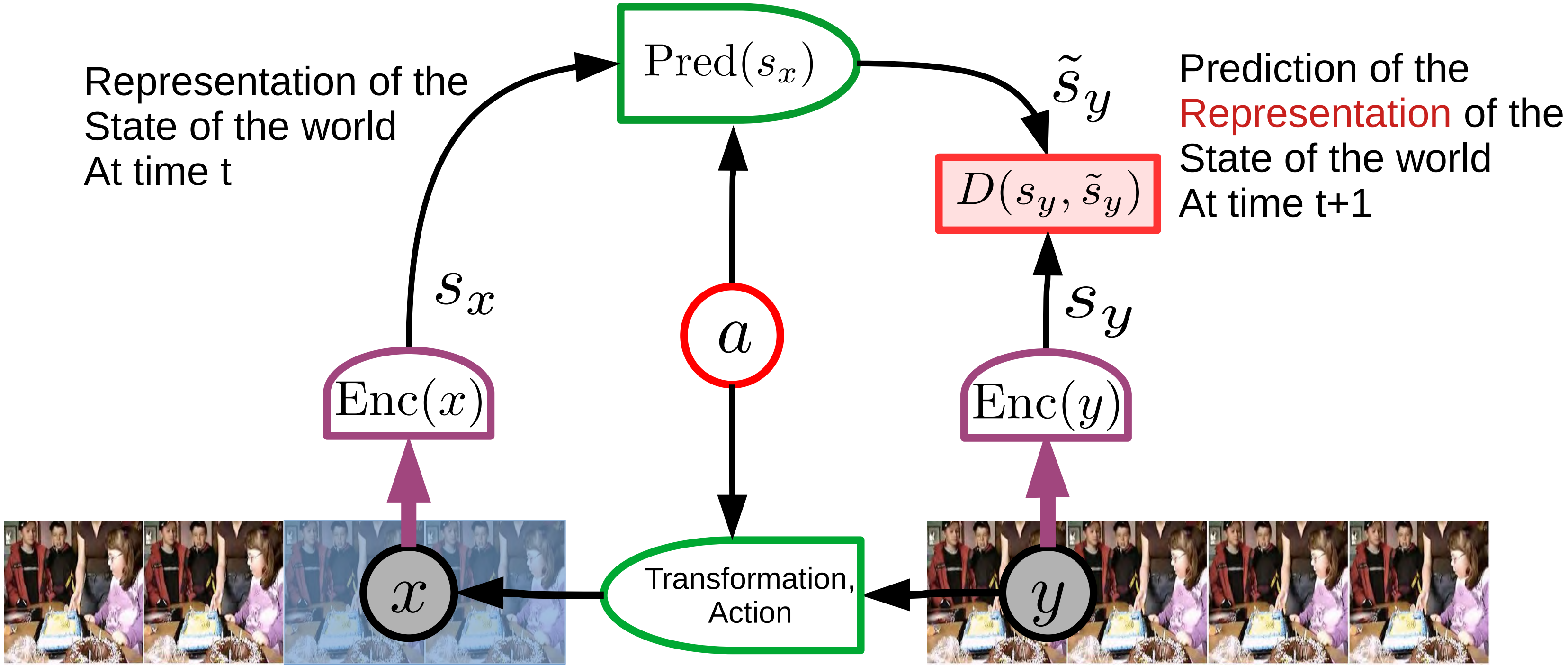
[Mathieu, Couprie, LeCun ICLR 2016]



[Henaff, Canziani, LeCun ICLR 2019]

Joint Embedding World Model: Self-Supervised Training

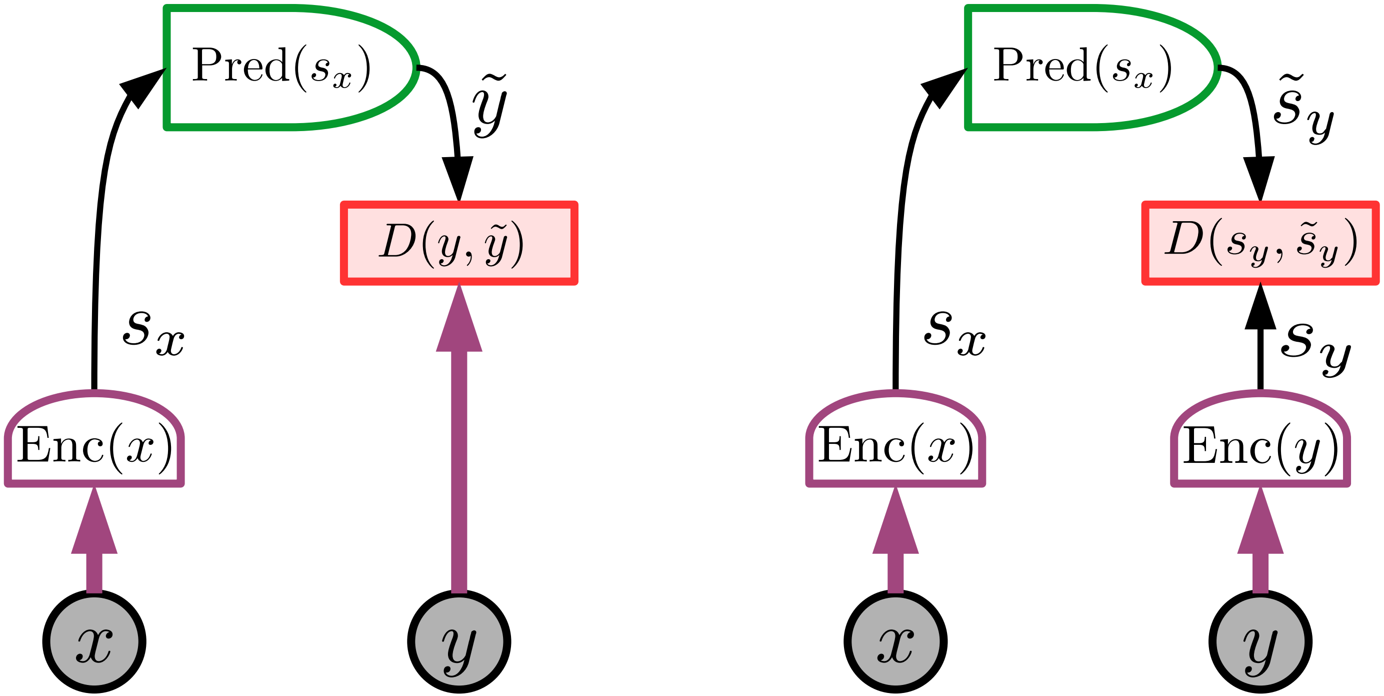
- **Joint Embedding Predictive Architecture [LeCun 2022], [Assran 2023]**



Architectures: Generative vs Joint Embedding

Y. LeCun

- **Generative: predicts y** (with all the details, including irrelevant ones)
- **Joint Embedding: predicts an abstract representation of y**

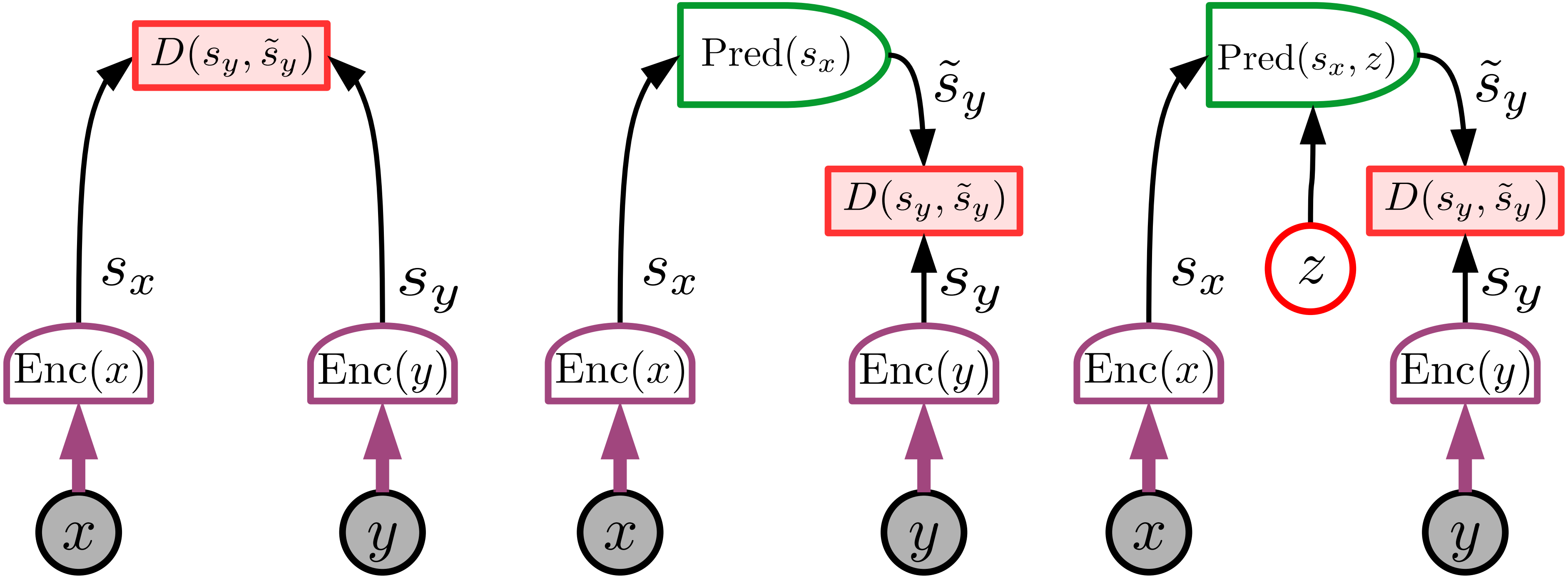


a) Generative Architecture
Examples: VAE, MAE...

b) Joint Embedding Architecture

Joint Embedding Architectures

- Computes abstract representations for x and y
- Tries to make them equal or predictable from each other.



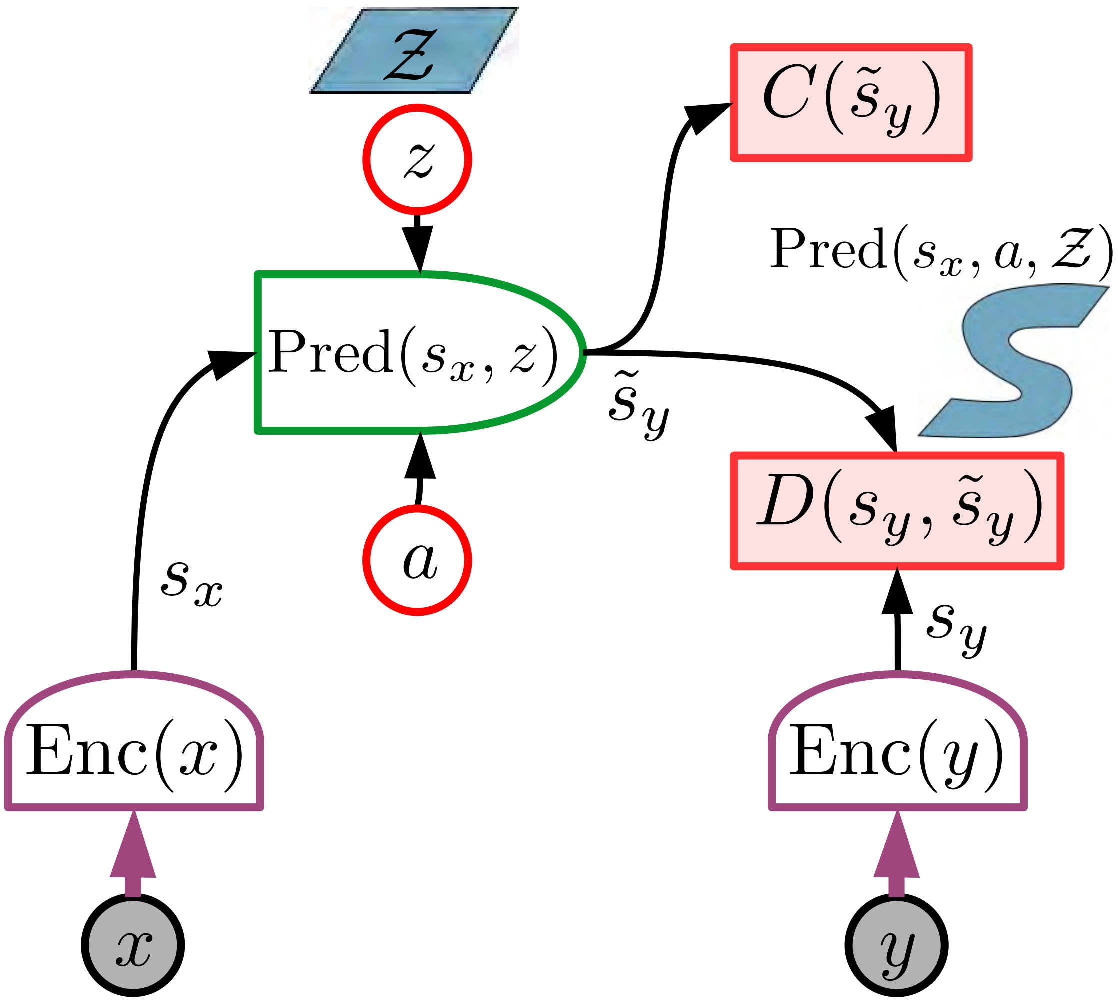
a) Joint Embedding Architecture (JEA)
Examples: Siamese Net, Pirl, MoCo, SimCLR, BarlowTwins, VICReg,

b) Deterministic Joint Embedding Predictive Architecture (DJEPA)
Examples: BYOL, VICRegL, I-JEPA

c) Joint Embedding Predictive Architecture (JEPA)
Examples: Equivariant VICReg
I-JEPA…..

Architecture for the world model: JEPA

- **JEPA: Joint Embedding Predictive Architecture.**
  - x: observed past and present
  - y: future
  - a: action
  - z: latent variable (unknown)
  - D( ): prediction cost
  - C( ): surrogate cost
  - JEPA predicts a representation of the future Sy from a representation of the past and present Sx

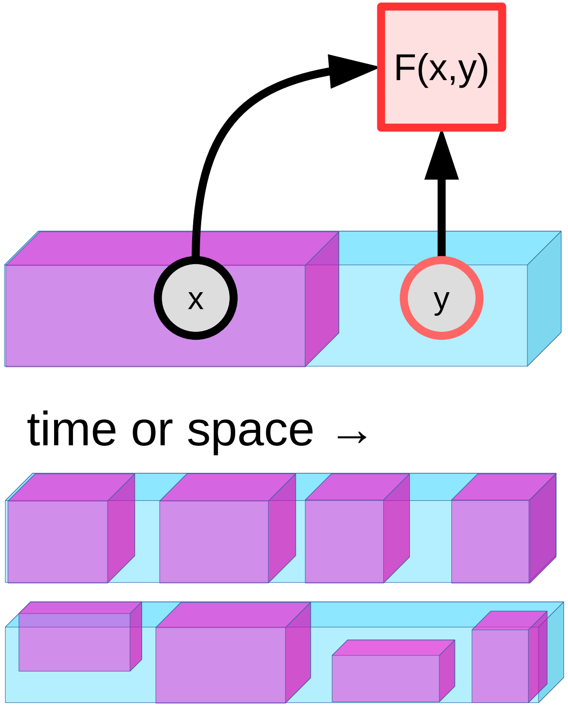


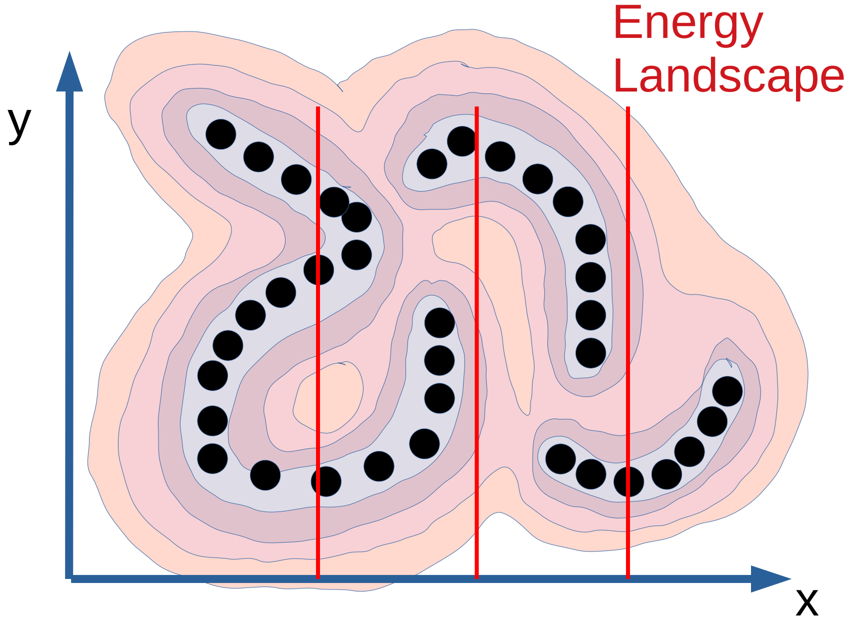
Energy-Based Models

Capturing dependencies through an energy function

Energy-Based Models: Implicit function

- **The only way to formalize & understand all model types**
  - Gives low energy to compatible pairs of x and y
  - Gives higher energy to incompatible pairs



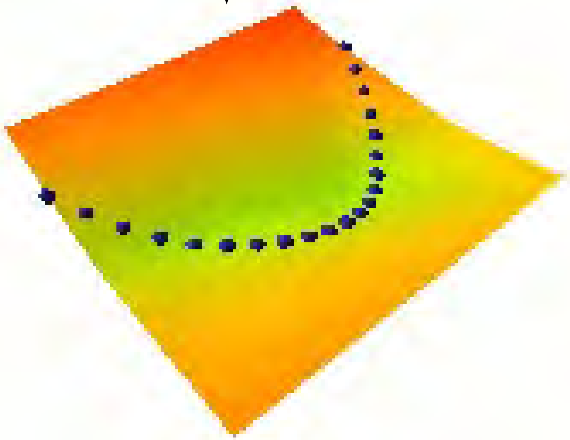


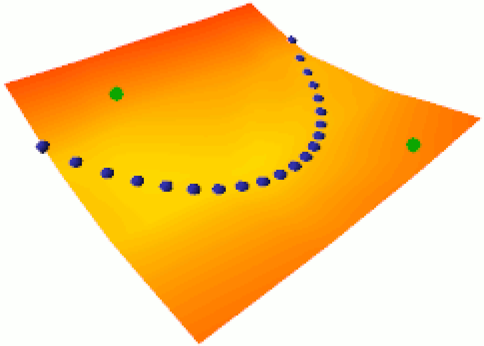
$$\check{y} = \text{argmin}_y F(x, y)$$

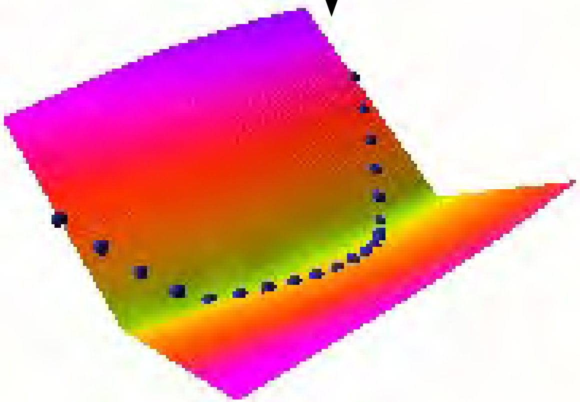
Training Energy-Based Models: Collapse Prevention

- **A flexible energy surface can take any shape.**
- **We need a loss function that shapes the energy surface so that:**
  - Data points have low energies
  - Points outside the regions of high data density have higher energies.

Collapse! **Contrastive Method** **Regularized Methods**

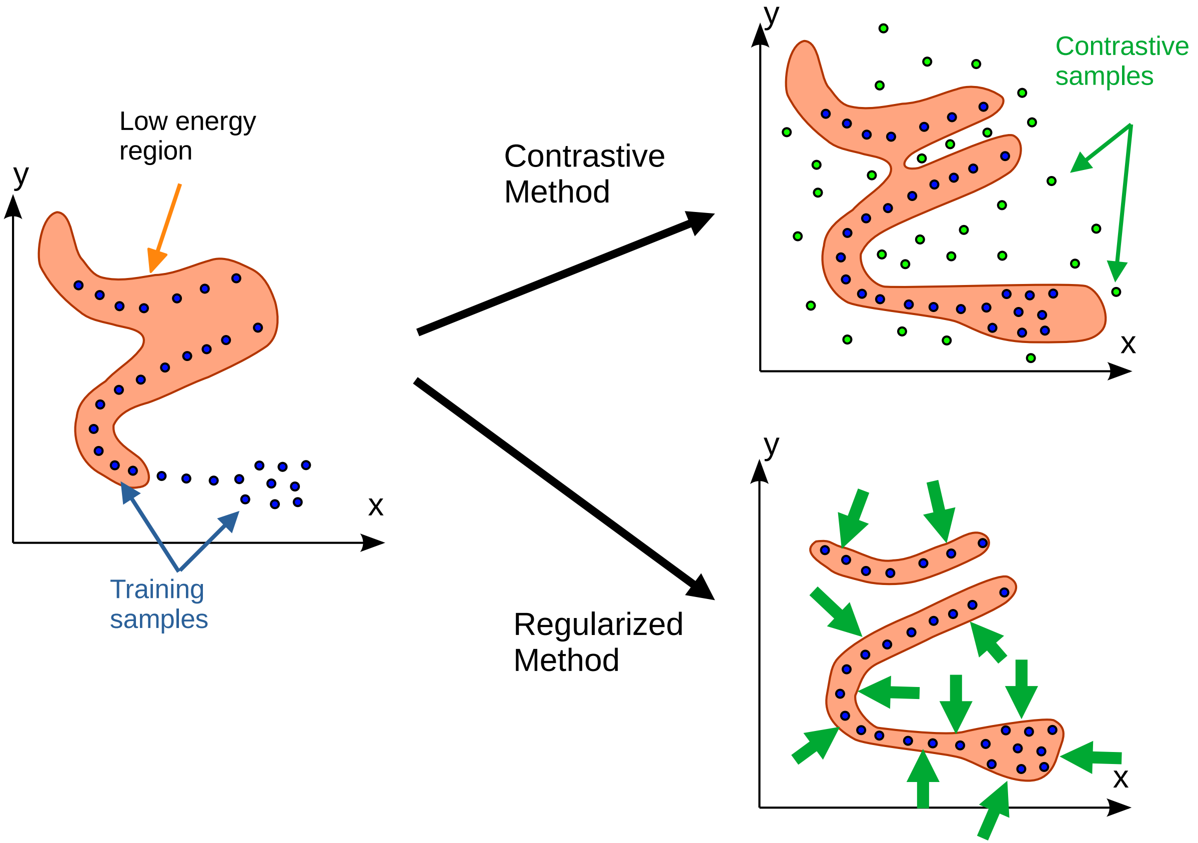






EBM Training: two categories of methods

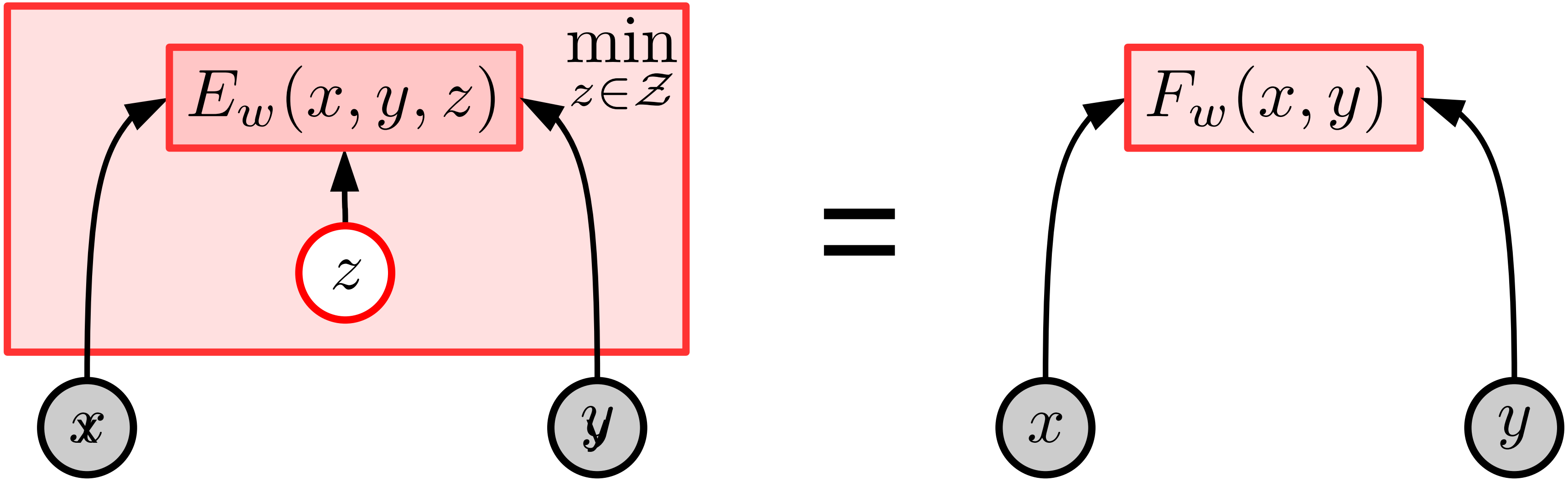
- **Contrastive methods**
  - Push down on energy of training samples
  - Pull up on energy of suitably-generated contrastive samples
  - Scales very badly with dimension
- **Regularized Methods**
  - Regularizer minimizes the volume of space that can take low energy



Latent-Variable EBM

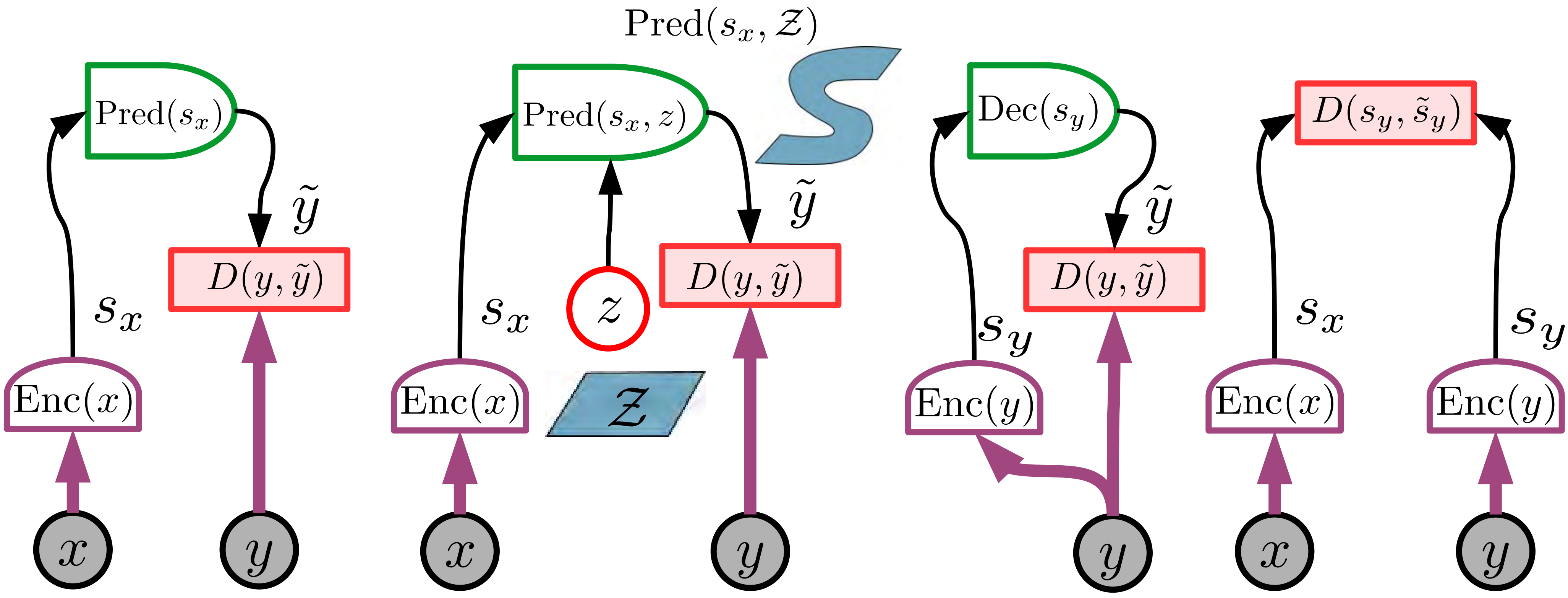
- **Latent variable z:**
  - Captures the information in y that is not available in x
  - Computed by minimization

$$\check{z} = \text{argmin}_{z \in \mathcal{Z}} E_w(x, y, z) \qquad F_w(x, y) = E_w(x, y, \check{z})$$



EBM Architectures

- Some architectures can lead to a collapse of the energy surface



a) Prediction / regression
NO COLLAPSE

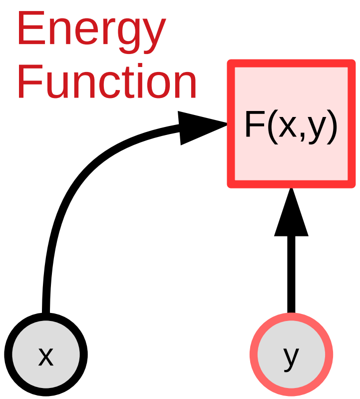
b) Generative latent-variable Architecture
CAN COLLAPSE

c) Auto-Encoder
CAN COLLAPSE

d) Joint Embedding Architecture
CAN COLLAPSE

Energy-Based Models vs Probabilistic Models

- **Probabilistic models are a special case of EBM**
  - Energies are like un-normalized negative log probabilities
- **Why use EBM instead of probabilistic models?**
  - EBM gives more flexibility in the choice of the scoring function.
  - More flexibility in the choice of objective function for learning
- **From energy to probability: Gibbs-Boltzmann distribution**
  - Beta is a positive constant



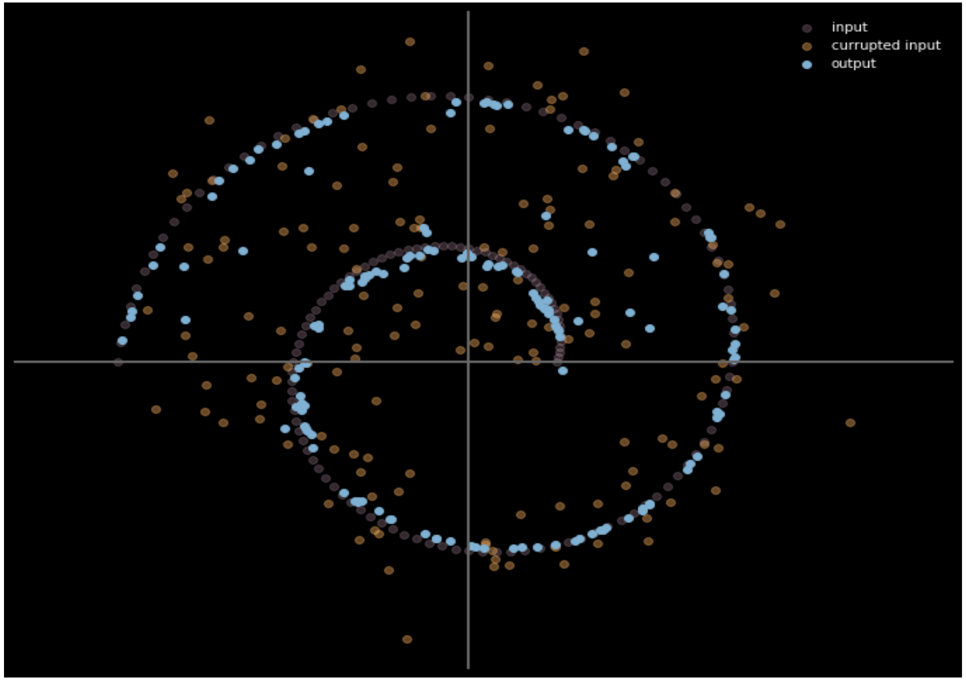
$$P(y|x) = \frac{e^{-\beta F(x,y)}}{\int_{y'} e^{-\beta F(x,y')}}$$

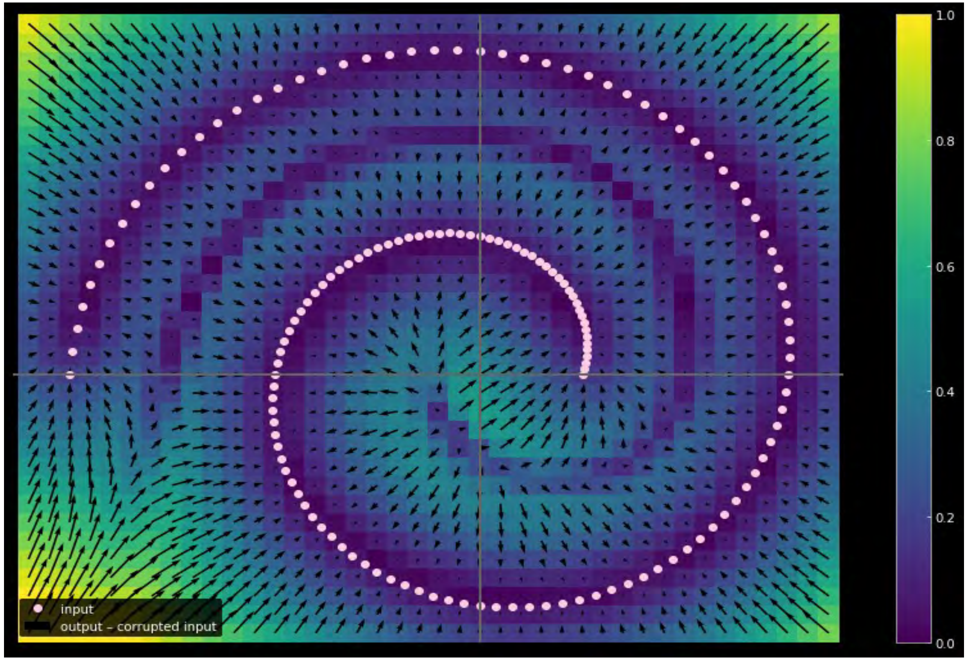
Contrastive Methods vs Regularized/Architectural Methods

- **Contrastive: [they all are different ways to pick which points to push up]**
  - C1: push down of the energy of data points, push up everywhere else: Max likelihood (needs tractable partition function or variational approximation)
  - C2: push down of the energy of data points, push up on chosen locations: max likelihood with MC/MMC/HMC, Contrastive divergence, Metric learning/Siamese nets, Ratio Matching, Noise Contrastive Estimation, Min Probability Flow, adversarial generator/GANs
  - C3: train a function that maps points off the data manifold to points on the data manifold: denoising auto-encoder, masked auto-encoder (e.g. BERT)
- **Regularized/Architectural: [Different ways to limit the information capacity of the latent representation]**
  - A1: build the machine so that the volume of low energy space is bounded: PCA, K-means, Gaussian Mixture Model, Square ICA, normalizing flows…
  - A2: use a regularization term that measures the volume of space that has low energy: Sparse coding, sparse auto-encoder, LISTA, Variational Auto-Encoders, discretization/VQ/VQVAE.
  - A3: F(x,y) = C(y, G(x,y)), make G(x,y) as "constant" as possible with respect to y: Contracting auto-encoder, saturating auto-encoder
  - A4: minimize the gradient and maximize the curvature around data points: score matching

Contrastive EBM Training: Denoising Auto-Encoder

- [LeCun 1987], [Seung 1998], [Vincent 2008, 2010]
- NLP: BERT [

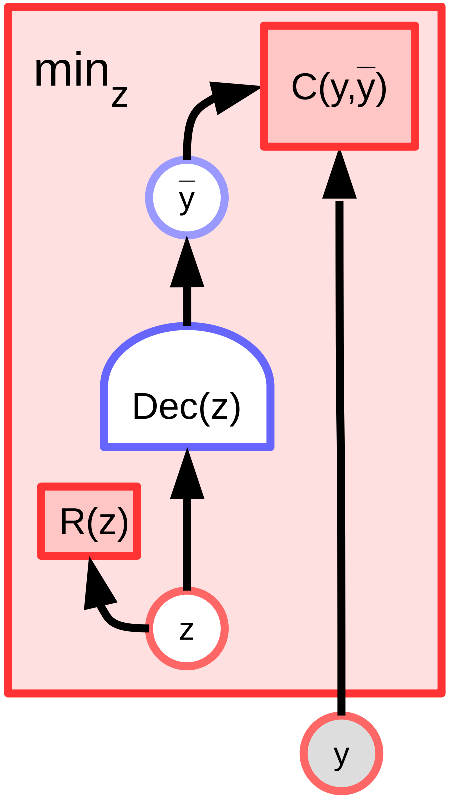




Figures: Alfredo Canziani

Example: Regularized Latent-Variable EBM

- **Basic idea: limiting the information capacity of the latent variable to limit the volume of low-energy regions**
- **Examples: K-Means, sparse coding**



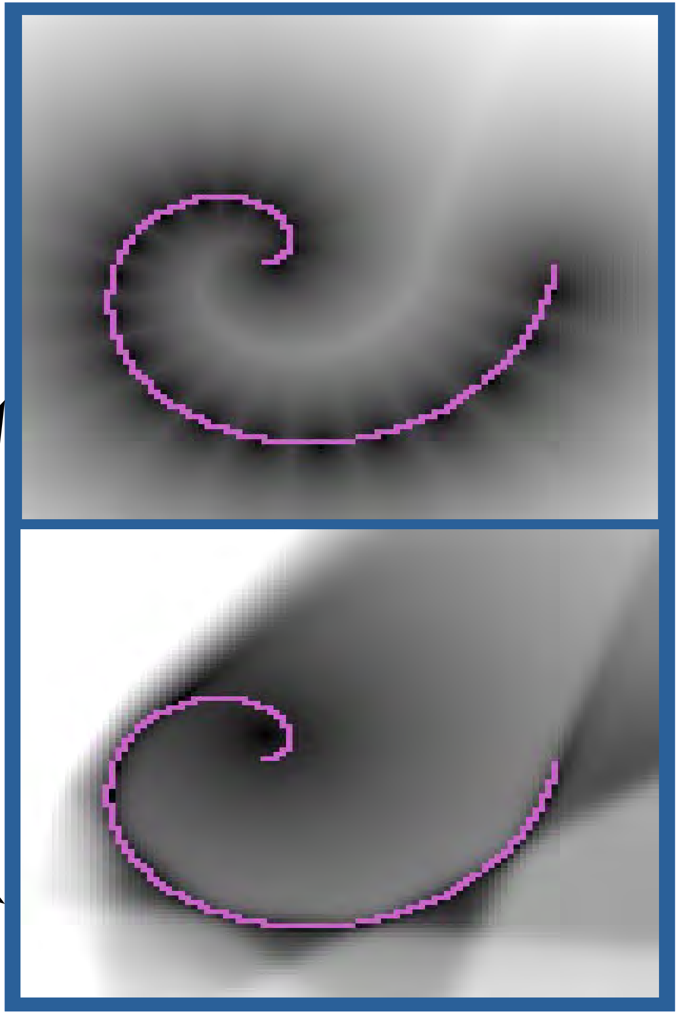
$$E(y,z) = C(y, \mathrm{Dec}(z)) + R(z)$$

$$F_\infty(x,y) = \min_z E(x,y,z)$$

$$\check{y}, \check{z} = \mathrm{argmin}_{y,z} E(x,y,z)$$

$$E(y,z) = ||y - Wz||^2 \quad z \in 1\, hot$$

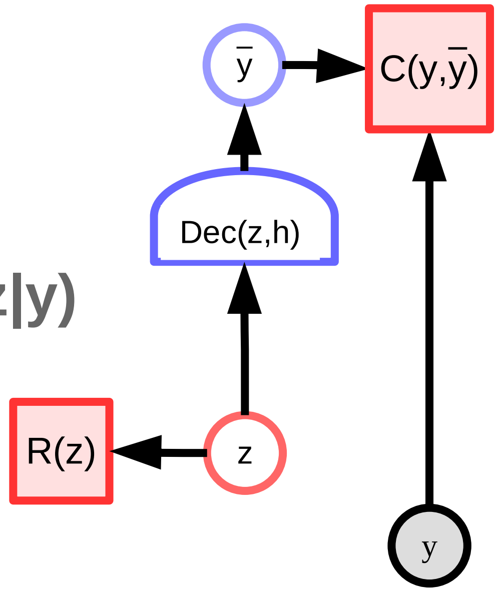
$$E(y,z) = ||y - wz||^2 + \lambda |z|_{L1|}$$



Regularizing z by making it “fuzzy” (stochastic)

- The information content of the latent variable z must be minimized
- One (probabilistic) way to do this:
  - make z “fuzzy” (e.g. stochastic)
  - z is a sample from a distribution q(z|y)

$$E(y,z) = C(y, Dec(z))$$



- Minimize the expected value of the energy under q(z|y)

$$< E(y) >= \int_z q(z|y) E(y,z)$$

- Minimize the information content of q(z|y) about y

Minimize expected energy & information content of z

- **Minimize the expected energy**

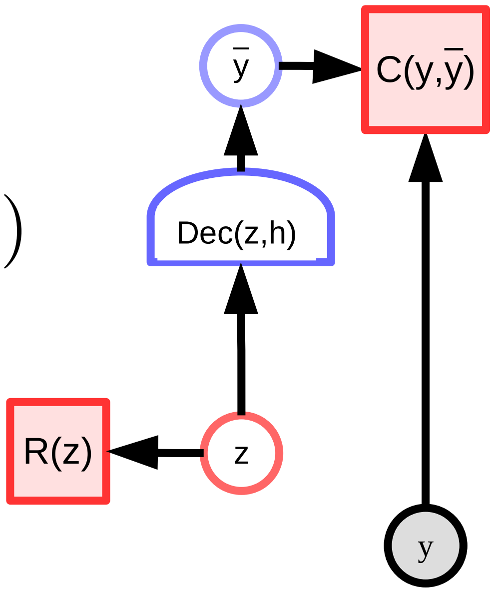
$$< E(y) >_q = \int_z q(z|y) E(y,z)$$

$$E(y,z) = C(y, Dec(z))$$

- **Minimize the relative entropy**
  - Between q(z|y) and a prior distribution p(z).

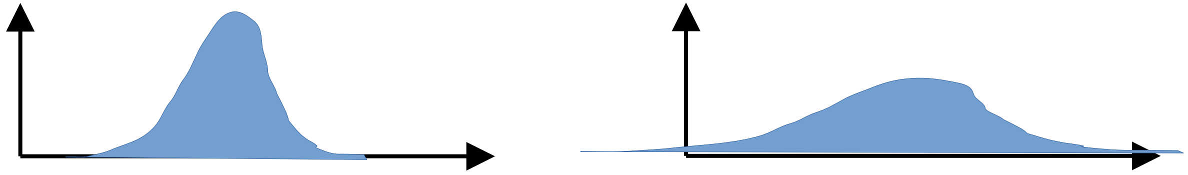
$$KL(q(z|y), p(z)) = \int_z q(z|y) \log_2(q(z|y)/p(z))$$

  - This is the number of bits one sample from q(z|y) will give us about z, knowing that z comes from p(z)



Variational free energy: trades average energy and information in z

- **Find a distribution q(z|y) that minimizes the expected energy while having maximum entropy**
  - high entropy distribution == small information content from a sample



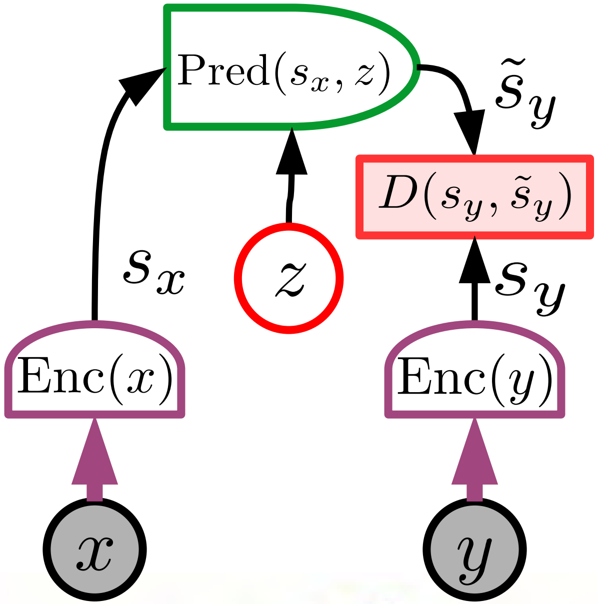
  - Pick a family of distributions q(z|y) (e.g. Gaussians) and find the one that minimizes the **variational free energy**:

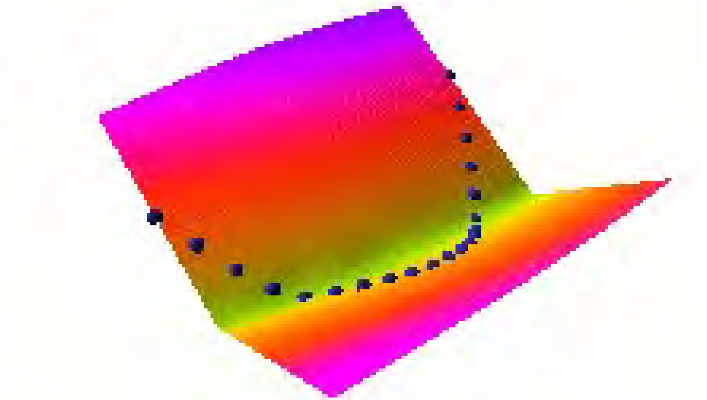
$$\tilde{F}_q(y) = \int_z q(z|y)E(y,z) + \frac{1}{\beta}\int_z q(z|y)\log_2(q(z|y)/p(z))$$

  - The trade-off between energy and entropy is controlled by the beta parameter.

Recommendations:

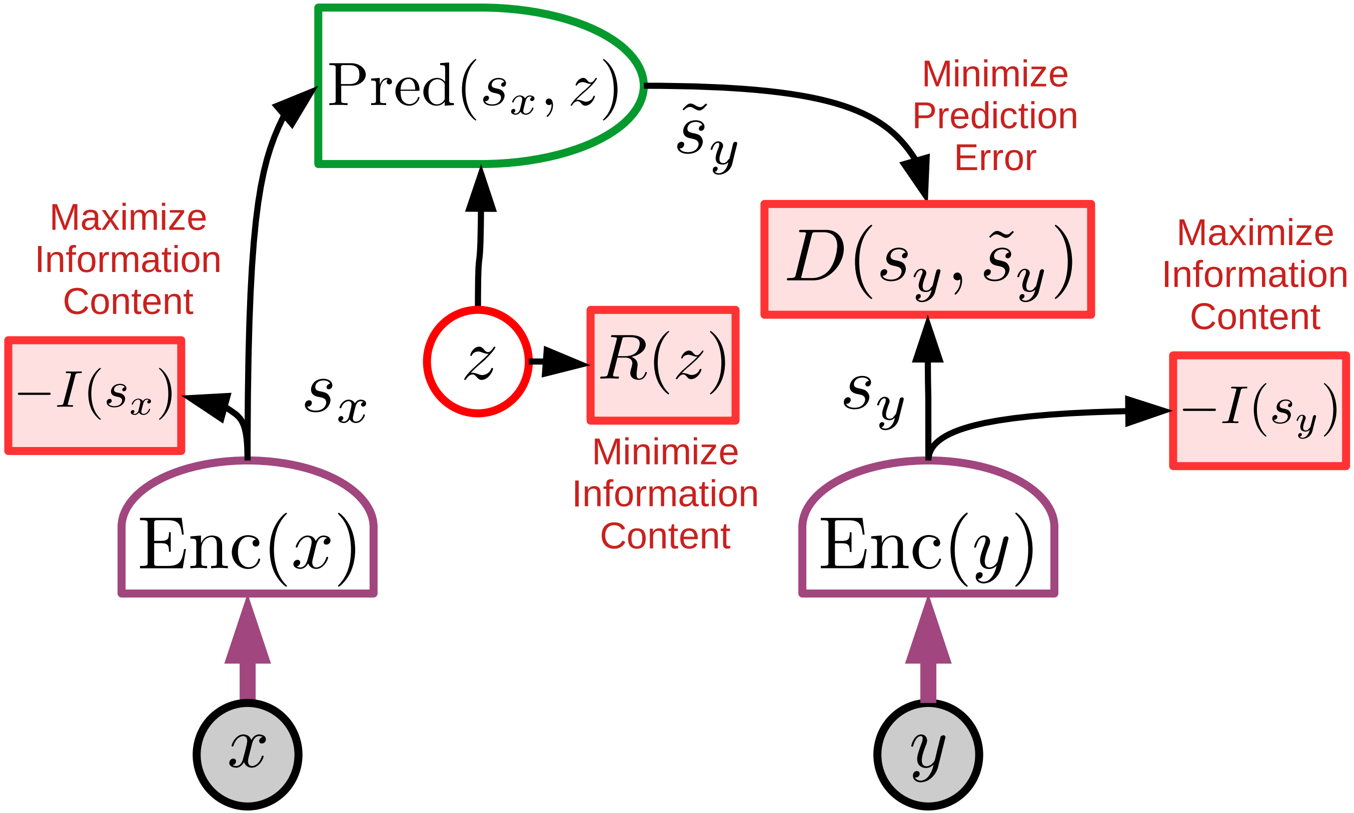
- **Abandon generative models**
  - in favor joint-embedding architectures
- **Abandon probabilistic model**
  - in favor of energy-based models
- **Abandon contrastive methods**
  - in favor of regularized methods
- **Abandon Reinforcement Learning**
  - In favor of model-predictive control
  - Use RL only when planning doesn't yield the predicted outcome, to adjust the world model or the critic.





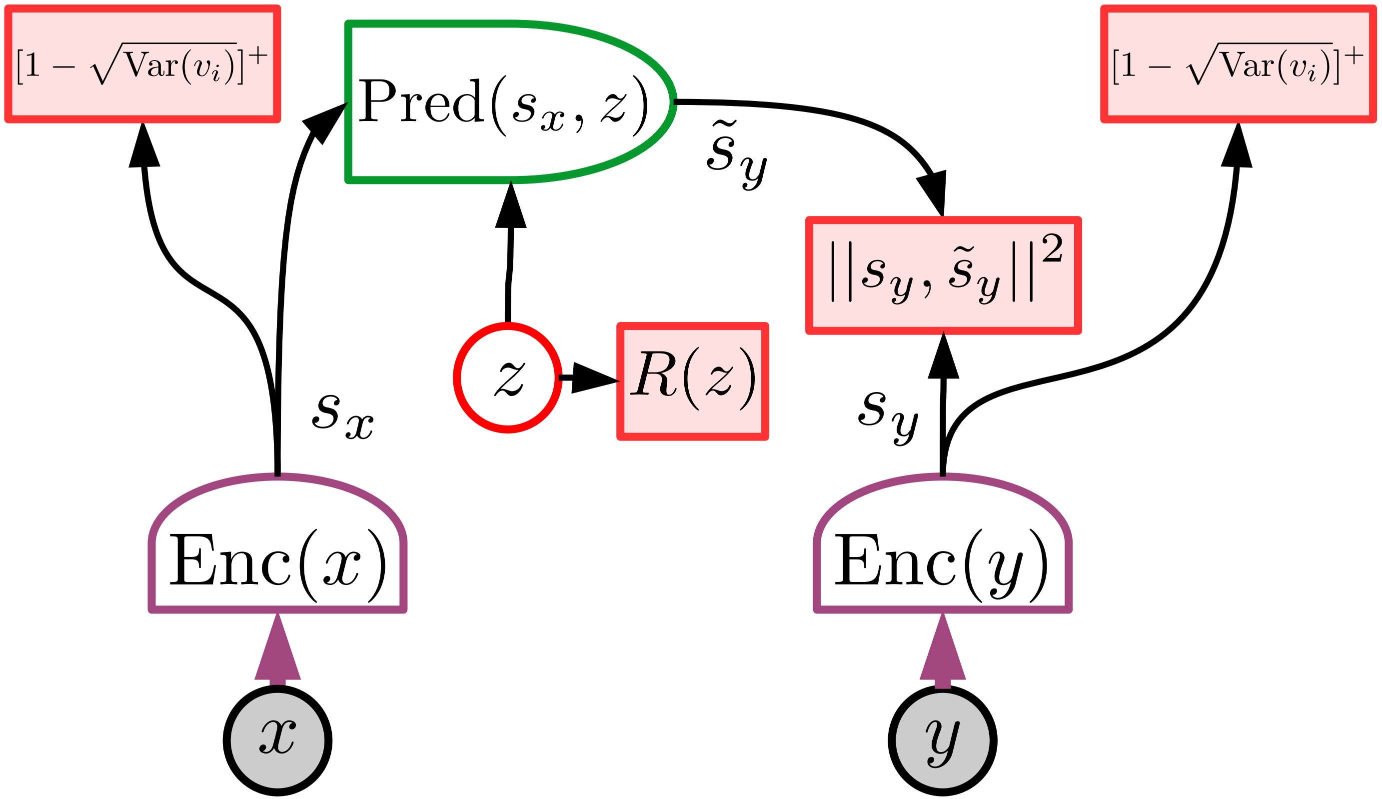
Training a JEPA with Regularized Methods

- **Four terms in the cost**
  - Maximize information content in representation of x
  - Maximize information content in representation of y
  - Minimize Prediction error
  - Minimize information content of latent variable z



VICReg: Variance, Invariance, Covariance Regularization

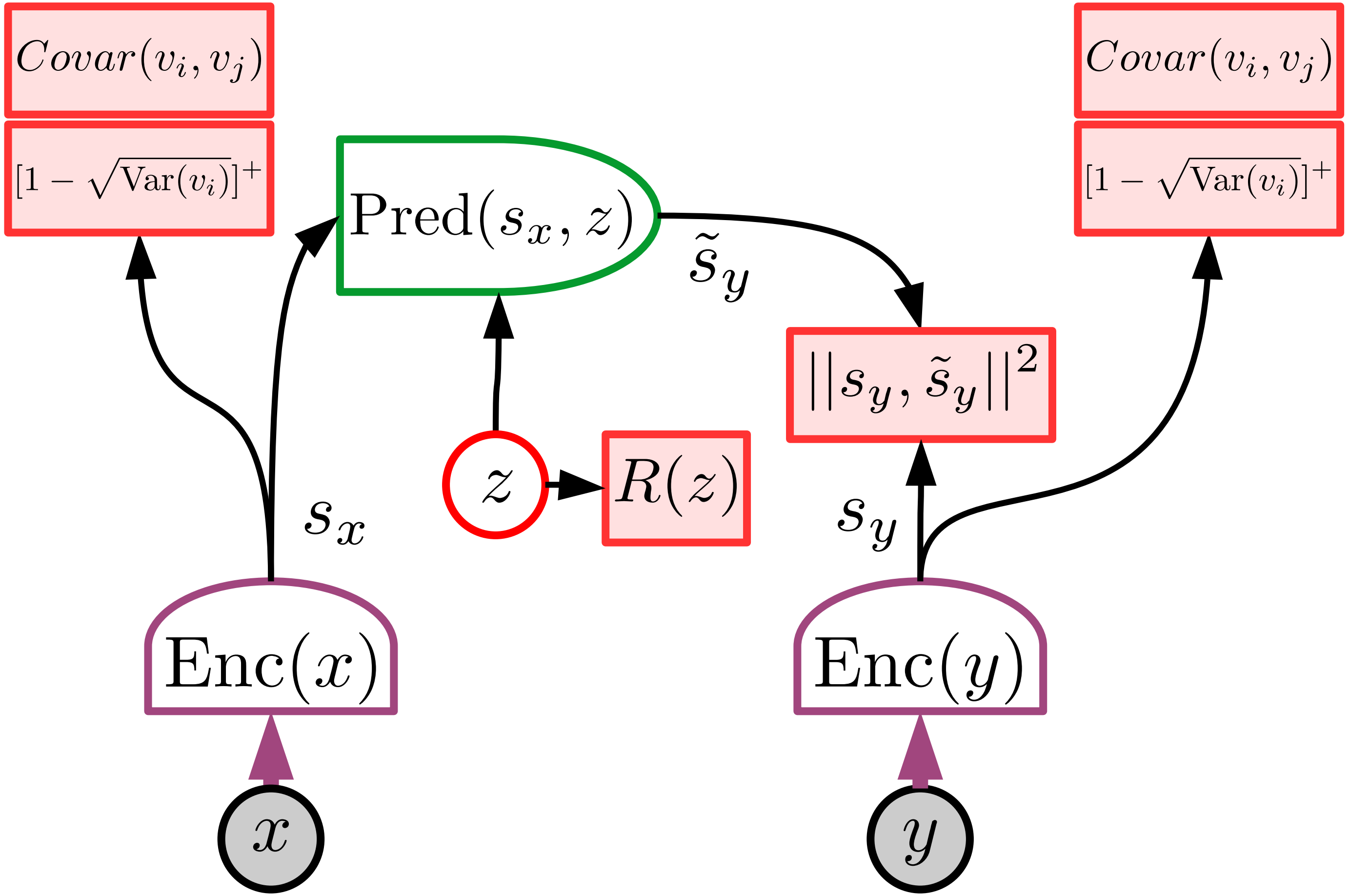
- **Variance:**
  - Maintains variance of components of representations
- **Invariance:**
  - Minimizes prediction error.



Barlow Twins [Zbontar et al. ArXiv:2103.03230], VICReg [Bardes, Ponce, LeCun arXiv:2105.04906, ICLR 2022], VICRegL [Bardes et al. NeurIPS 2022], MCR2 [Yu et al. NeurIPS 2020][Ma, Tsao, Shum, 2022]

VICReg: Variance, Invariance, Covariance Regularization

- **Variance:**
  - Maintains variance of components of representations
- **Covariance:**
  - Decorrelates components of covariance matrix of representations
- **Invariance:**
  - Minimizes prediction error.



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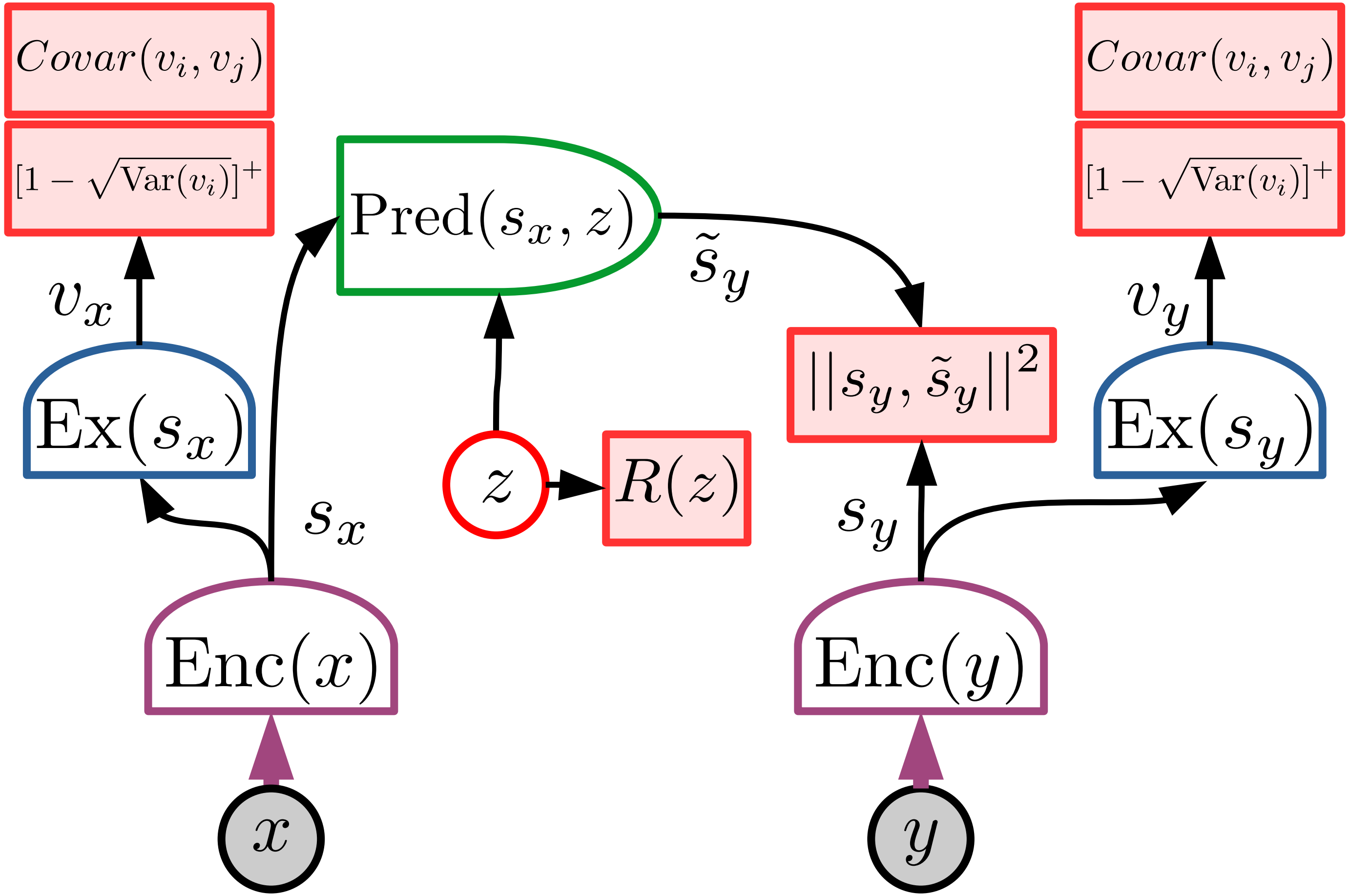
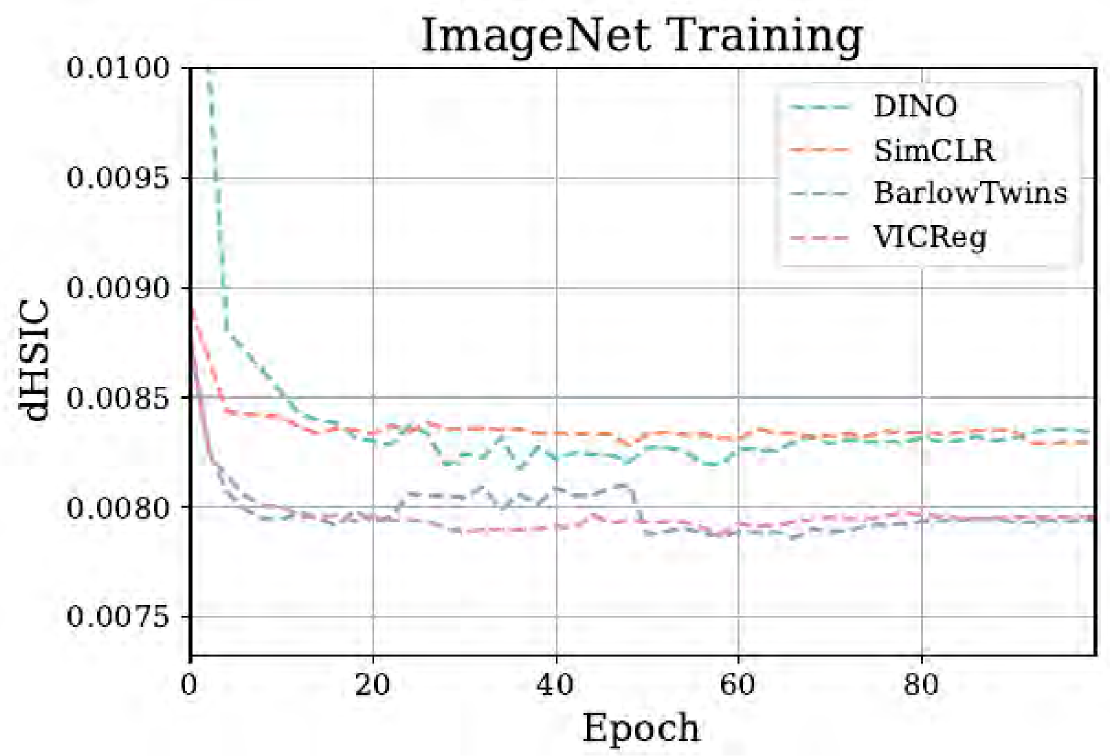
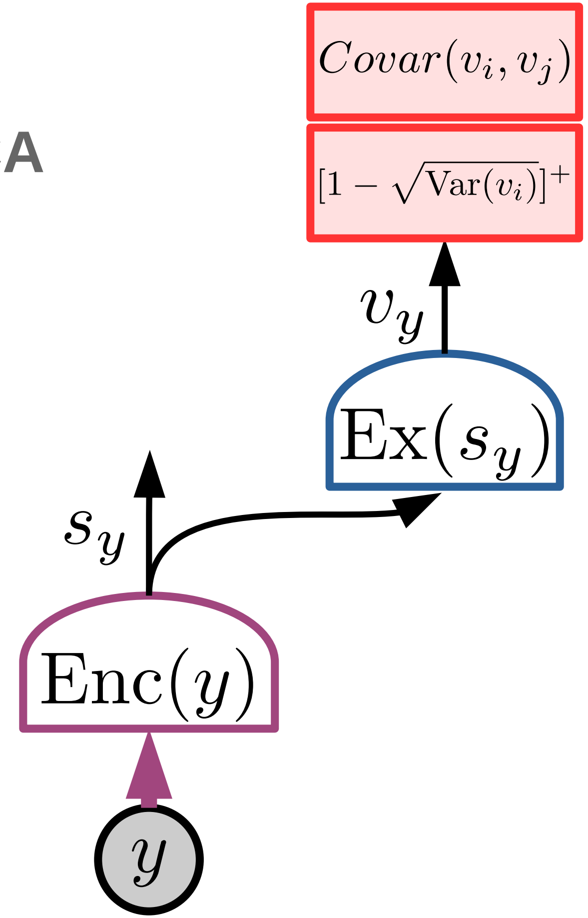


Barlow Twins [Zbontar et al. ArXiv:2103.03230], VICReg [Bardes, Ponce, LeCun arXiv:2105.04906, ICLR 2022], VICRegL [Bardes et al. NeurIPS 2022], MCR2 [Yu et al. NeurIPS 2020][Ma, Tsao, Shum, 2022]

VICReg: expander makes variables pairwise independent

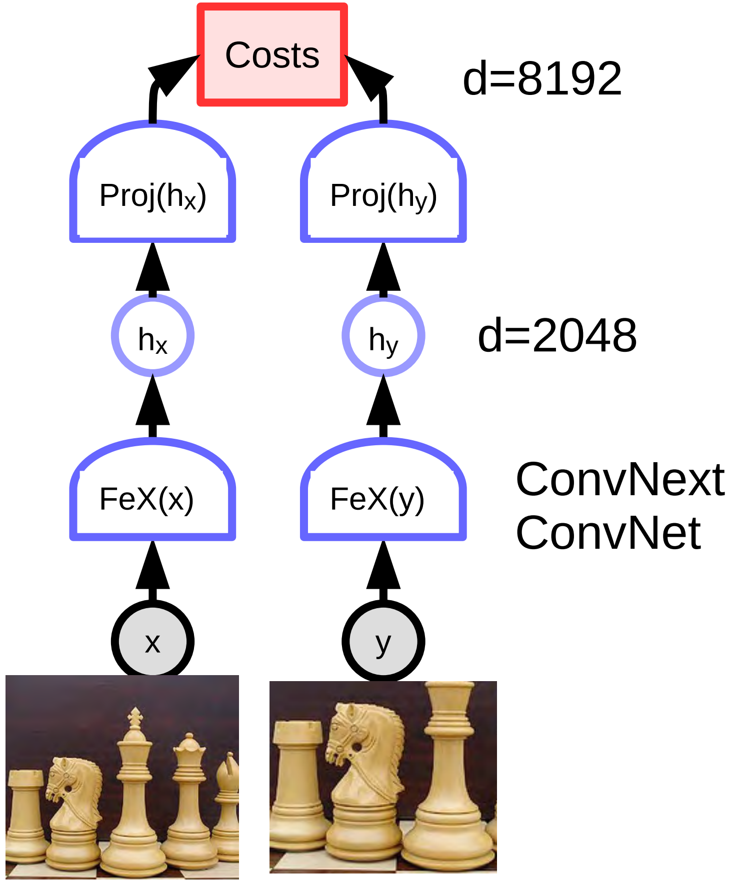
- [Mialon, Balestriero, LeCun arxiv:2209.14905]
- VC criterion can be used for source separation / ICA



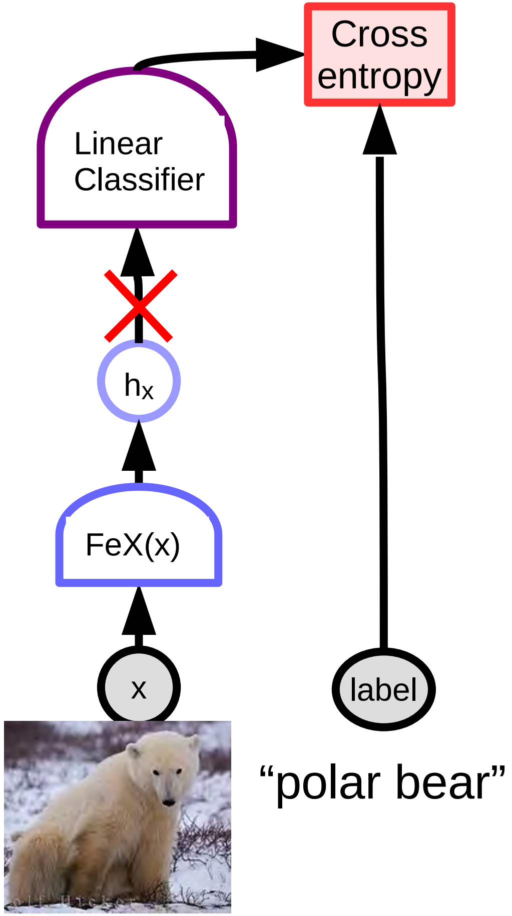


SSL-Pretrained Joint Embedding for Image Recognition

JEA pretrained with VICReg



Training a supervised linear head



VICReg: Results with linear head and semi-supervised.

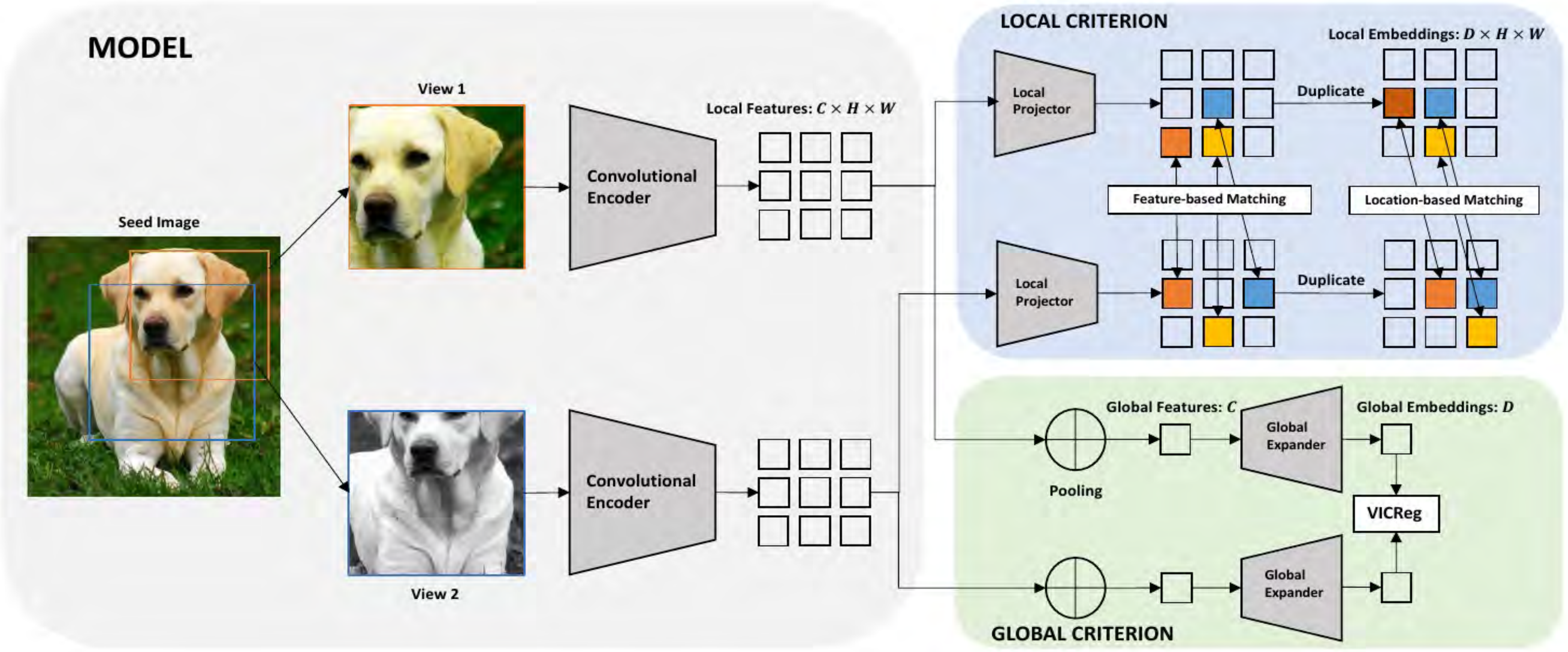
Method	Linear Top-1	Linear Top-5	Semi-supervised Top-1 1%	Semi-supervised Top-1 10%	Semi-supervised Top-5 1%	Semi-supervised Top-5 10%
Supervised	76.5	-	25.4	56.4	48.4	80.4
MoCo He et al. (2020)	60.6	-	-	-	-	-
PIRL Misra & Maaten (2020)	63.6	-	-	-	57.2	83.8
CPC v2 Hénaff et al. (2019)	63.8	-	-	-	-	-
CMC Tian et al. (2019)	66.2	-	-	-	-	-
SimCLR Chen et al. (2020a)	69.3	89.0	48.3	65.6	75.5	87.8
MoCo v2 Chen et al. (2020c)	71.1	-	-	-	-	-
SimSiam Chen & He (2020)	71.3	-	-	-	-	-
SwAV Caron et al. (2020)	71.8	-	-	-	-	-
InfoMin Aug Tian et al. (2020)	73.0	91.1	-	-	-	-
OBoW Gidaris et al. (2021)	73.8	-	-	-	82.9	90.7
BYOL Grill et al. (2020)	74.3	91.6	53.2	68.8	78.4	89.0
SwAV (w/ multi-crop) Caron et al. (2020)	75.3	-	53.9	70.2	78.5	89.9
Barlow Twins Zbontar et al. (2021)	73.2	91.0	55.0	69.7	79.2	89.3
VICReg (ours)	73.2	91.1	54.8	69.5	79.4	89.5

VICReg: Results with transfer tasks.

Method	Linear Classification			Object Detection		
	Places205	VOC07	iNat18	VOC07+12	COCO det	COCO seg
Supervised	53.2	87.5	46.7	81.3	39.0	35.4
MoCo He et al. (2020)	46.9	79.8	31.5	-	-	-
PIRL Misra & Maaten (2020)	49.8	81.1	34.1	-	-	-
SimCLR Chen et al. (2020a)	52.5	85.5	37.2	-	-	-
MoCo v2 Chen et al. (2020c)	51.8	86.4	38.6	82.5	39.8	36.1
SimSiam Chen & He (2020)	-	-	-	82.4	-	-
BYOL Grill et al. (2020)	54.0	<u>86.6</u>	<u>47.6</u>	-	<u>40.4</u>†	<u>37.0</u>†
SwAV (m-c) Caron et al. (2020)	<u>56.7</u>	<u>88.9</u>	<u>48.6</u>	<u>82.6</u>	<u>41.6</u>	<u>37.8</u>
OBoW Gidaris et al. (2021)	<u>56.8</u>	<u>89.3</u>	-	<u>82.9</u>	-	-
Barlow Twins Grill et al. (2020)	54.1	86.2	46.5	<u>82.6</u>	<u>40.0</u>†	<u>36.7</u>†
VICReg (ours)	<u>54.3</u>	<u>86.6</u>	<u>47.0</u>	82.4	39.4	36.4

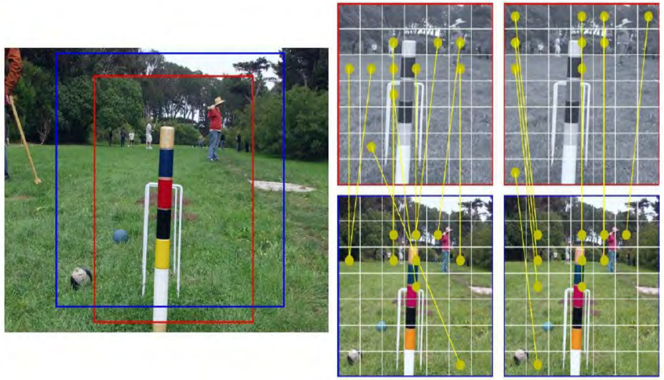
VICRegL: local matching latent variable for segmentation

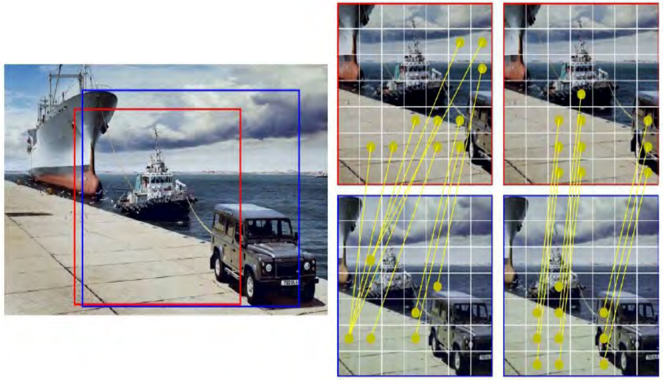
- **Latent variable optimization:**
  - Finds a pairing between local feature vectors of the two images
  - [Bardes, Ponce, LeCun, NeurIPS 2022, arXiv:2210.01571]



VICRegL: local matching latent variable for segmentation

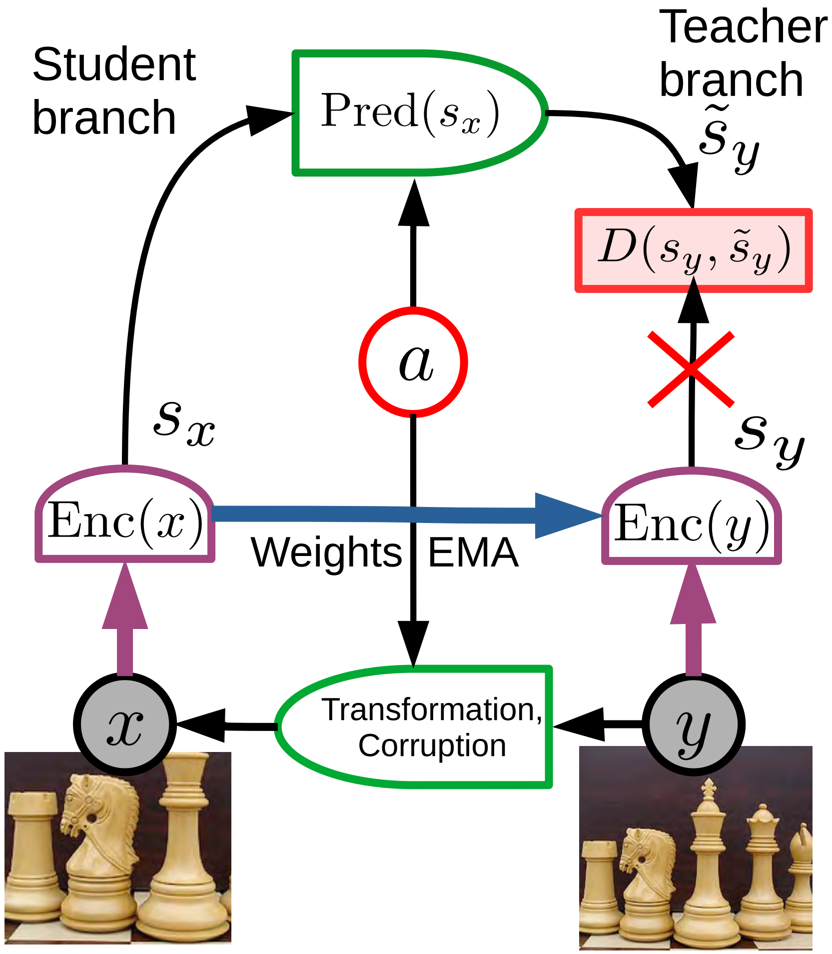
		Linear Cls. (%)	Linear Seg. (mIoU)		
		ImageNet	Pascal VOC		Cityscapes
Method	Epochs	Frozen	Frozen	Fine-Tuned	Frozen
Global features					
MoCo v2 [Chen et al., 2020b]	200	67.5	35.6	64.8	14.3
SimCLR [Chen et al., 2020a]	400	68.2	45.9	65.4	17.9
BYOL [Grill et al., 2020]	300	**72.3**	47.1	65.7	22.6
VICReg [Bardes et al., 2022]	300	71.5	47.8	65.5	23.5
Local features					
PixPro [Xie et al., 2021]	400	60.6	52.8	67.5	22.6
DenseCL [Wang et al., 2021]	200	65.0	45.3	66.8	11.2
DetCon [Hénaff et al., 2021]	1000	66.3	53.6	67.4	16.2
InsLoc [Yang et al., 2022]	400	45.0	24.1	64.4	7.0
CP^2 [Wang et al., 2022]	820	53.1	21.7	65.2	8.4
ReSim [Xiao et al., 2021]	400	59.5	51.9	67.3	12.3
Ours					
VICRegL $\alpha = 0.9$	300	71.2	54.0	66.6	25.1
VICRegL $\alpha = 0.75$	300	70.4	**55.9**	**67.6**	**25.2**





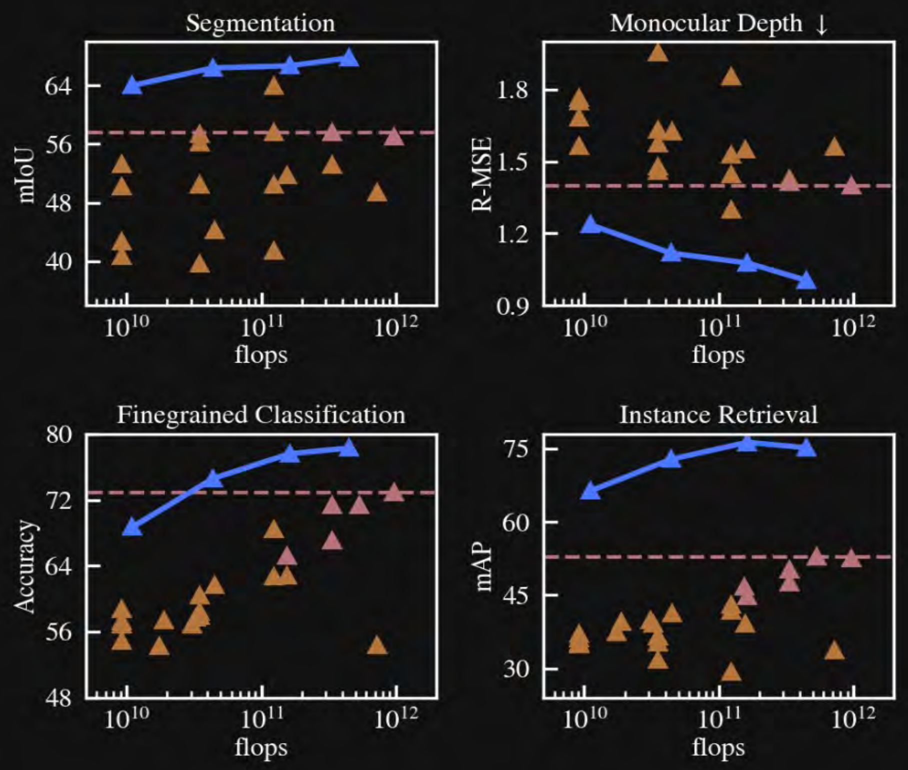
Distillation Methods

- **Modified Siamese nets**
  - Predictor head eliminates variation of representations due to distortions
- **Examples:**
  - Bootstrap Your Own Latents [Grill arXiv:2006.07733]
  - SimSiam [Chen & He arXiv:2011.10566]
  - DINOv2 [Oquab arXiv:2304.07193]
- **Advantages**
  - No negative samples
- **Disadvantage:**
  - we don't completely understand why it works! [Tian et al. ArXiv:2102.06810]



DINOv2: image foundation model

- **self-supervised generic image features**
- **Demo: https://dinov2.metademolab.com/**
- **Paper: [Oquab et al. ArXiv:2304.07193]**
  - Classification
    - 86.5% on IN1k with frozen features and linear head.
  - Fine-grained classification
  - Depth estimation
  - Semantic segmentation
  - Instance Retrieval
  - Dense & sparse feature matching



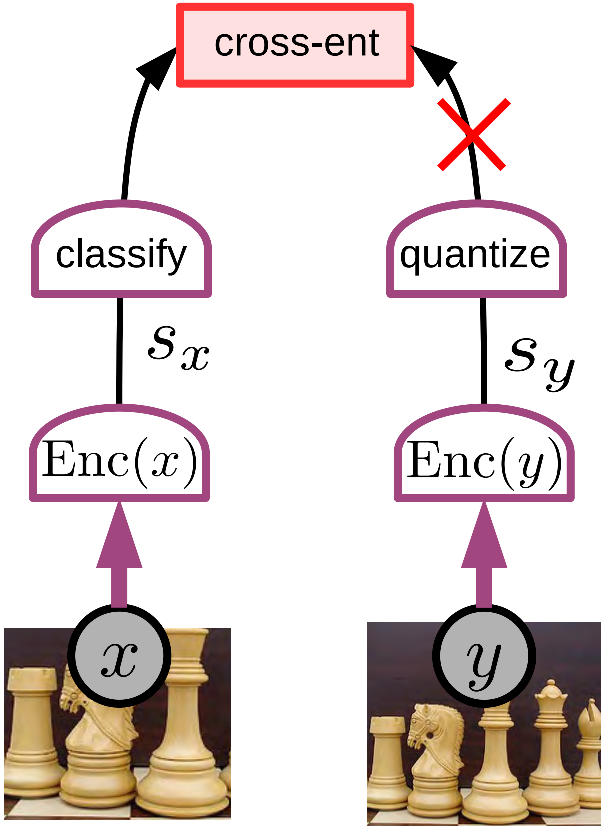
The DINOv2 family of models **drastically improves** over the previous state of the art in self-supervised learning (SSL), and **reaches performance comparable** with weakly-supervised features (WSL).

DINOv2: image foundation model

- **Demo: https://dinov2.metademolab.com/**
- **Paper: [Oquab et al. ArXiv:2304.07193]**

DINOv2: Joint Embedding Architecture

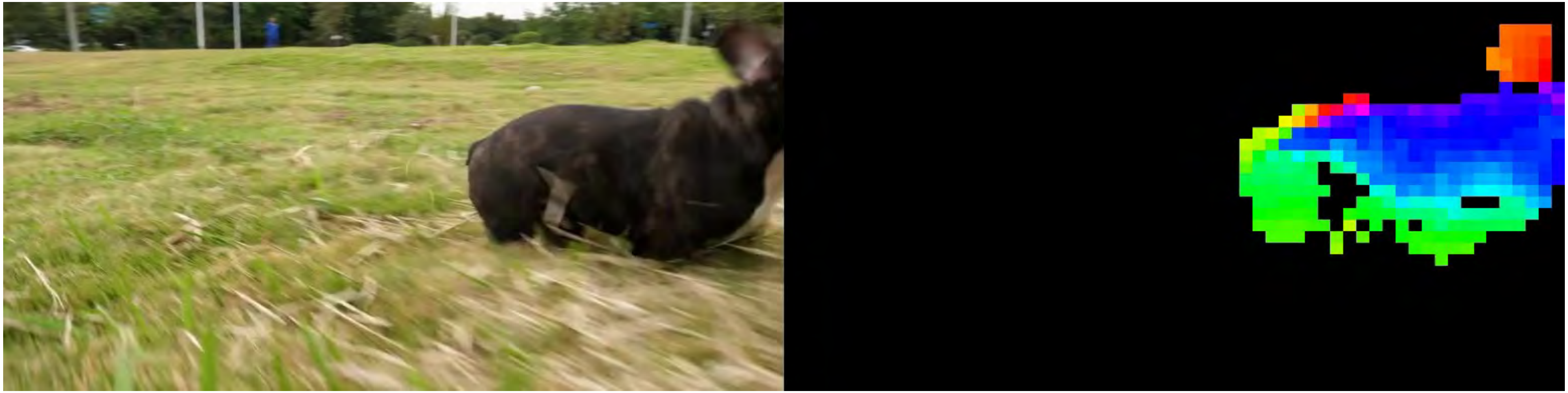
- **SSL by distillation**



Method	Arch.	Data	Text sup.	kNN val	linear val	linear ReaL	linear V2
Weakly supervised							
CLIP	ViT-L/14	WIT-400M	✓	79.8	84.3	88.1	75.3
CLIP	ViT-L/14$_{336}$	WIT-400M	✓	80.5	85.3	88.8	75.8
SWAG	ViT-H/14	IG3.6B	✓	82.6	85.7	88.7	77.6
OpenCLIP	ViT-H/14	LAION	✓	81.7	84.4	88.4	75.5
OpenCLIP	ViT-G/14	LAION	✓	83.2	86.2	89.4	77.2
EVA-CLIP	ViT-g/14	custom*	✓	**83.5**	86.4	89.3	77.4
Self-supervised							
MAE	ViT-H/14	INet-1k	✗	49.4	76.6	83.3	64.8
DINO	ViT-S/8	INet-1k	✗	78.6	79.2	85.5	68.2
SEERv2	RG10B	IG2B	✗	–	79.8	–	–
MSN	ViT-L/7	INet-1k	✗	79.2	80.7	86.0	69.7
EsViT	Swin-B/W=14	INet-1k	✗	79.4	81.3	87.0	70.4
Mugs	ViT-L/16	INet-1k	✗	80.2	82.1	86.9	70.8
iBOT	ViT-L/16	INet-22k	✗	72.9	82.3	87.5	72.4
DINOv2	ViT-S/14	LVD-142M	✗	79.0	81.1	86.6	70.9
	ViT-B/14	LVD-142M	✗	82.1	84.5	88.3	75.1
	ViT-L/14	LVD-142M	✗	**83.5**	86.3	89.5	78.0
	ViT-g/14	LVD-142M	✗	**83.5**	**86.5**	**89.6**	**78.4**

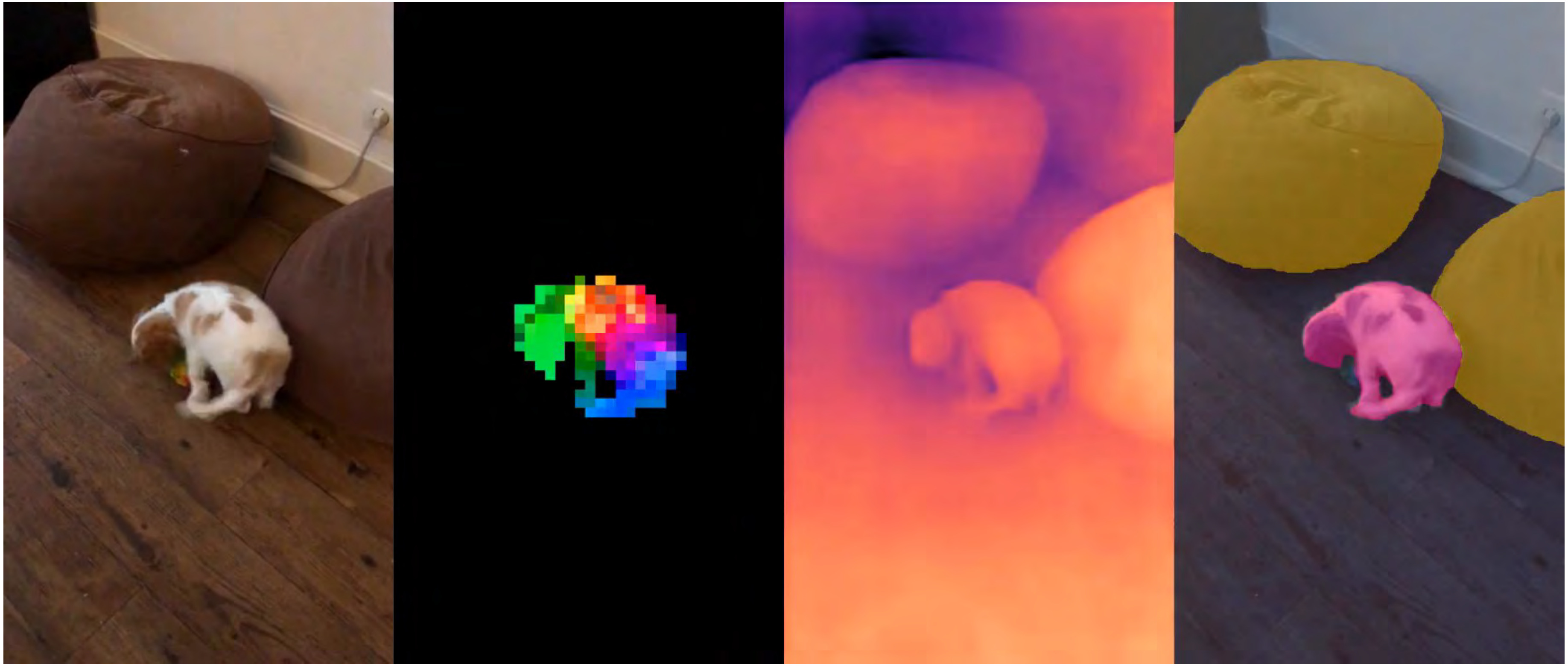
DINOv2

- **Feature visualization: RGB = top 3 principal components**



DINOv2

- **Feature extraction, depth estimation, segmentation**



Canopy Height Map using DINOv2

- **Estimates tree canopy height from satellite images using DINOv2 features**
  - Using ground truth from Lidar images
  - 0.5 meter resolution images
- **[ArXiv:2304.07213]**
  - Tolan et al.: Sub-meter resolution canopy height maps using self-supervised learning and a vision transformer trained on Aerial and GEDI Lidar

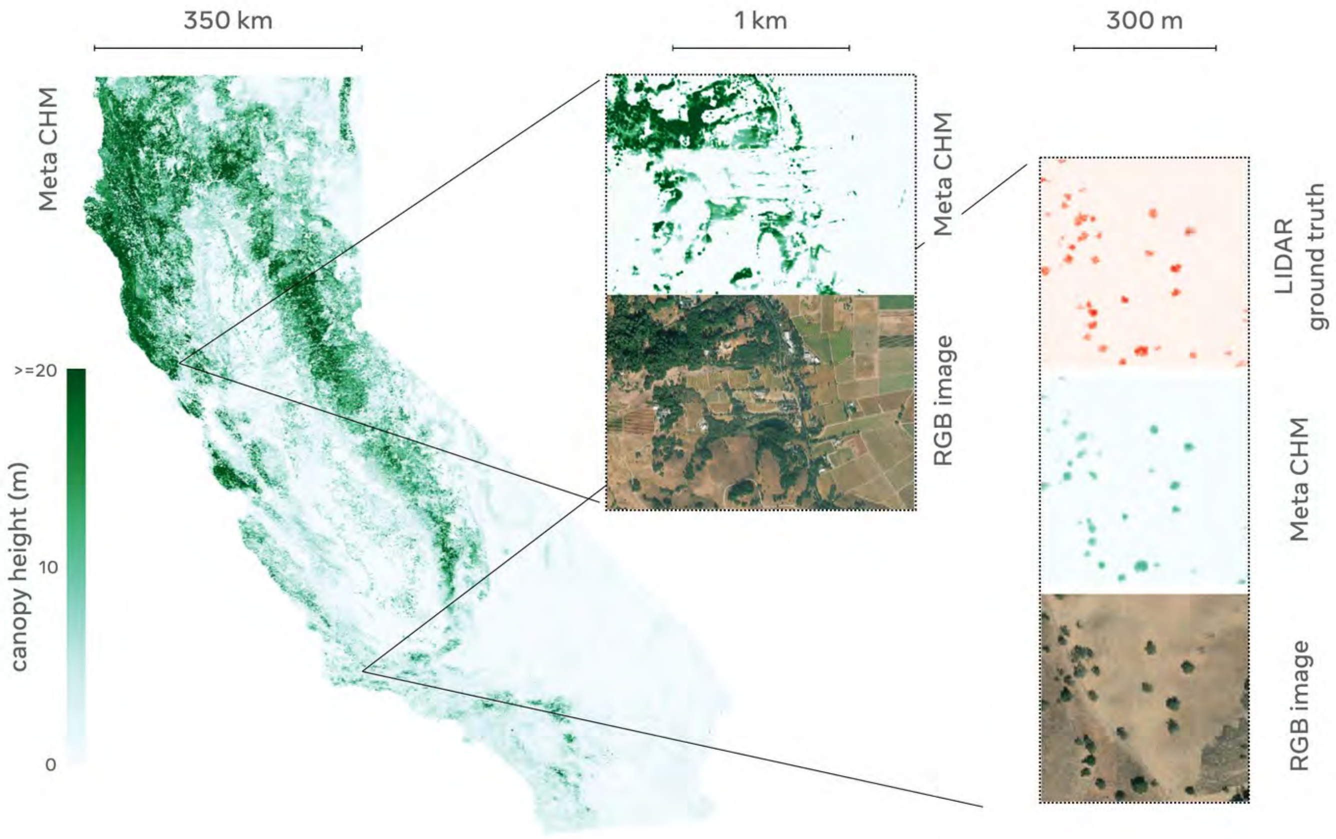
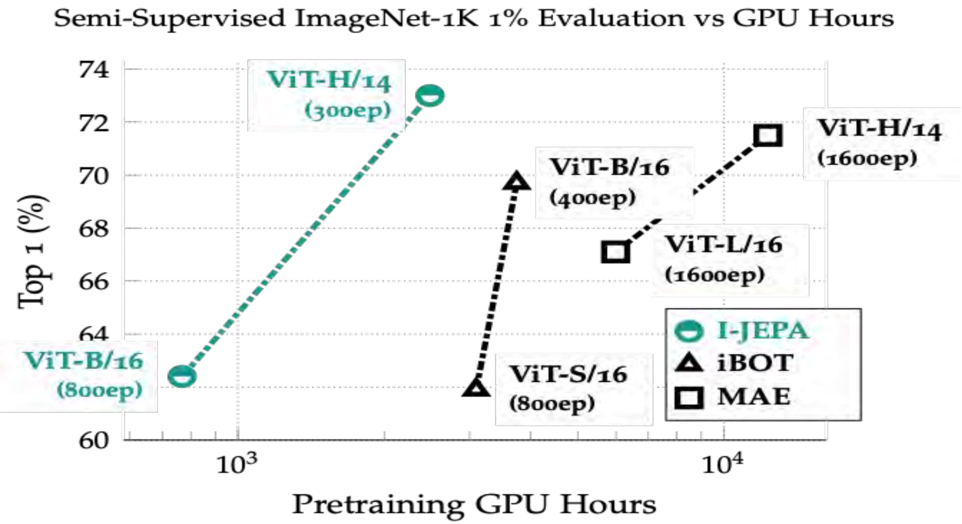
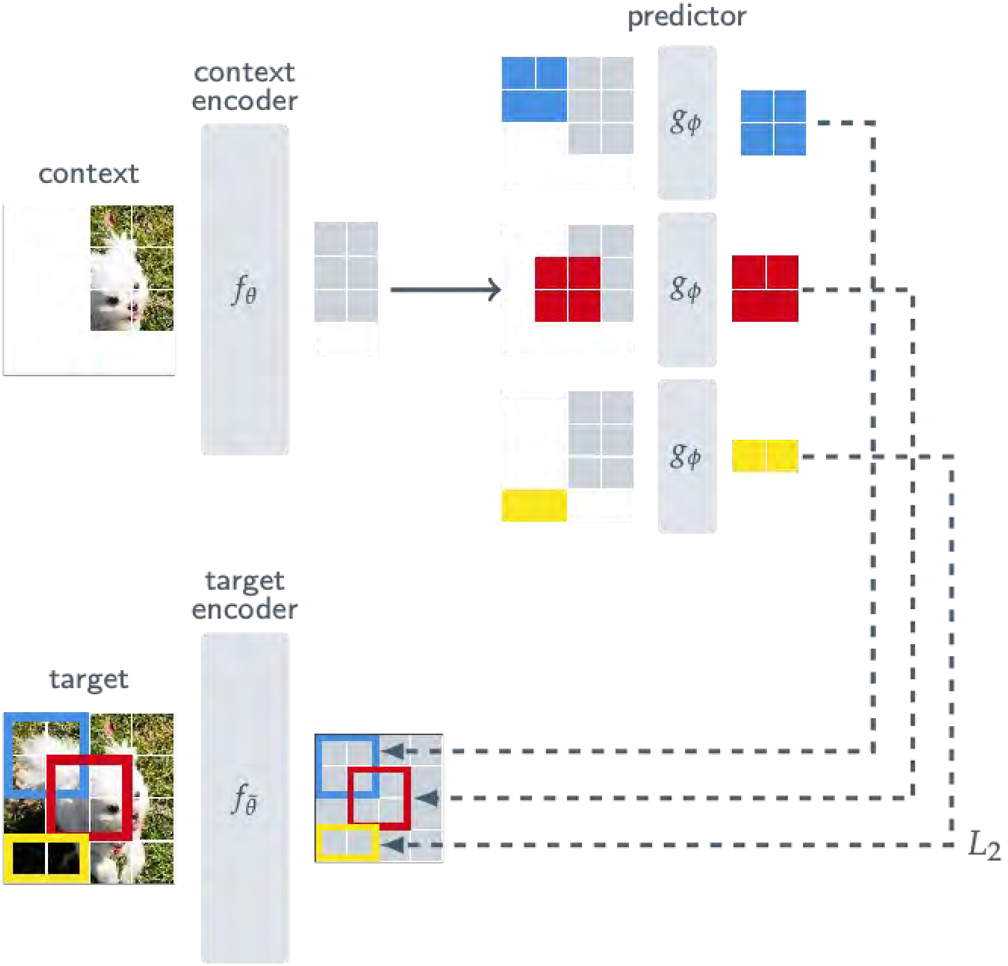


Figure 1: Canopy Height Map (CHM) for California, with inset showing zoomed-in region with input RGB imagery and LIDAR ground truth

Image-JEPA: uses masking & transformer architectures

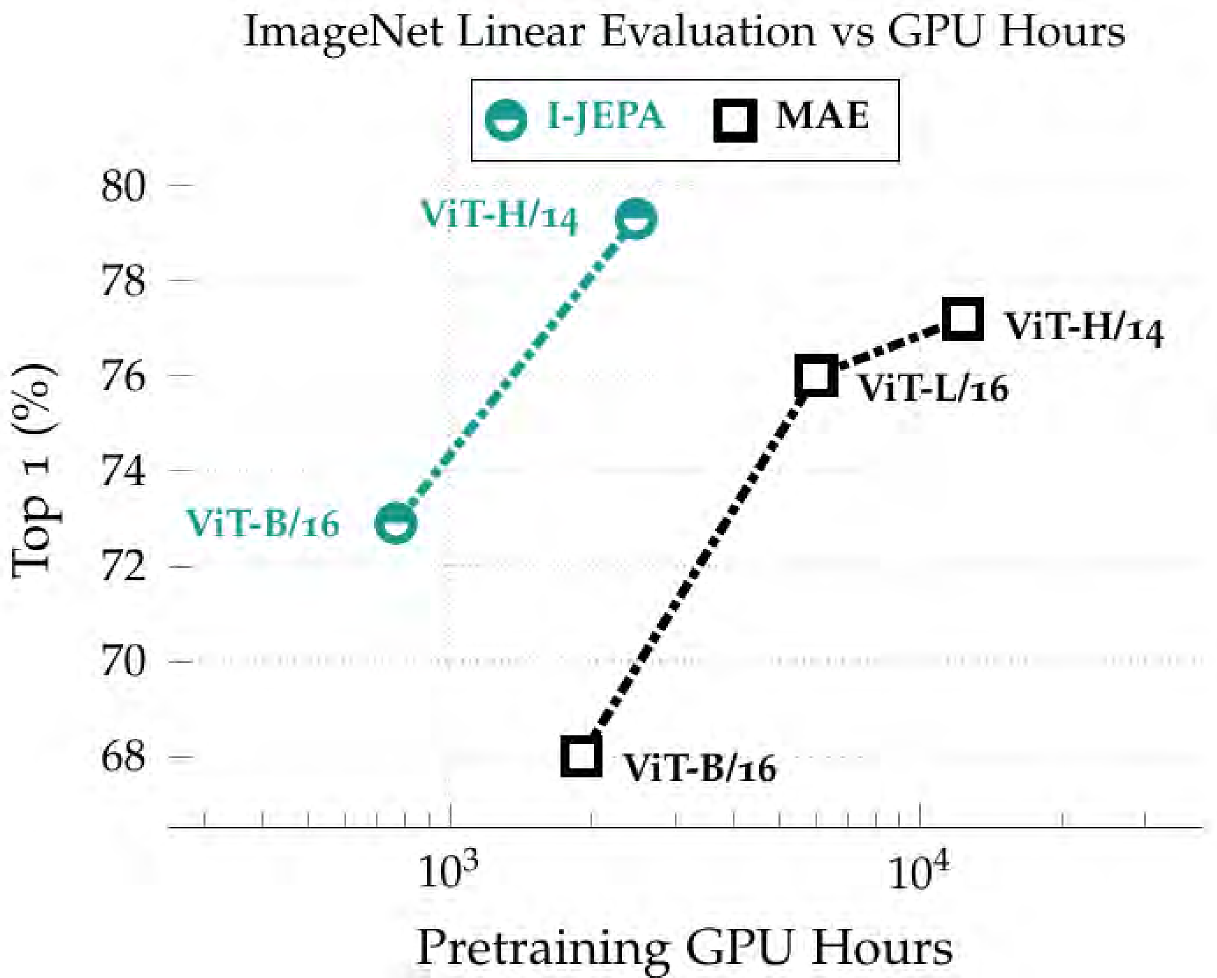
- **"SSL from images with a JEPA"**
  - [M. Assran et al arxiv:2301.08243]
- **Jointly embeds a context and a number of neighboring patches.**
  - Uses predictors
  - Uses only masking





I-JEPA Results

- **Training is fast**
- **Non-generative method beat reconstruction-based generative methods such as Masked Auto-Encoder**
  - (with a frozen trunk).



I-JEPA Results on ImageNet

- **JEPA better than generative architecture on pixels.**

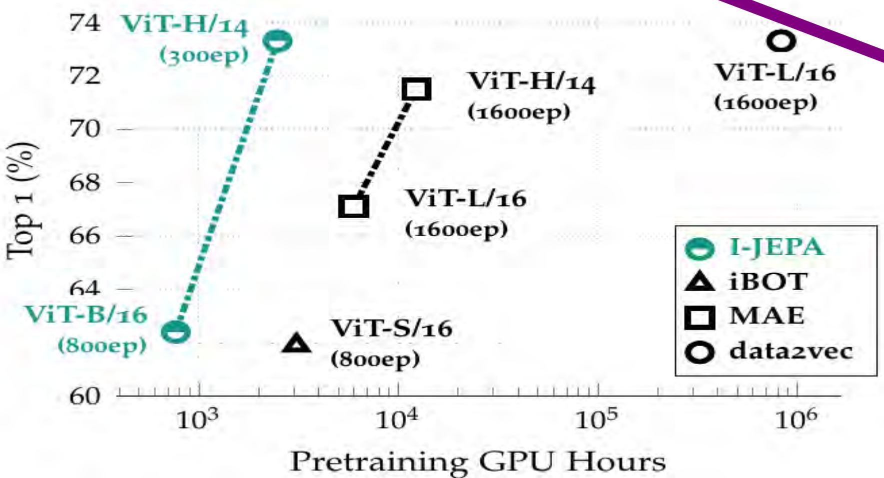
Targets	Arch.	Epochs	Top-1
Target-Encoder Output	ViT-L/16	500	**66.9**
Pixels	ViT-L/16	800	40.7

- **Closing the gap with methods that use data augments**
- **Methods with only masking**
  - No data augmentation
- **Methods with data augmentation**
  - Similar to SimCLR

Method	Arch.	Epochs	Top-1
Methods without view data augmentations			
data2vec [7]	ViT-L/16	1600	53.5
MAE [34]	ViT-B/16	1600	68.0
	ViT-L/16	1600	76.0
	ViT-H/14	1600	77.2
I-JEPA	ViT-B/16	600	72.9
	ViT-L/16	600	77.5
	ViT-H/14	300	79.3
	ViT-H/16_{448}	300	**81.1**
Methods using extra view data augmentations			
SimCLR v2 [20]	RN152 (2×)	800	79.1
DINO [17]	ViT-B/8	300	80.1
iBOT [74]	ViT-L/16	250	**81.0**

I-JEPA Results on ImageNet with 1% training

- JEPA better than generative architecture on pixels.
- Closing the gap with methods that use data augments
- Methods with only masking
- Methods with data augmentation



Method	Arch.	Epochs	Top-1
Methods without view data augmentations			
data2vec [7]	ViT-L/16	1600	73.3
MAE [34]	ViT-L/16	1600	67.1
	ViT-H/14	1600	71.5
I-JEPA	ViT-L/16	600	69.4
	ViT-H/14	300	73.3
	ViT-H/16_{448}	300	**77.3**
Methods using extra view data augmentations			
iBOT [74]	ViT-B/16	250	69.7
DINO [17]	ViT-B/8	300	70.0
SimCLR v2 [33]	RN151 (2×)	800	70.2
BYOL [33]	RN200 (2×)	800	71.2
MSN [3]	ViT-B/4	300	**75.7**

Sample contrastive vs Dimension contrastive?

- **[Garrido et al. Arxiv:2206.02574 , ICLR2023]** (outstanding paper, honorable mention)
  - "ON THE DUALITY BETWEEN CONTRASTIVE AND NON CONTRASTIVE SELF-SUPERVISED LEARNING"

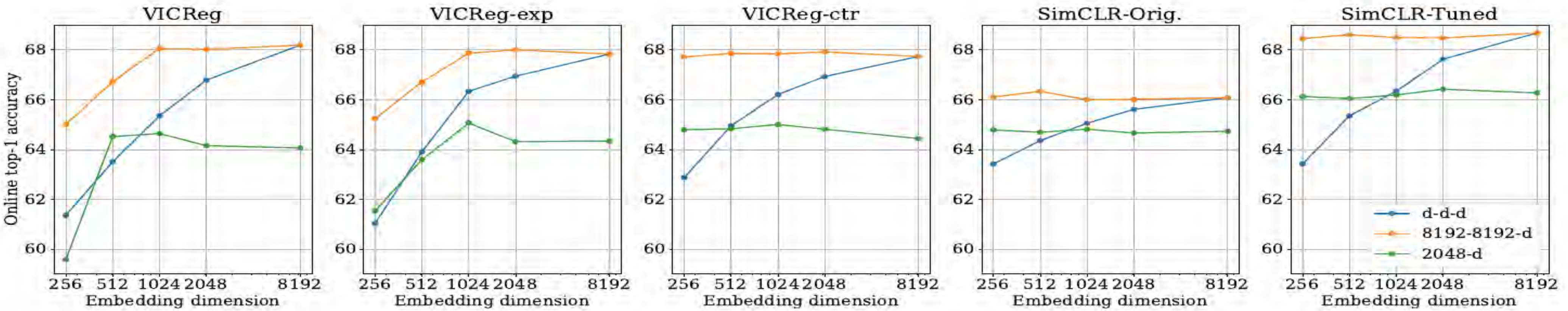


Figure 1: VICReg, VICReg-exp and VICReg-ctr perform similarly in 100 epochs training, validating empirically our theoretical result. While the original implementation of SimCLR performs significantly worse – which is unexpected per our theory – we are able to improve its performance to VICReg's level. This further validates our findings. While different projector architectures impact performance, behaviours are similar across methods. Confer supplementary section H for numerical values and hyperparameters.

Video-JEPA

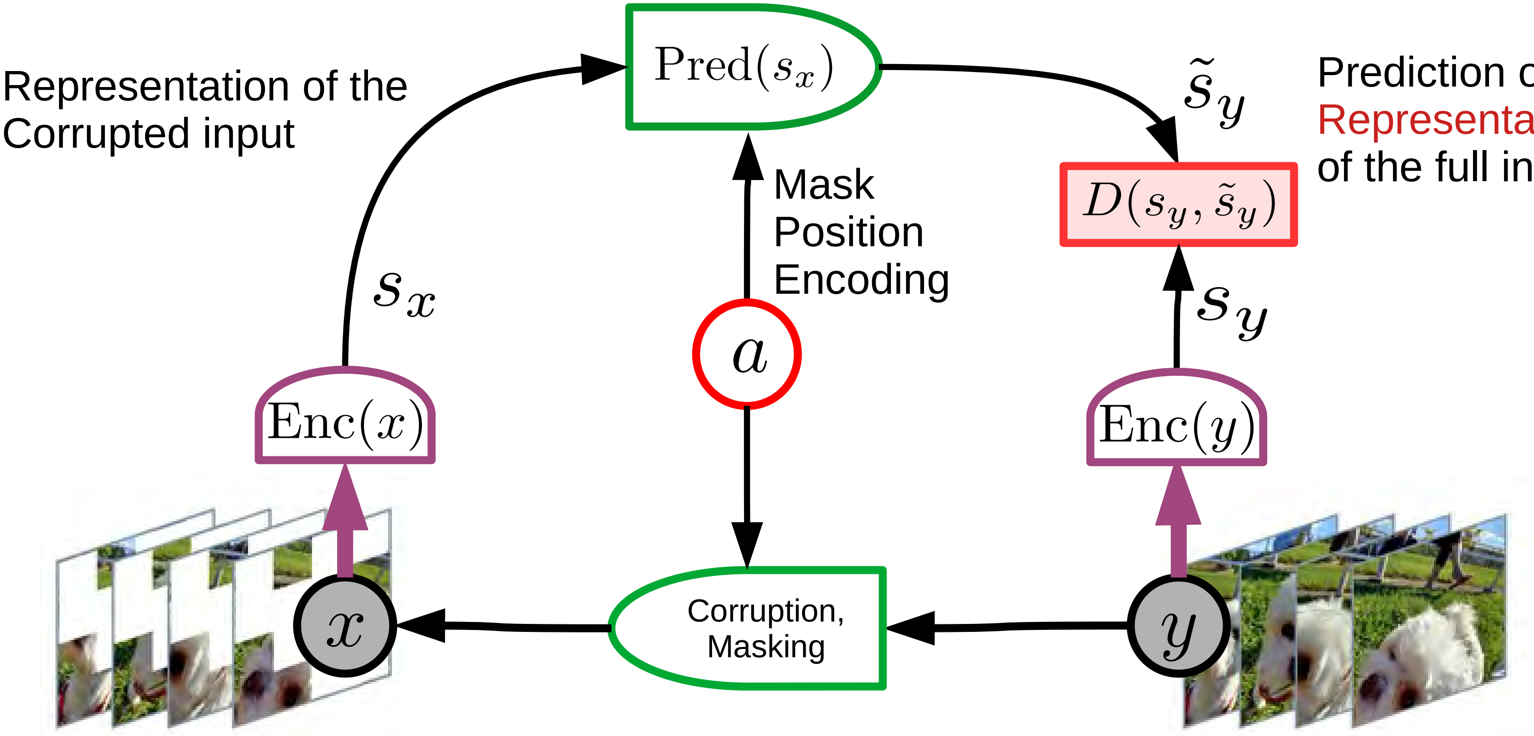
https://github.com/facebookresearch/jepa

Search for V-JEPA

“Revisiting Feature Prediction for Learning Visual Representations from Video”
Adrien Bardes, Quentin Garrido, Jean Ponce, Xinlei Chen, Michael Rabbat,
Yann LeCun, Mahmoud Assran1, Nicolas Ballas

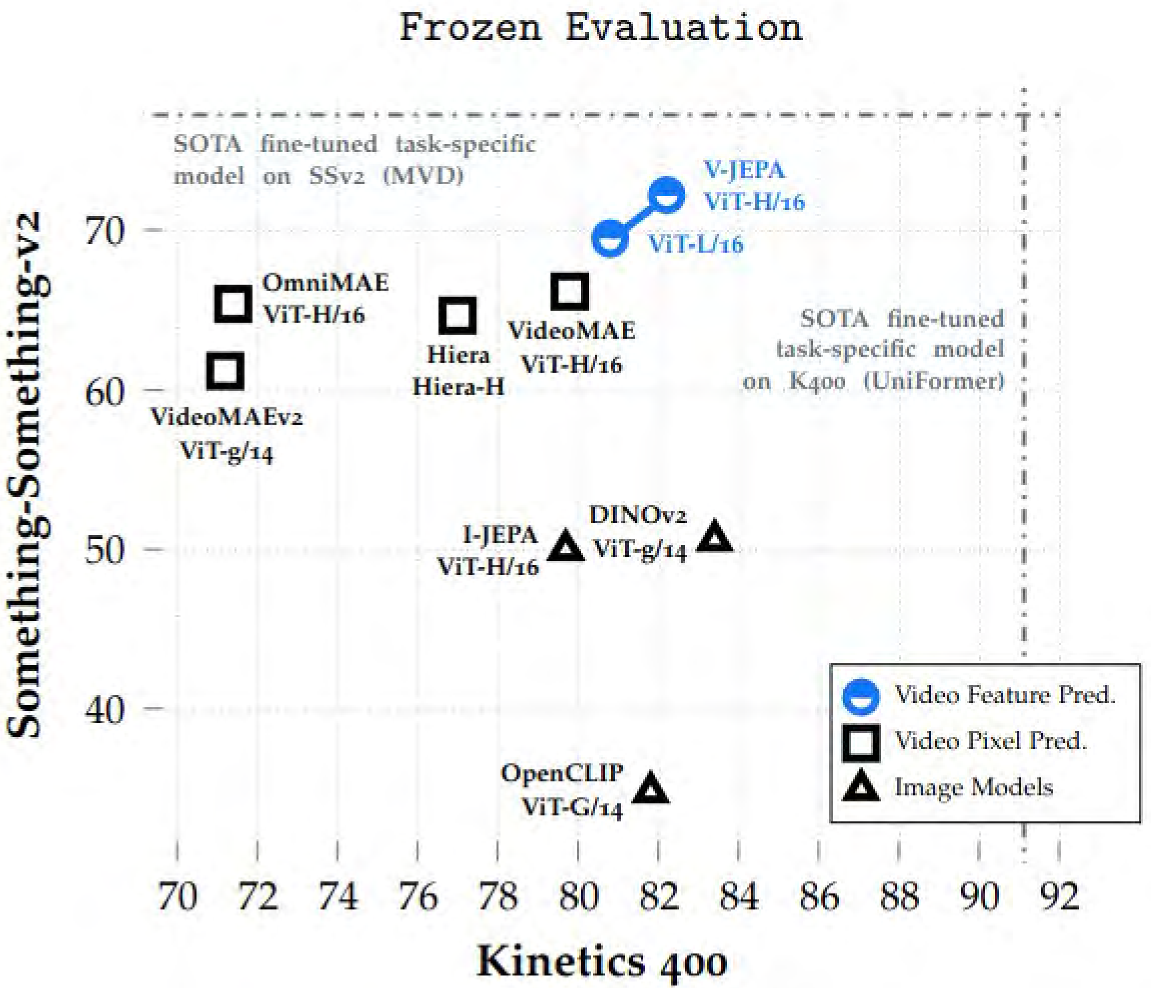
Video-JEPA

- **[Bardes et al. 2024]**



V-JEPA: results on action recognition

- Supervised head on frozen backbone.
- Comparison with generative models: OmniMAE, VideoMAE, Hiera
- Comparison with image models: I-JEPA, DINOv2, OpenCLIP



V-JEPA: results for low-shot action recognition

- Rows 1-3: generative architectures with reconstruction
- Row 4: V-JEPA
- Supervised head on frozen backbone.

		Frozen Evaluation					
		K400 (16×8×3)			SSv2 (16×2×3)		
Method	Arch.	5%	10%	50%	5%	10%	50%
MVD	ViT-L/16	62.6 ± 0.2	68.3 ± 0.2	77.2 ± 0.3	42.9 ± 0.8	49.5 ± 0.6	61.0 ± 0.2
VideoMAE	ViT-H/16	62.3 ± 0.3	68.5 ± 0.2	78.2 ± 0.1	41.4 ± 0.8	48.1 ± 0.2	60.5 ± 0.4
VideoMAEv2	ViT-g/14	37.0 ± 0.3	48.8 ± 0.4	67.8 ± 0.1	28.0 ± 1.0	37.3 ± 0.3	54.0 ± 0.3
V-JEPA	ViT-H/16$_{384}$	68.2 ± 0.2	72.8 ± 0.2	80.6 ± 0.2	54.0 ± 0.2	59.3 ± 0.5	67.9 ± 0.2

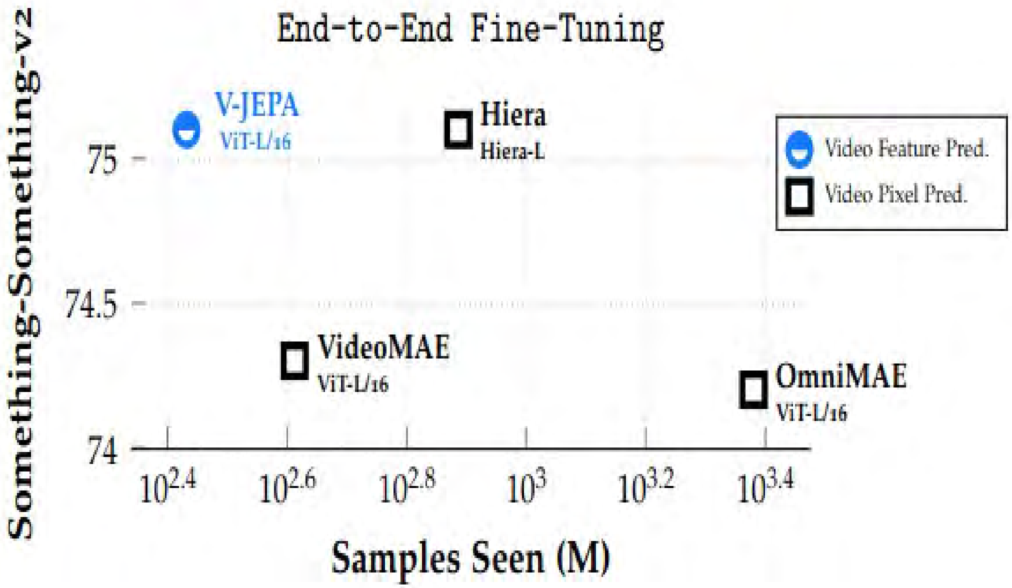
V-JEPA: training on video vs training on images

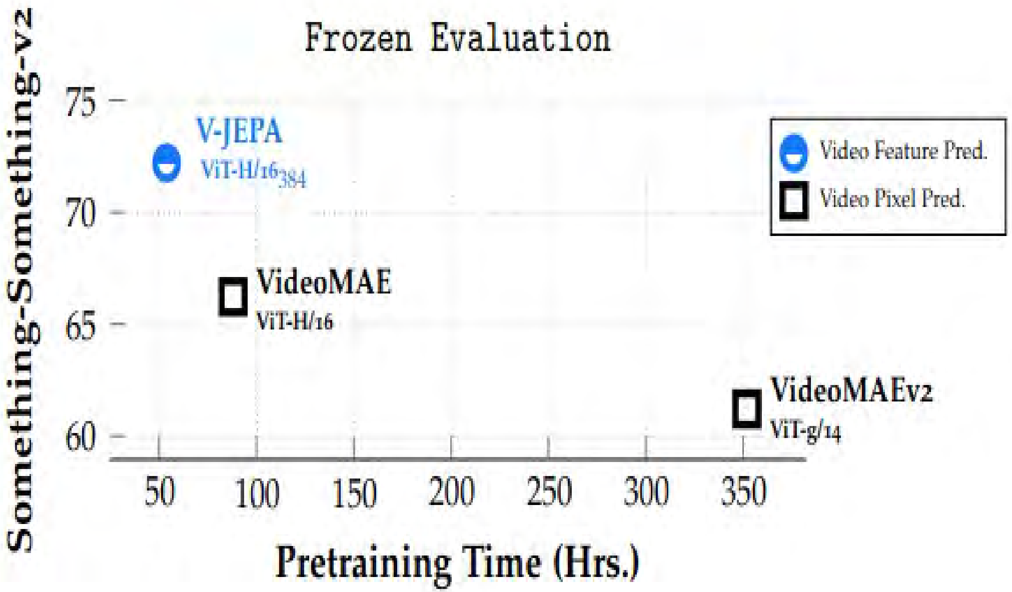
- Frozen evaluation
- Pre-training on video gives better results on action recognition
- V-JEPA: best results on ImageNet1K among video models

Method	Arch.	Params.	Data	Video Tasks			Image Tasks		
				K400 (16×8×3)	SSv2 (16×2×3)	AVA	IN1K	Places205	iNat21
Methods pretrained on Images									
I-JEPA	ViT-H/16_{512}	630M	IN22K	79.7	50.0	19.8	84.4	66.5	85.7
OpenCLIP	ViT-G/14	1800M	LAION	81.8	34.8	23.2	85.3	**70.2**	83.6
DINOv2	ViT-g/14	1100M	LVD-142M	**83.4**	50.6	24.3	**86.2**	68.4	**88.8**
Methods pretrained on Videos									
MVD	ViT-L/16	200M	IN1K+K400	79.4	66.5	19.7	73.3	59.4	65.7
OmniMAE	ViT-H/16	630M	IN1K+SSv2	71.4	65.4	16.0	76.3	60.6	72.4
VideoMAE	ViT-H/16	630M	K400	79.8	66.2	20.7	72.3	59.1	65.5
VideoMAEv2	ViT-g/14	1100M	Un.Hybrid	71.2	61.2	12.9	71.4	60.6	68.3
Hiera	Hiera-H	670M	K400	77.0	64.7	17.5	71.4	59.5	61.7
V-JEPA	ViT-L/16	200M	VideoMix2M	80.8	69.5	25.6	74.8	60.3	67.8
	ViT-H/16	630M		**82.0**	71.4	**25.8**	75.9	61.7	67.9
	ViT-H/16_{384}	630M		81.9	**72.2**	25.0	**77.4**	**62.8**	**72.6**

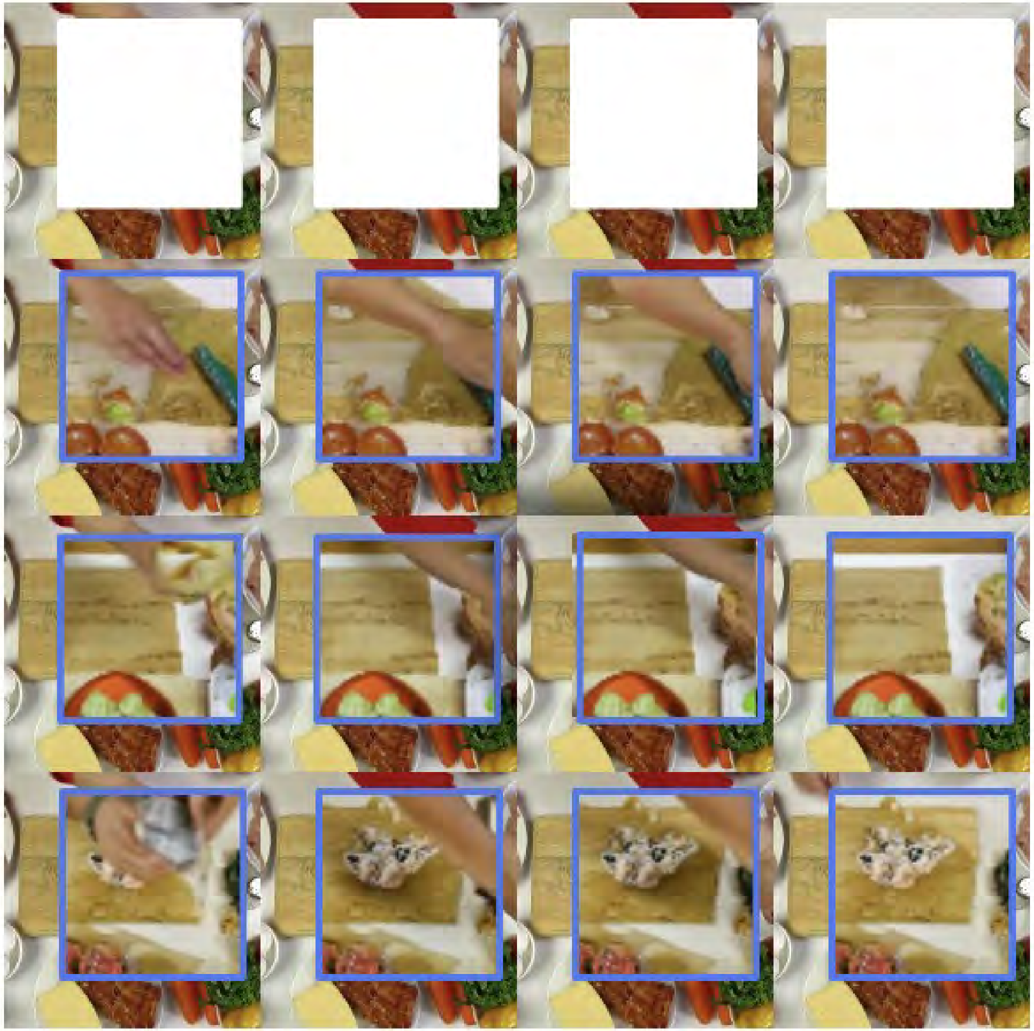
V-JEPA: sample efficiency and learning speed

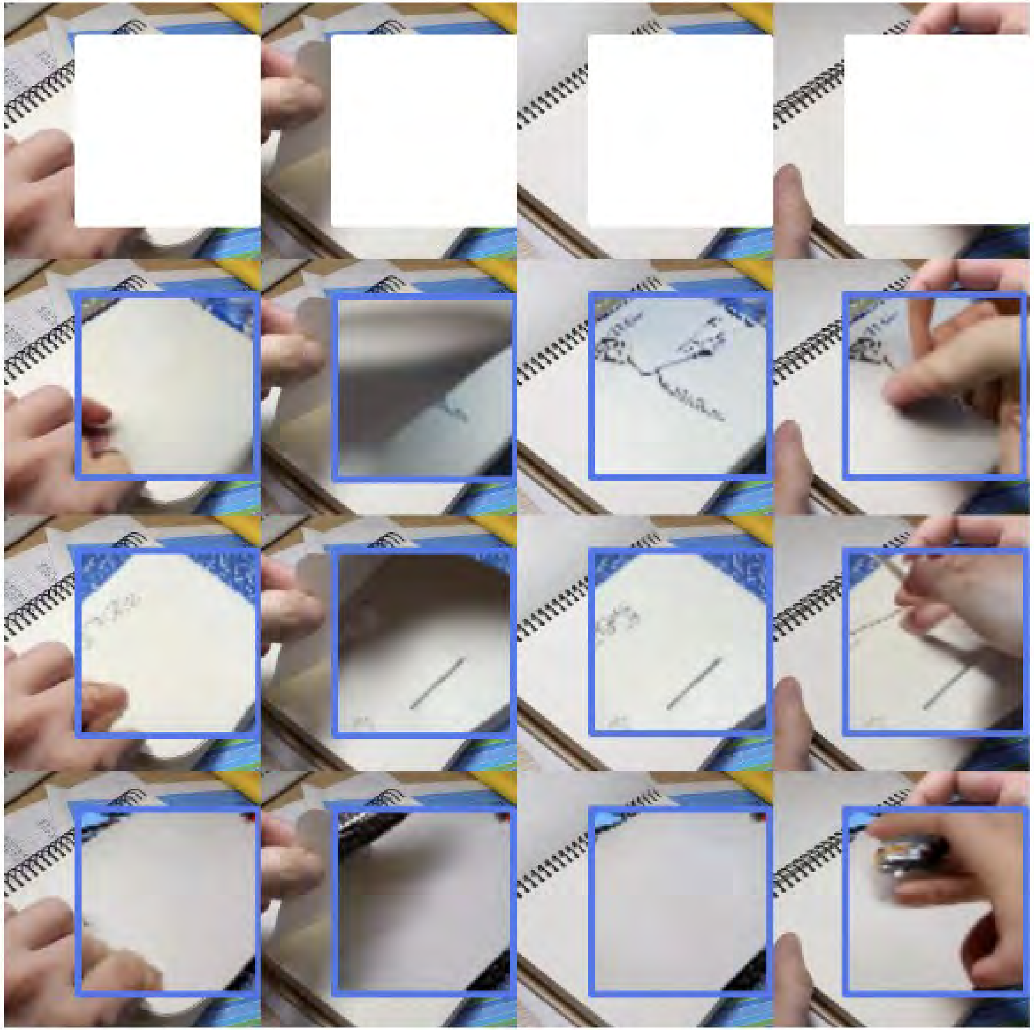
- Evaluation on Something-Something-v2
- Comparison with reconstruction-based generative methods





V-JEPA: Reconstruction with a separately-trained decoder





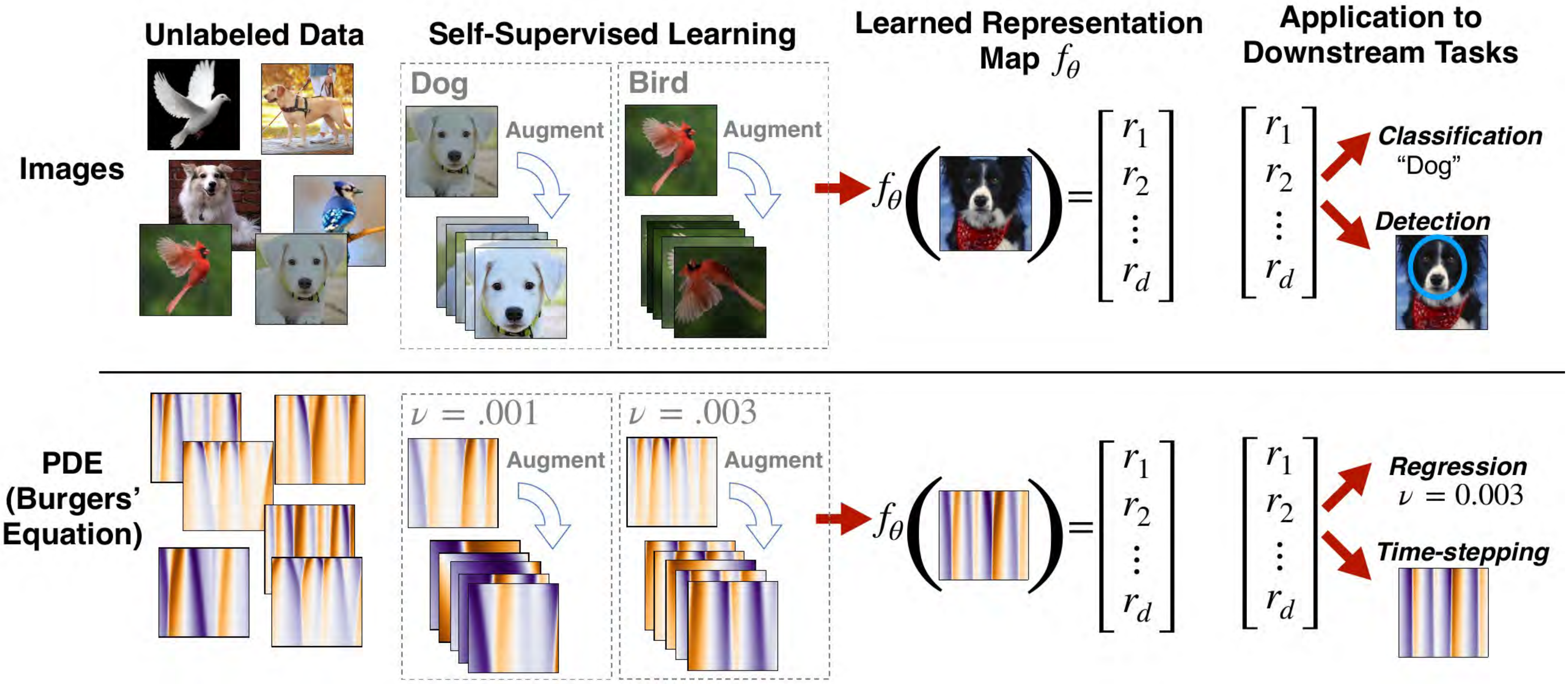
SSL for PDEs

ArXiv:2307.05432   NeurIPS 2023

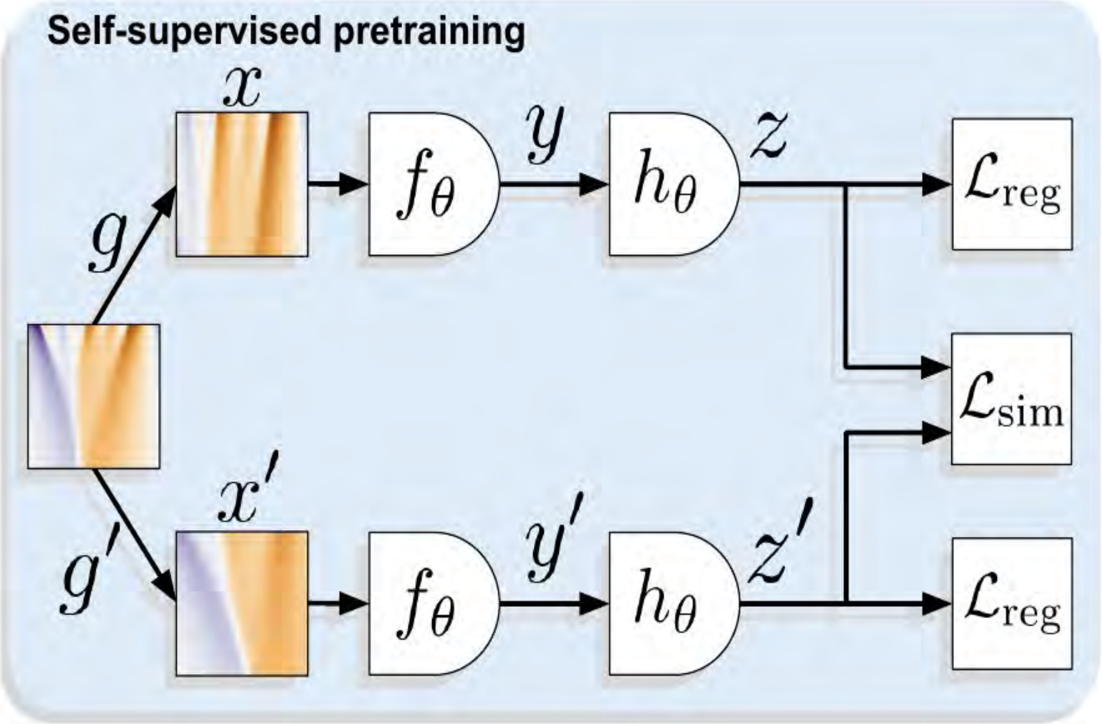
Self-Supervised Learning with Lie Symmetries for Partial Differential Equations

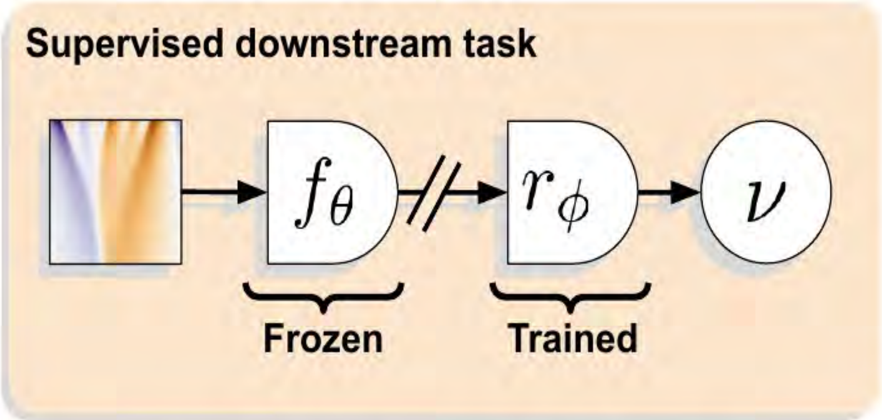
Grégoire Mialon, Quentin Garrido, Hannah Lawrence, Danyal Rehman, Yann LeCun, Bobak T. Kiani

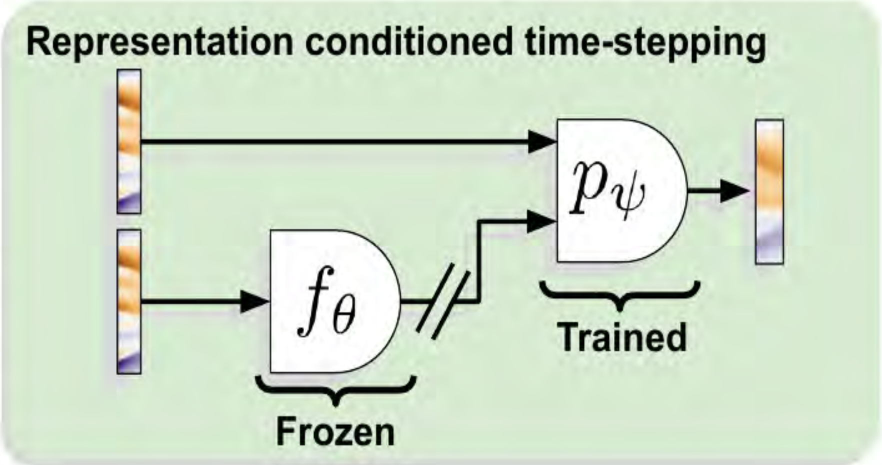
SSL for PDE: extracting dynamical parameters with VICReg



Using VICReg to learn representations of the equation.







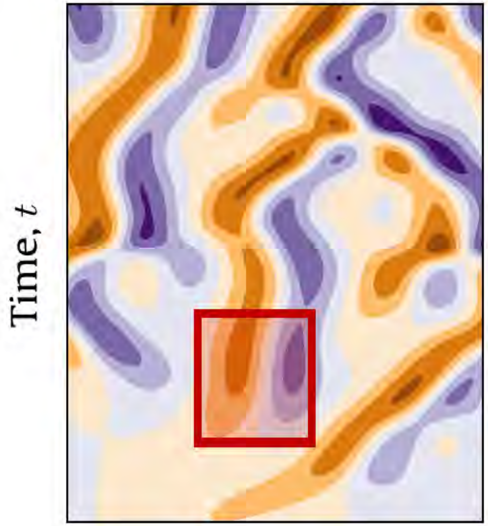
SSL for PDE

An example: the **Kuramoto-Sivashinsky (KS)** equation is a model of chaotic flow given by

$$u_t + uu_x + u_{xx} + u_{xxxx} = 0,$$

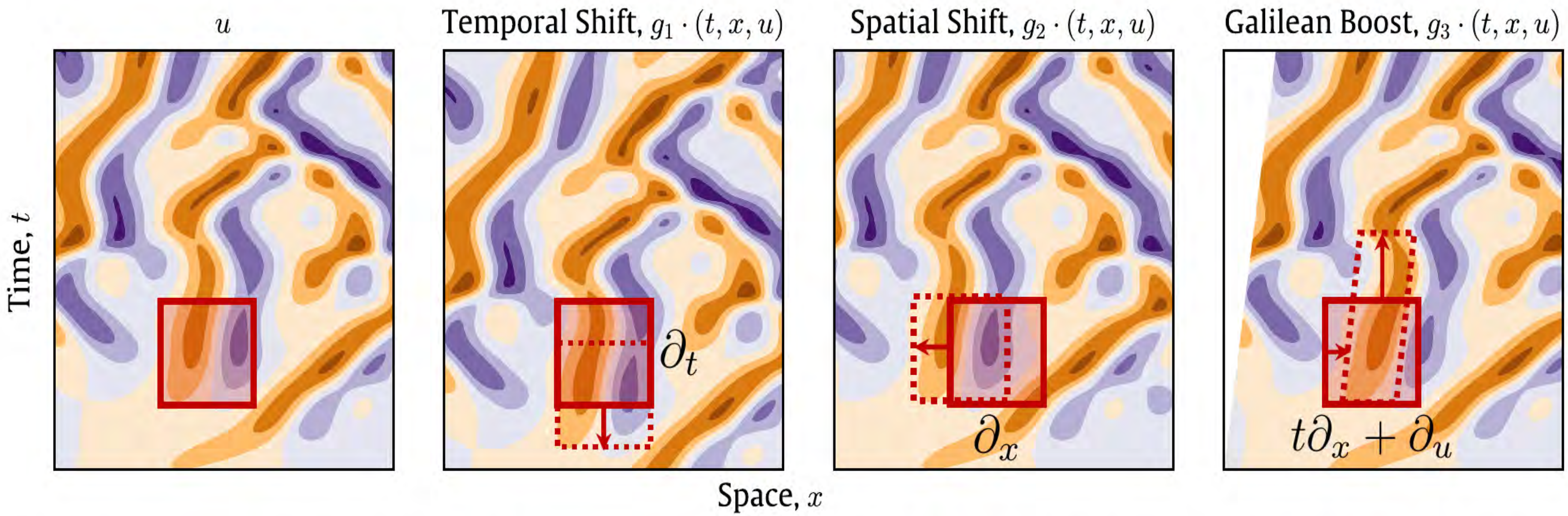
where $u(x, t)$ is the dependent variable.

- Often shows up in reaction-diffusion systems or flame propagation problems.
- Solution can be seen as an image...
- Admit Lie point symmetries: smooth transformations of a solution producing another solution to the same PDE.
- Can be used to learn models [Brandstetter et al., 2022].



A 1D solution to KS (x-axis is space).

SSL for PDE: Data "augmentation"



One parameter Lie point symmetries for the Kuramoto-Sivashinsky (KS) PDE. Left to right: un-modified solution (u), temporal shifts (g_1), spatial shifts (g_2), and Galilean boosts (g_3) with corresponding infinitesimal transformations in the Lie algebra placed inside the figure. The shaded red square denotes the original (x, t), while the dotted line represents the same points after the augmentation is applied.

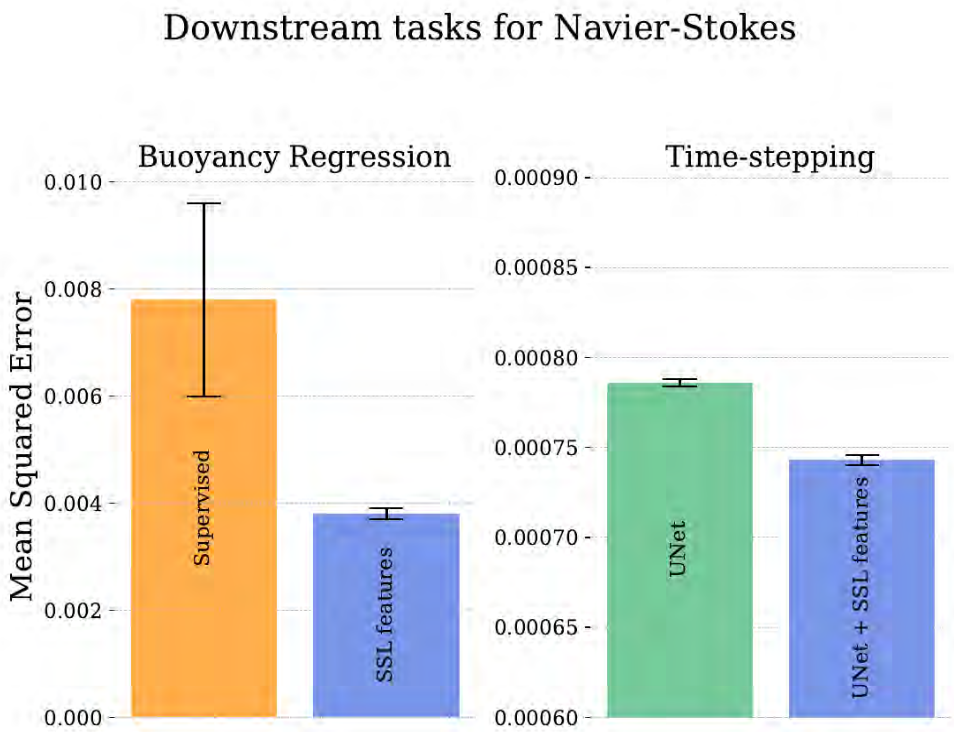
$$\begin{aligned}
\text{Temporal Shift:} \quad & g_1(\epsilon) : (x, t, u) \mapsto (x, t + \epsilon, u) \\
\text{Spatial Shift:} \quad & g_2(\epsilon) : (x, t, u) \mapsto (x + \epsilon, t, u) \\
\text{Galilean Boost:} \quad & g_3(\epsilon) : (x, t, u) \mapsto (x + \epsilon t, t, u + \epsilon)
\end{aligned}$$

SSL for Predicting Buoyancy in Navier-Stokes

The **incompressible Navier-Stokes** equation is given by

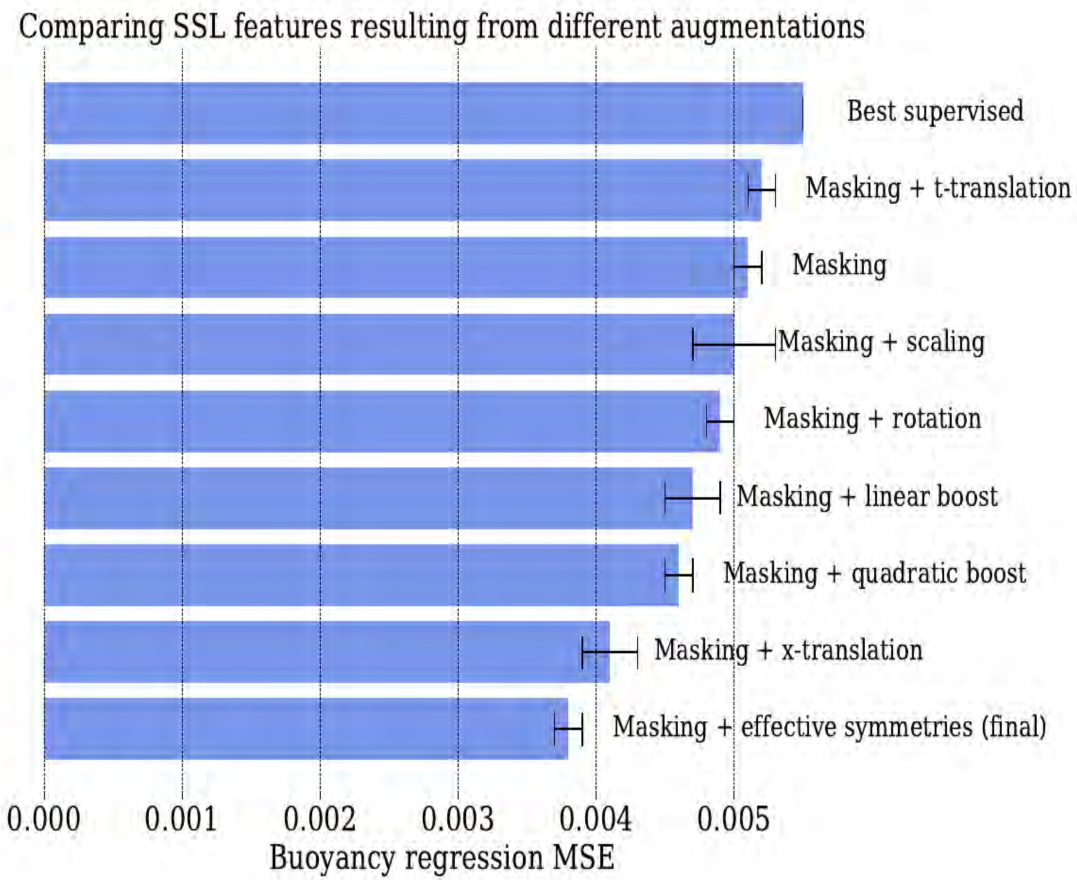
$$\boldsymbol{u}_t = -\boldsymbol{u} \cdot \nabla \boldsymbol{u} - \frac{1}{\rho}\nabla p + \nu \nabla^2 \boldsymbol{u} + \boldsymbol{f}, \quad \nabla \boldsymbol{u} = 0.$$

- 26k 2D trajectories, 56 frames (128x128) each [Gupta and Brandstetter, 2023].
- Task 1: regressing buoyancy $\boldsymbol{f}$.
- Task 2: Time-stepping, predict next frames given past frames.
- SSL features are effective and easy to use.



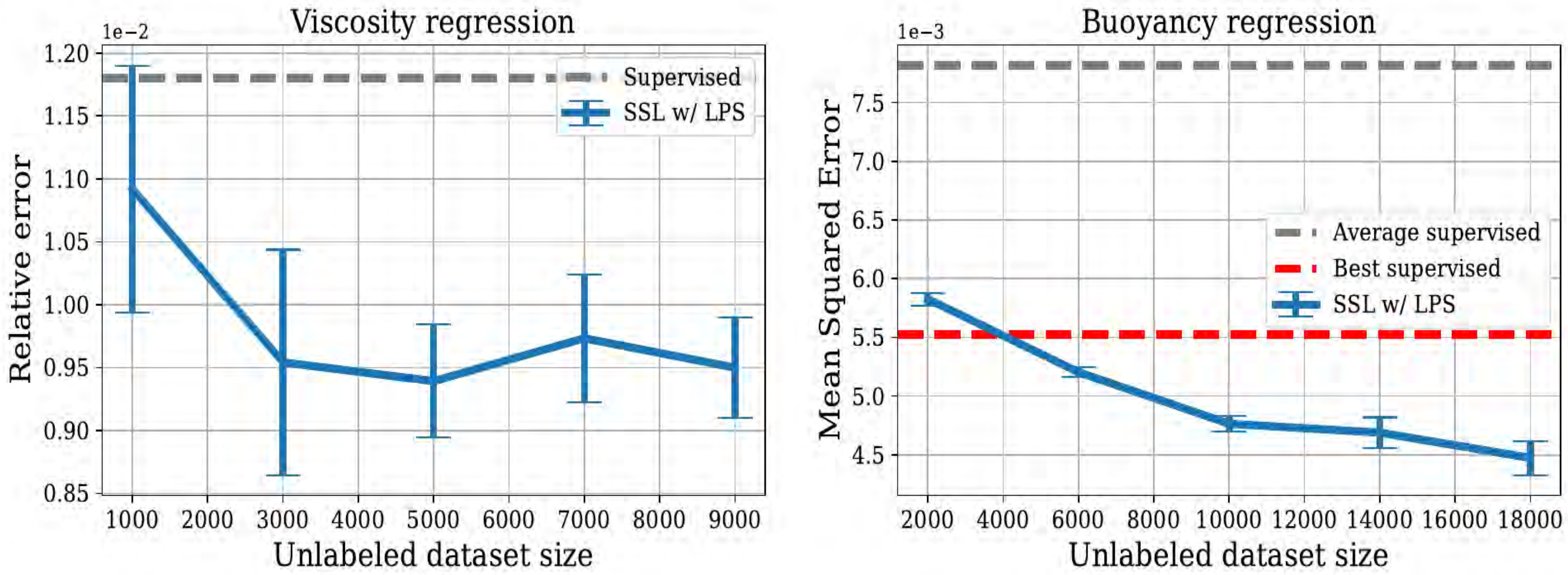
SSL for Predicting Buoyancy in Navier-Stokes

- Navier-Stokes: 8 Lie symmetrie groups, with varying strength.
- Intuition is not sufficient to select augmentations.
- Optimal mix is different from supervised [Brandstetter et al., 2022].
- Masking is necessary but not really sufficient.



SSL pre-training gives better results than purely supervised

SSL vs. supervised: open question in vision [Sariyildiz et al., 2023, Oquab et al., 2023]. Here, big discrepancy.



Influence of dataset size on regression tasks. **(Left)** Kinematic regression on Burger's equation. **(Right)** Buoyancy regression on Navier-Stokes' equation.

Problems to Solve

- **Mathematical Foundations of Energy-Based Learning**
  - The geometry of energy surfaces, scaling laws, bounds...
- **JEPA with regularized latent variables**
  - Learning and planning in non-deterministic environments
- **Planning algorithms in the presence of uncertainty**
  - Gradient-based methods and combinatorial search methods
- **Learning Cost Modules (Inverse RL)**
  - Energy-based approach: give low cost to observed trajectories
- **Planning with inaccurate world models**
  - Preventing bad plans in uncertain parts of the space
- **Exploration to adjust world models**
  - Intrinsic objectives for curiosity

Things we are working on

- **Self-Supervised Learning from Video**
  - Hierarchical Video-JEPA trained with SSL
- **LLMs that can reason & plan, driven by objectives**
  - Dialog systems that plan in representation space and use AR-LLM to turn representations into text
- **Learning hierarchical planning**
  - Training a multi-timescale H-JEPA on toy planning problems.

Points

- **Computing power**
  - AR-LLM use a fixed amount of computation per token
  - Objective-Driven AI is Turing complete (inference == optimization)
- **We are still missing essential concepts to reach human-level AI**
  - Scaling up auto-regressive LLMs will **not** take us there
  - We need machines to learn how the world works
- **Learning World Models with Self-Supervised Learning and JEPA**
  - Non-generative architecture, predicts in representation space
- **Objective-Driven AI Architectures**
  - Can plan their answers
  - Must satisfy objectives: are **steerable & controllable**
  - Guardrail objectives can make them **safe** by construction.

Future Universal Virtual Assistant

- **All of our interactions with the digital world will be mediated by AI assistants.**
  - They will constitute a repository of all human knowledge and culture
  - They will constitute a shared infrastructure Like the Internet today.
- **These AI platform MUST be open source**
  - Otherwise, our culture will be controlled by a few companies on the West Coast of the US or in China.
  - Training them will have to be crowd-sourced
- **Open source AI platforms are necessary**

What does this vision mean for policy?

- **AI systems will become a common platform**
- **The platforms (foundation models) will be open source**
  - They will condense all of human knowledge
  - Guardrail objectives will be shared for safety
- **Training and fine-tuning will be crowd-sourced**
  - Linguistic, cultural, and interest groups will fine-tune base models to cater to their interests.
- **Proprietary systems for vertical applications will be built on top**
- **When everyone has an AI assistant, we will need**
  - Massive computing infrastructure for inference: efficient inference chips.
- **OPEN SOURCE AI MUST NOT BE REGULATED OUT OF EXISTENCE**
  - **AI Alliance: Meta, IBM, Intel, Sony, academia, startups….**

Questions

- **How long is it going to take to reach human-level AI?**
  - Years to decades. Many problems to solve on the way.
  - Before we get to HLAI, we will get to cat-level AI, dog-level AI,...
- **What is AGI?**
  - There is no such thing. Intelligence is highly multidimensional
  - Intelligence is a collection of skills + ability to learn new skills quickly
  - Even humans can only accomplish a tiny subset of all tasks
- **Will machines surpass human intelligence**
  - Yes, they already do in some narrow domains.
  - **There is no question that machine will eventually surpass human intelligence in all domains where humans are intelligent (and more)**

Questions

- **Are there short-term risks associated with powerful AI?**
  - Yes, as with every technology.
  - Disinformation, propaganda, hate, spam,...: **AI is the solution!**
  - Concentration of information sources
  - All those risks can be mitigated
- **Are there long-term risks with (super-)human-level AI?**
  - Robots will not take over the world! a mistaken projection of human nature on machines
  - Intelligence is not correlated with a desire to dominate, even in humans
  - Objective-Driven AI systems will be made subservient to humans
  - AI will not be a “species” competing with us.
  - We will design its goals and guardrails.

Questions

- **How to solve the alignment problem?**
  - Through trial and error and testing in sand-boxed systems
  - We are very familiar with designing objectives for human and superhuman entities. It’s called law making.
  - What if bad people get their hand on on powerful AI?

    Their Evil AI will be taken down by the Good Guys’ AI police.
- **What are the benefits of human-level AI?**
  - AI will amplify human intelligence, progress will accelerate
  - As if everyone had a super-smart staff working for them
  - The effect on society may be as profound as the printing press
- **By amplifying human intelligence, AI will bring a new era of enlightenment, a new renaissance for humanity.**

Thank you!

NEW YORK UNIVERSITY

Meta AI