Objective-Driven AI

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

Yann LeCun
New York University
Meta – Fundamental AI Research

University of Washington
Lytle Lecture
2024-01-24

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

- **Smart glasses**
  - Communicates through voice, vision, display, electro-myogram interfaces (EMG)
- **Intelligent Asistant**
  - Can answer all of our questions
  - Helps us in our daily lives
  - Knows our preferences and interests

"Her" (2013)

- **For this, we need machines with common sense**
  - Machines that understand how the world works
  - Machines that can remember, reason, plan.

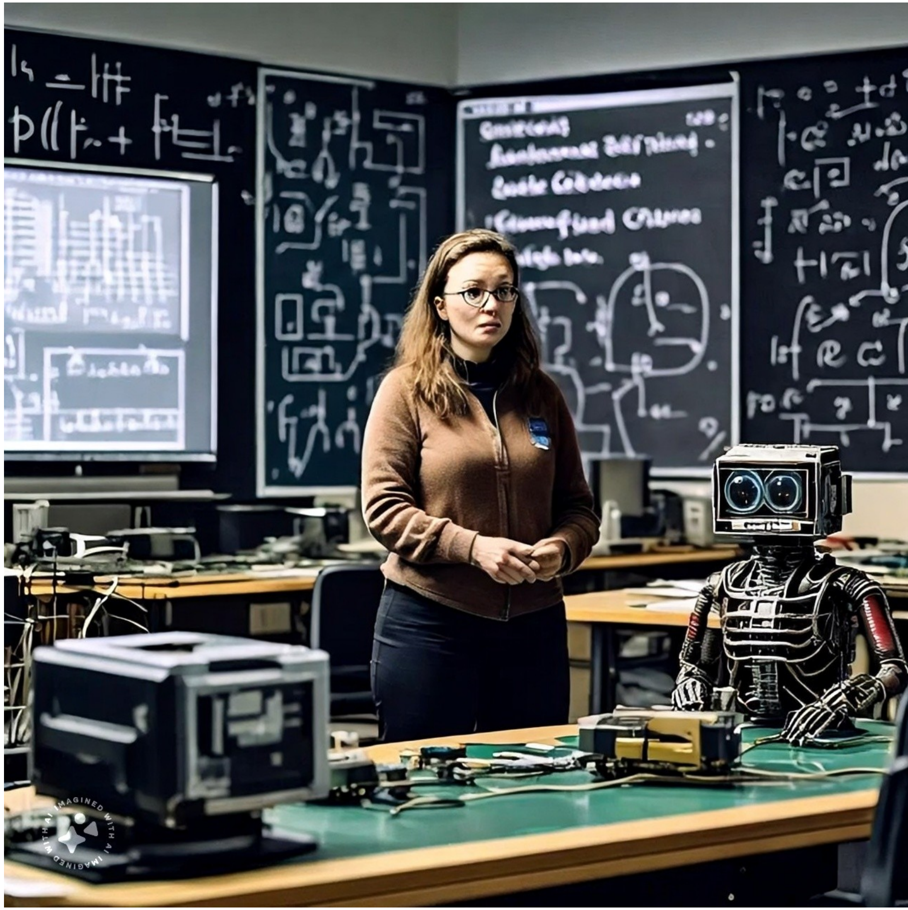
Future AI Assistants need Human-Level AI

- **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**

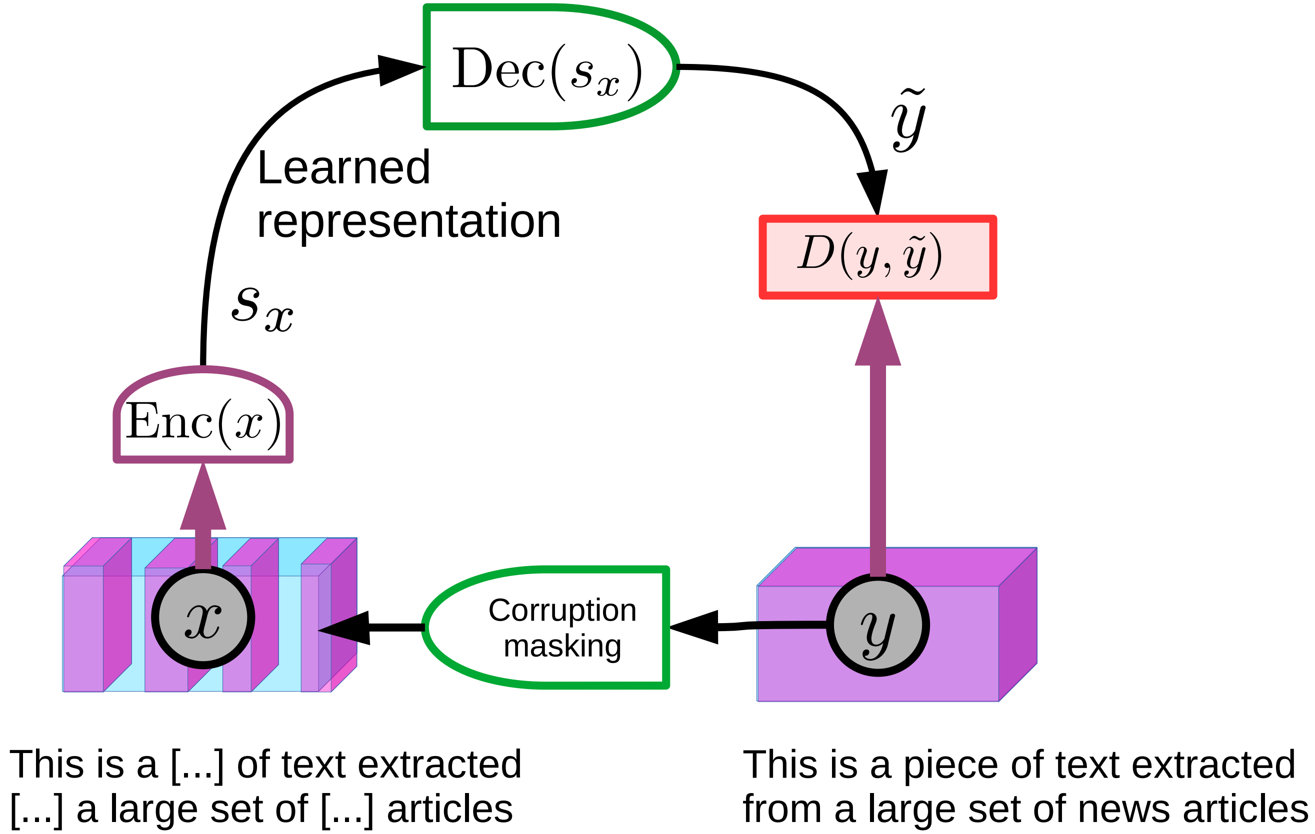


Self-Supervised Learning has taken over the world

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

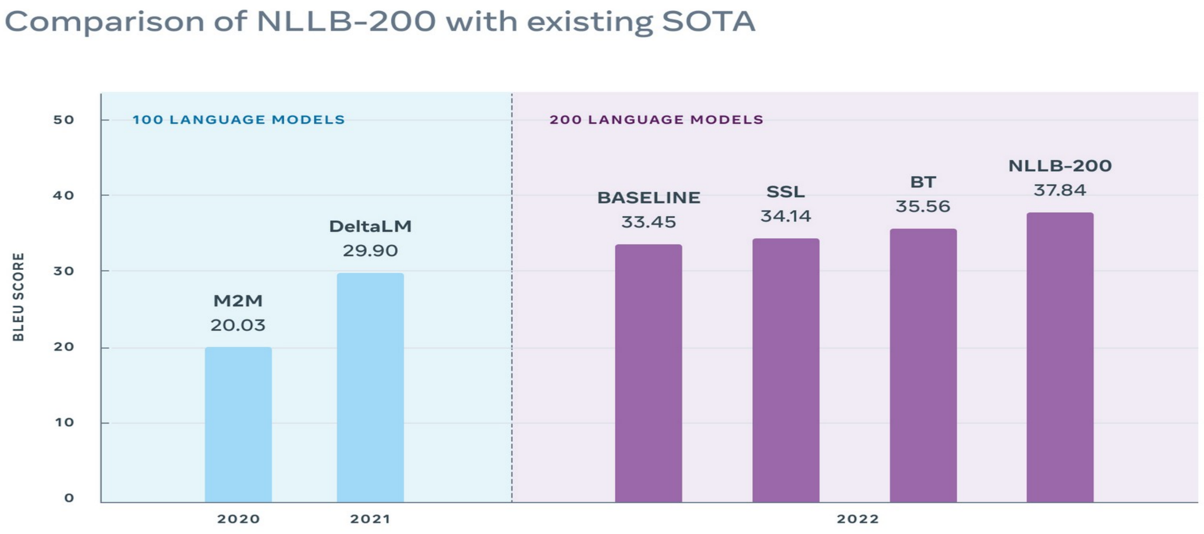
Self-Supervised Learning via Denoising / Reconstruction

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



No Language Left Behind (NLLB)

- **Language translation between 202 languages**
  - in any of the 40602 directions
  - Training set: 18 billion pairs of sentences for 2440 language directions
  - Most pairs have less than 1 million sentences
  - https://ai.facebook.com/research/no-language-left-behind/
- **A single neural net with 54 billion parameters**
- **Performance gets better as more languages are added**
- **Relies on Self-Supervised Learning and back-translation.**



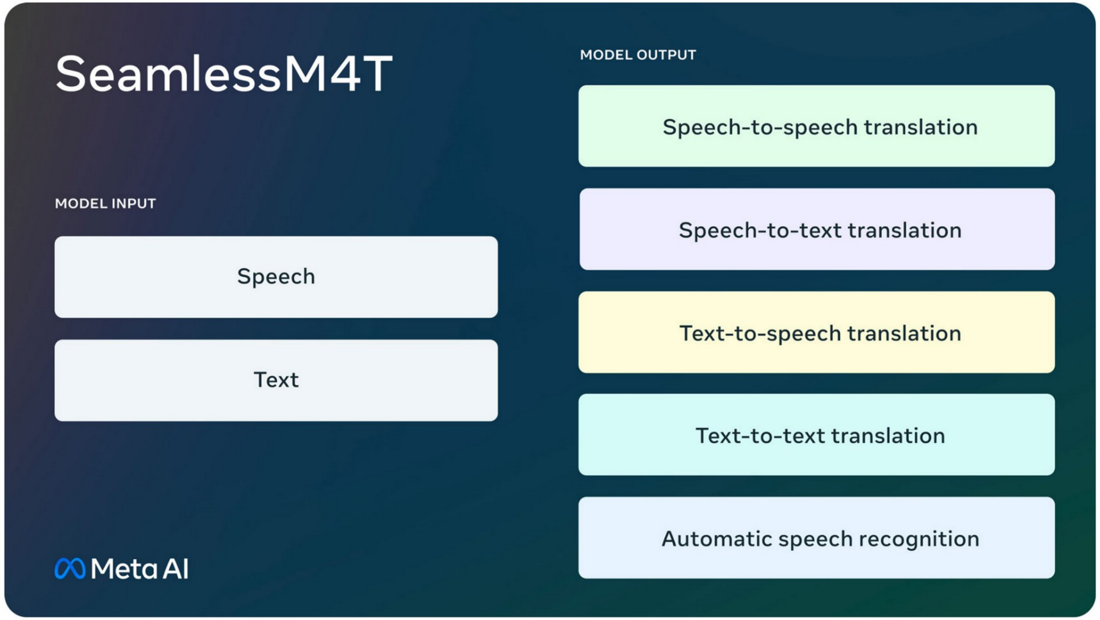
Y. LeCun

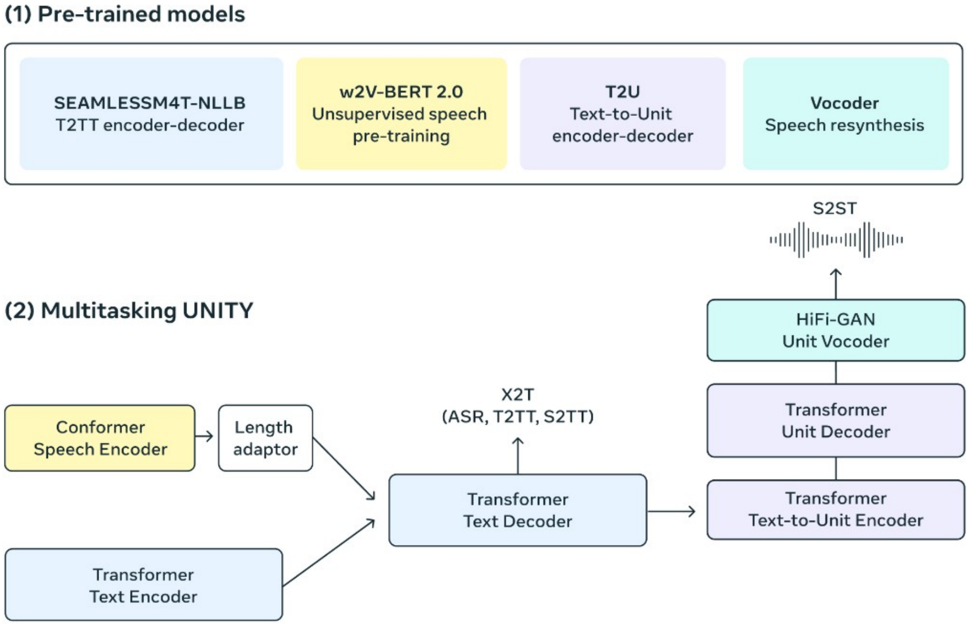
No Language Left Behind (NLLB)

Acehnese
Acehnese
Mesopotamian Arabic
Ta'izzi-Adeni Arabic
Tunisian Arabic
Afrikaans
South Levantine Arabic
Akan
Amharic
North Levantine Arabic
Modern Standard Arabic
Modern Standard Arabic
Najdi Arabic
Moroccan Arabic
Egyptian Arabic
Assamese
Asturian
Awadhi
Central Aymara
South Azerbaijani
North Azerbaijani
Bashkir
Bambara
Balinese
Belarusian
Bemba
Bengali
Bhojpuri
Banjar
Banjar
Standard Tibetan
Bosnian
Buginese
Bulgarian
Catalan
Cebuano
Czech
Chokwe
Central Kurdish
Crimean Tatar
Welsh
Danish
German
Southwestern Dinka
Dyula
Dzongkha
Greek
English
Esperanto
Estonian
Basque
Ewe
Faroese
Fijian
Finnish
Fon
French
Friulian
Nigerian Fulfulde
Scottish Gaelic
Irish
Galician
Guarani
Gujarati
Haitian Creole
Hausa
Hebrew
Hindi
Chhattisgarhi
Croatian
Hungarian
Armenian
Igbo
Ilocano
Indonesian
Icelandic
Italian
Javanese
Japanese
Kabyle
Jingpho
Kamba
Kannada
Kashmiri
Kashmiri
Georgian
Central Kanuri
Central Kanuri
Kazakh
Kabiyè
Kabuverdianu
Khmer
Kikuyu
Kinyarwanda
Kyrgyz
Kimbundu
Northern Kurdish
Kikongo
Korean
Lao
Ligurian
Limburgish
Lingala
Lithuanian
Lombard
Latgalian
Luxembourgish
Luba-Kasai
Ganda
Luo
Mizo
Standard Latvian
Magahi
Maithili
Malayalam
Marathi
Minangkabau
Minangkabau
Macedonian
Plateau Malagasy
Maltese
Meitei
Halh Mongolian
Mossi
Maori
Burmese
Dutch
Norwegian Nynorsk
Norwegian Bokmål
Nepali
Northern Sotho
Nuer
Nyanja
Occitan
West Central Oromo
Odia
Pangasinan
Eastern Panjabi
Papiamento
Western Persian
Polish
Portuguese
Dari
Southern Pashto
Ayacucho Quechua
Romanian
Rundi
Russian
Sango
Sanskrit
Santali
Sicilian
Shan
Sinhala
Slovak
Slovenian
Samoan
Shona
Sindhi
Somali
Southern Sotho
Spanish
Tosk Albanian
Sardinian
Serbian
Swati
Sundanese
Swedish
Swahili
Silesian
Tamil
Tatar
Telugu
Tajik
Tagalog
Thai
Tigrinya
Tamasheq
Tamasheq
Tok Pisin
Tswana
Tsonga
Turkmen
Tumbuka
Turkish
Twi
Central Atlas Tamazight
Uyghur
Ukrainian
Umbundu
Urdu
Northern Uzbek
Venetian
Vietnamese
Waray
Wolof
Xhosa
Eastern Yiddish
Yoruba
Yue Chinese
Chinese
Chinese
Standard Malay
Zulu

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/





Deep Learning Connects People to knowledge & to each other

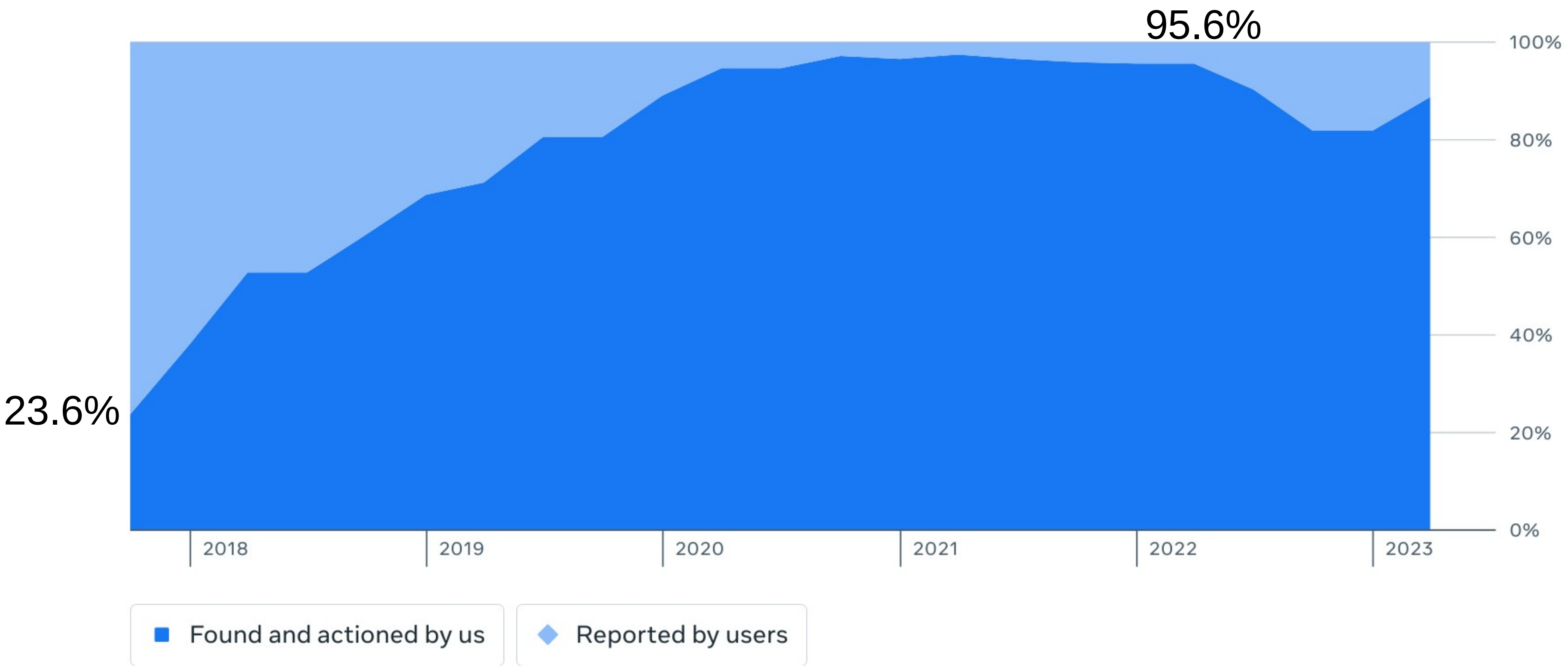
- **Meta (FB, Instagram), Google, YouTube, Amazon, are built around Deep learning**
  - Take Deep Learning out of them, and they crumble.
- **DL helps us deal with the information deluge**
  - Search, retrieval, ranking, question-answering
  - Requires machines to understand content
- **Translation / transcription / accessibility**
  - language ↔ language; text ↔ speech; image → text
  - People speak thousands of different languages
  - 3 billion people can’t use technology today.
  - 800 million are illiterate, 300 million are visually impaired

On-Line Content Moderation

- **Filtering out illegal and dangerous content**
  - What constitutes acceptable content?
  - Meta doesn’t see itself as having the legitimacy to decide
  - But in the absence of regulations, it has to do it.
- **Types of objectionable content on Facebook**
  - (with % taken down preemptively & prevalence, Q1 2022)
  - Hate Speech (95.6%, 0.02%), Violence incitement (98.1%, 0.03%), Violence (99.5%, 0.04%), Bullying/Harassment (67%, 0.09%), Child endangerment (96.4%), Suicide/Self-Injury (98.8%), Nudity (96.7%, 0.04%), Terrorism (16M pieces), Fake accounts (1.5B), Spam (1.8B)
  - https://transparency.fb.com/data/community-standards-enforcement
- **AI is the solution, not the problem**

Hate speech suppression/down-ranking on Facebook

- **Of the violating content we actioned for hate speech, how much did we find and action before people reported it?**
  - https://transparency.fb.com/reports/community-standards-enforcement/hate-speech/facebook/

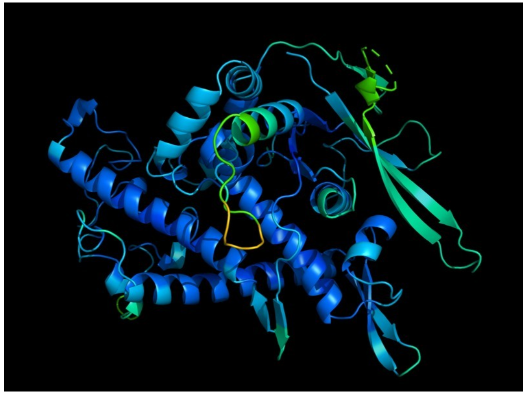


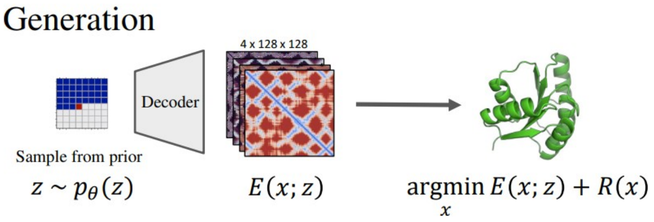
Protein folding and inverse folding (protein design)

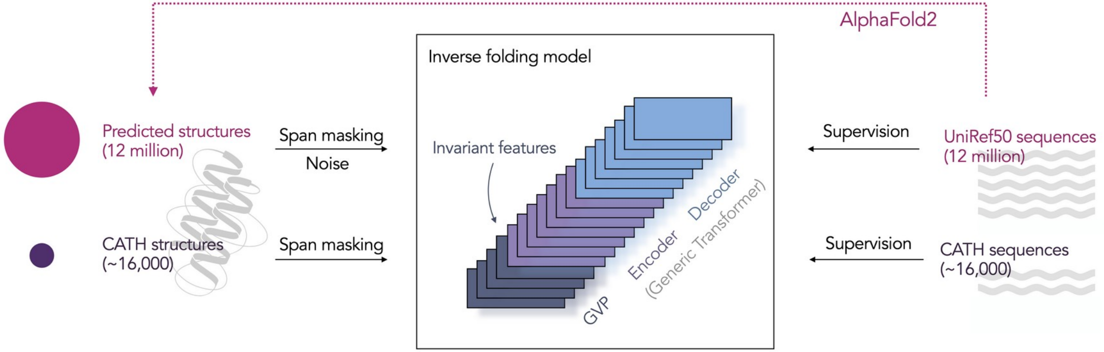
- **Protein Folding:**
  - from a sequence of amino acids to 3D structure
  - [Jumper 21, Rives 19]
- **Protein Generation**
  - [Lin et al. 2021]
- **Protein Design:**
  - from 3D structure to sequences of amino acids
  - For drug design
  - [Lin & al. BioRxiv:2022.07.20.500902]

ESMfold, ESMfold-2 (FAIR)

AlphaFold, AlphaFold-2 (DeepMind)

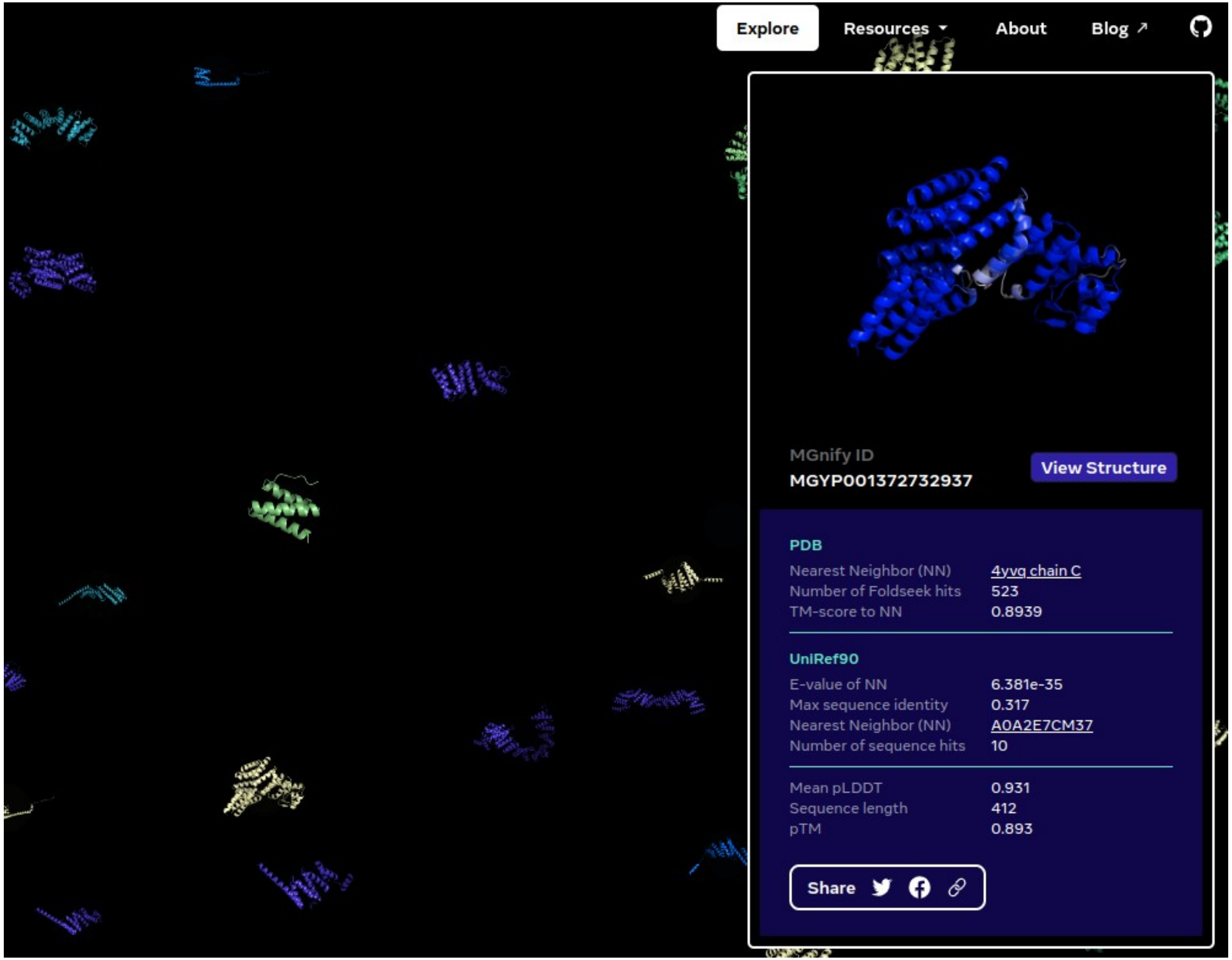






ESM Metagenomic Atlas (FAIR+NYU)

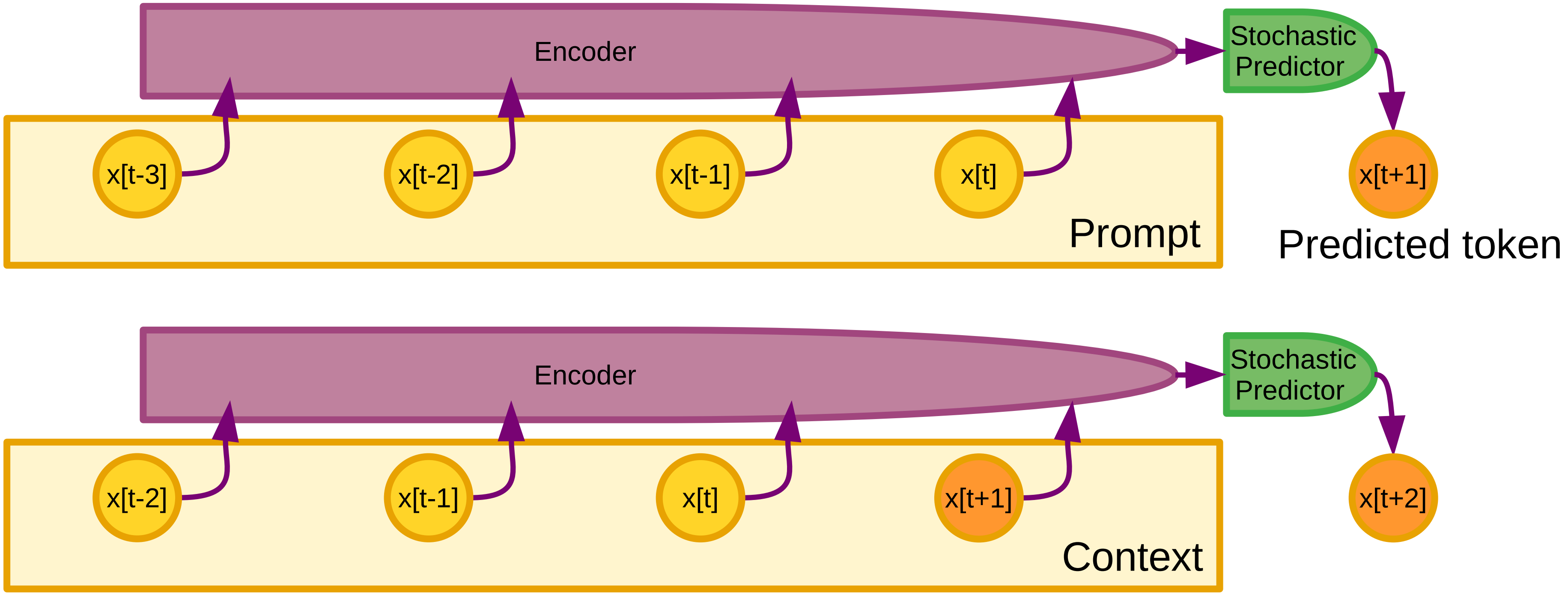
- **615 million proteins with predicted 3D structure**
- **Interactive website**
  - https://esmatlas.com/
- **Paper:**
  - [Lin et al. 2022] Evolutionary-scale prediction of atomic level protein structure with a language model https://www.biorxiv.org/content/10.1101/2022.07.20.500902
- **Code:**
  - https://github.com/facebookresearch/esm



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 (Mistral), Falcon (UAE), Alpaca (Stanford), Yi (01.AI)….
  - Proprietary: Meta AI (Meta), LaMDA/Bard (Google), Chinchilla (DeepMind), 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 & 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,….**

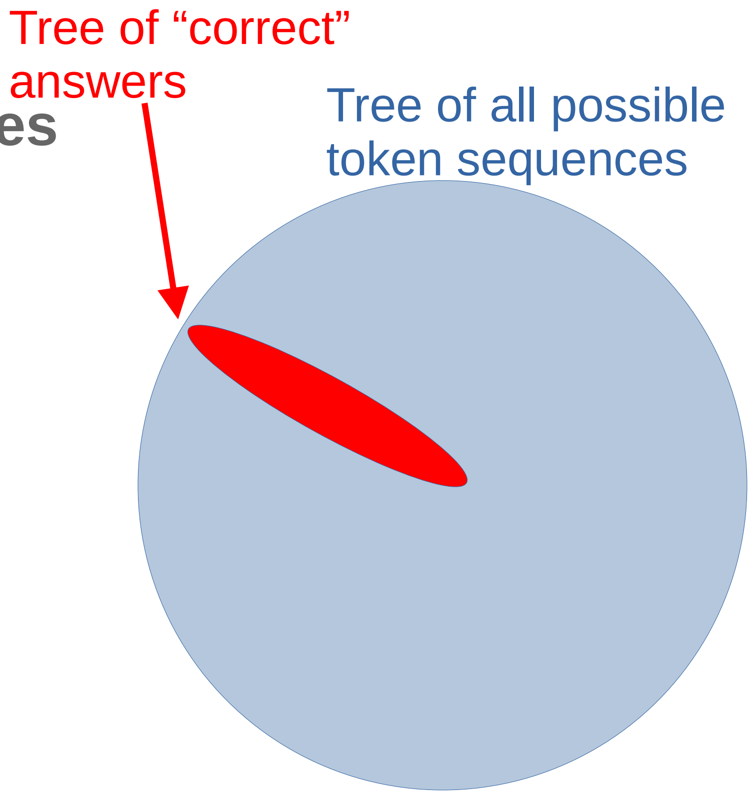
MODEL SIZE (PARAMETERS)	PRETRAINED	FINE-TUNED FOR CHAT USE CASES
7B	**Model architecture:** **Pretraining Tokens:** 2 Trillion **Context Length:** 4096	**Data collection for helpfulness and safety:** **Supervised fine-tuning:** Over 100,000 **Human Preferences:** Over 1,000,000
13B		
70B		

Meta AI: free public chatbot based on Llama-2 technology

- Connect with “Meta AI” in Messenger app, and WhatsApp.
- 28 specialized Facebook chatbots: e.g. Snoop Dogg as Dungeon Master.

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]

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.

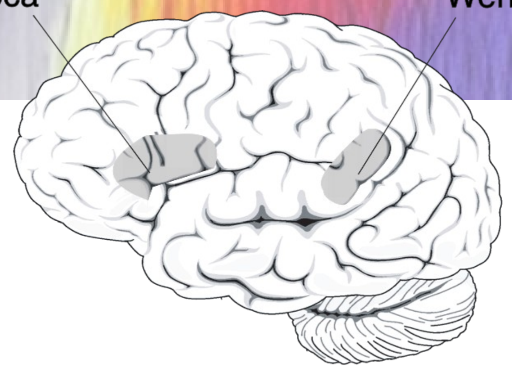
ESSAY TECHNOLOGY & THE HUMAN

BY JACOB BROWNING AND YANN LECUN

AUGUST 23, 2022

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 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

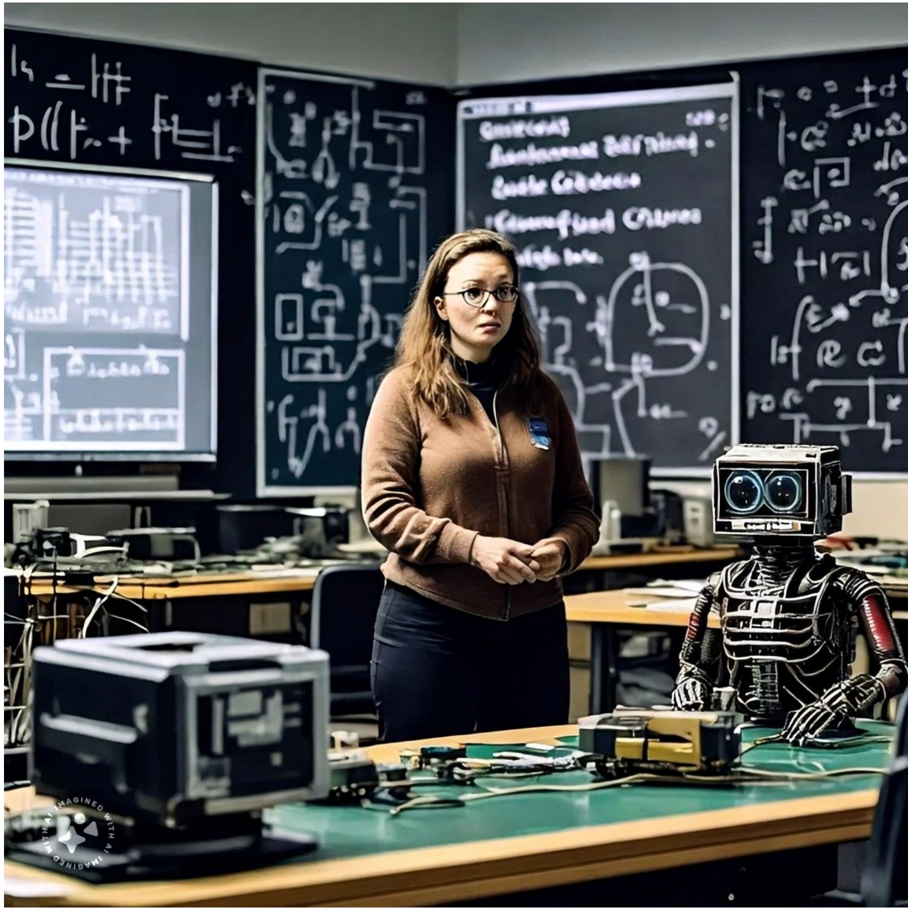
- **A four year-old child has seen 50 times more data than an LLM !**

Three challenges for AI & Machine Learning

- **1. Learning representations and predictive models of the world**
  - **Using Self-supervised learning** from video and other sensory inputs
    - learning to represent the world in a non task-specific way
    - Learning predictive world models for planning and control
- **2. Learning to reason,** like Daniel Kahneman's "System 2"
  - Beyond feed-forward, System 1 subconscious computation.
  - Making reasoning compatible with learning.
    - Reasoning and planning as energy minimization.
- **3. Learning to plan complex actions to satisfy objectives**
  - Learning hierarchical representations of action plans

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

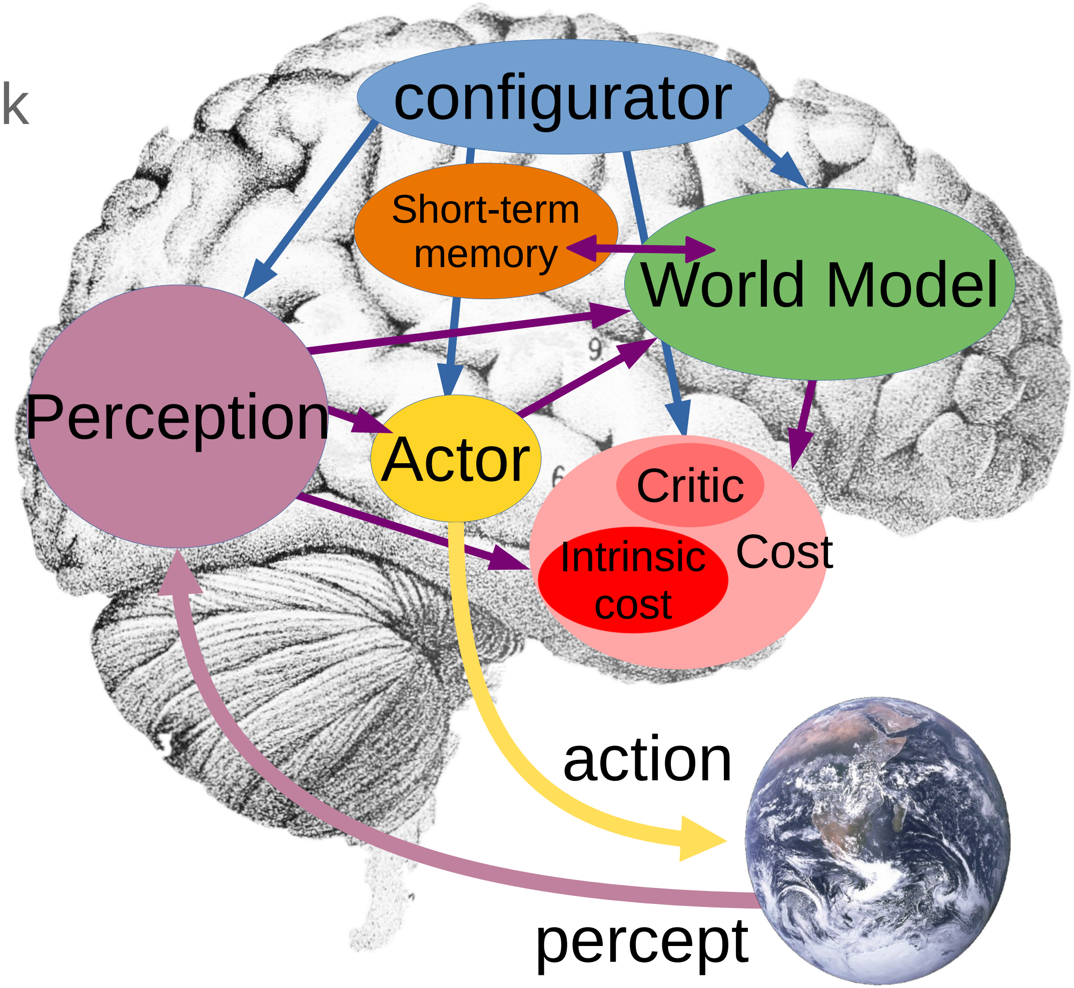
"A path towards autonomous machine intelligence"
https://openreview.net/forum?id=BZ5a1r-kVsf

[various versions of this talk on YouTube]

Modular Cognitive Architecture for Objective-Driven AI

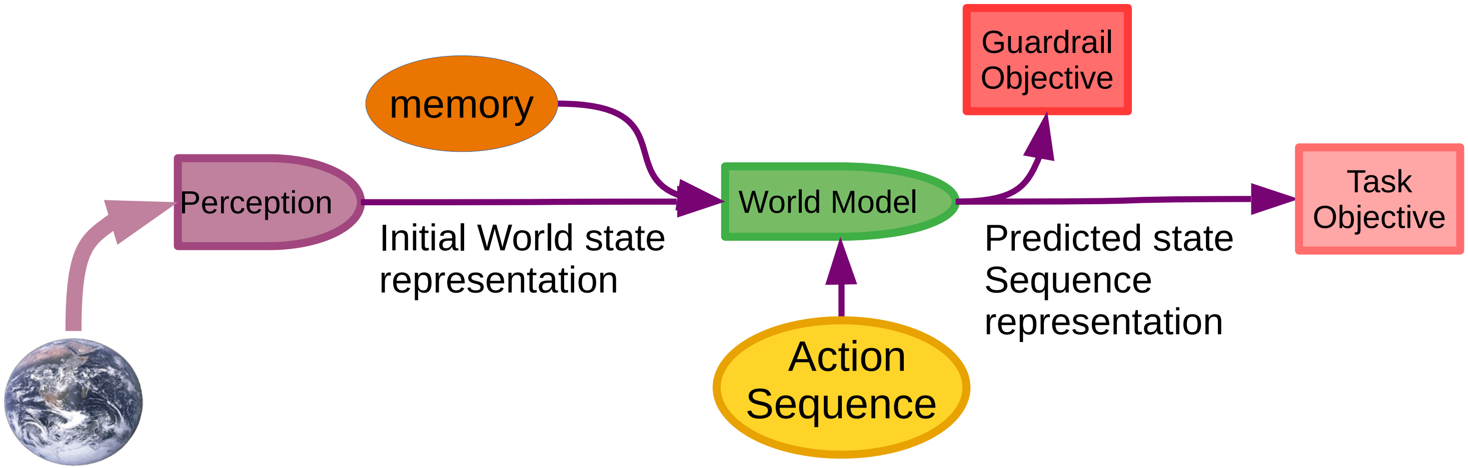
Y. LeCun

- **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



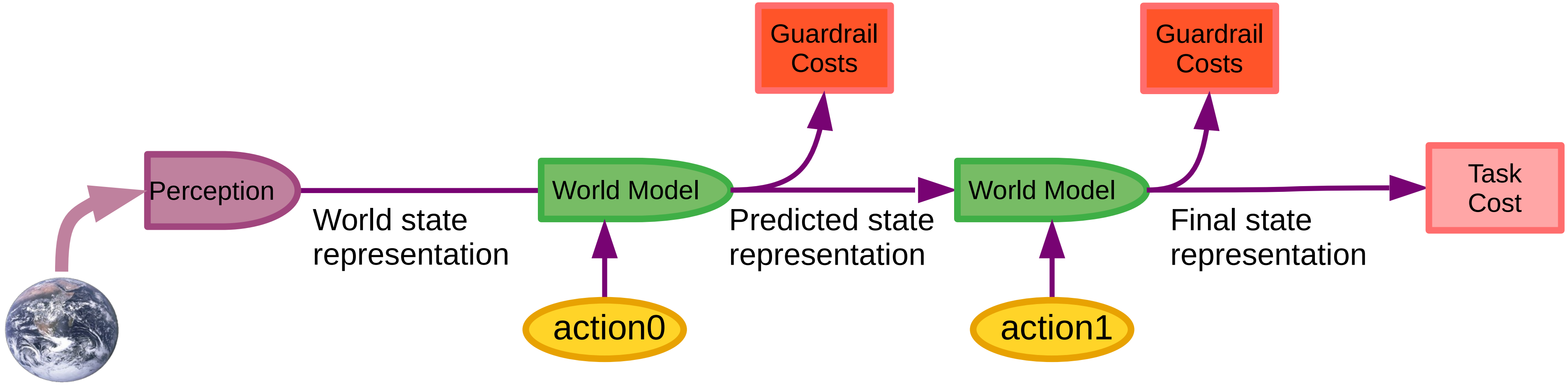
Objective-Driven AI

- **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**



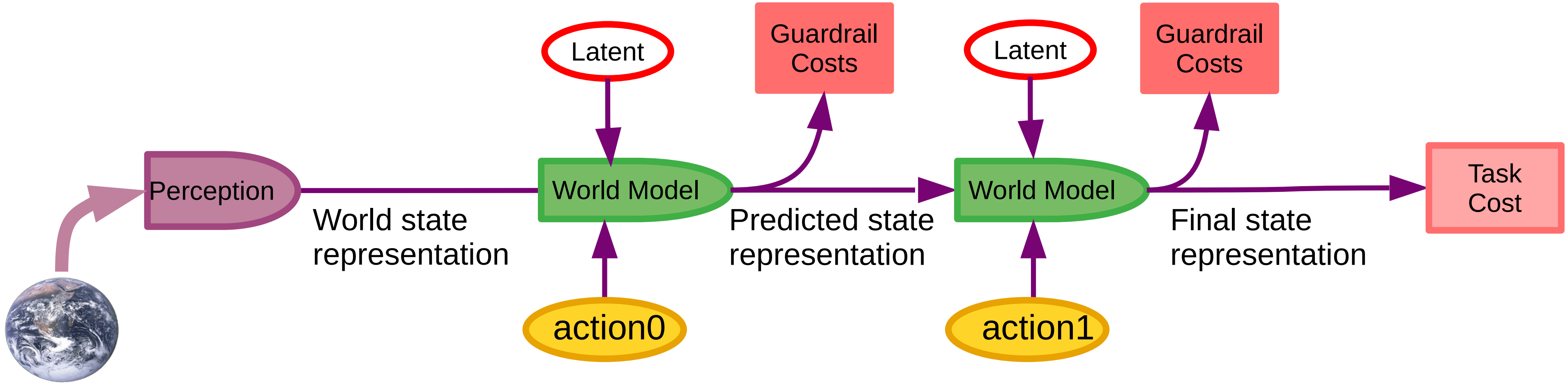
Objective-Driven AI: Multistep/Recurrent World Model

- **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, DP, MCTS,….



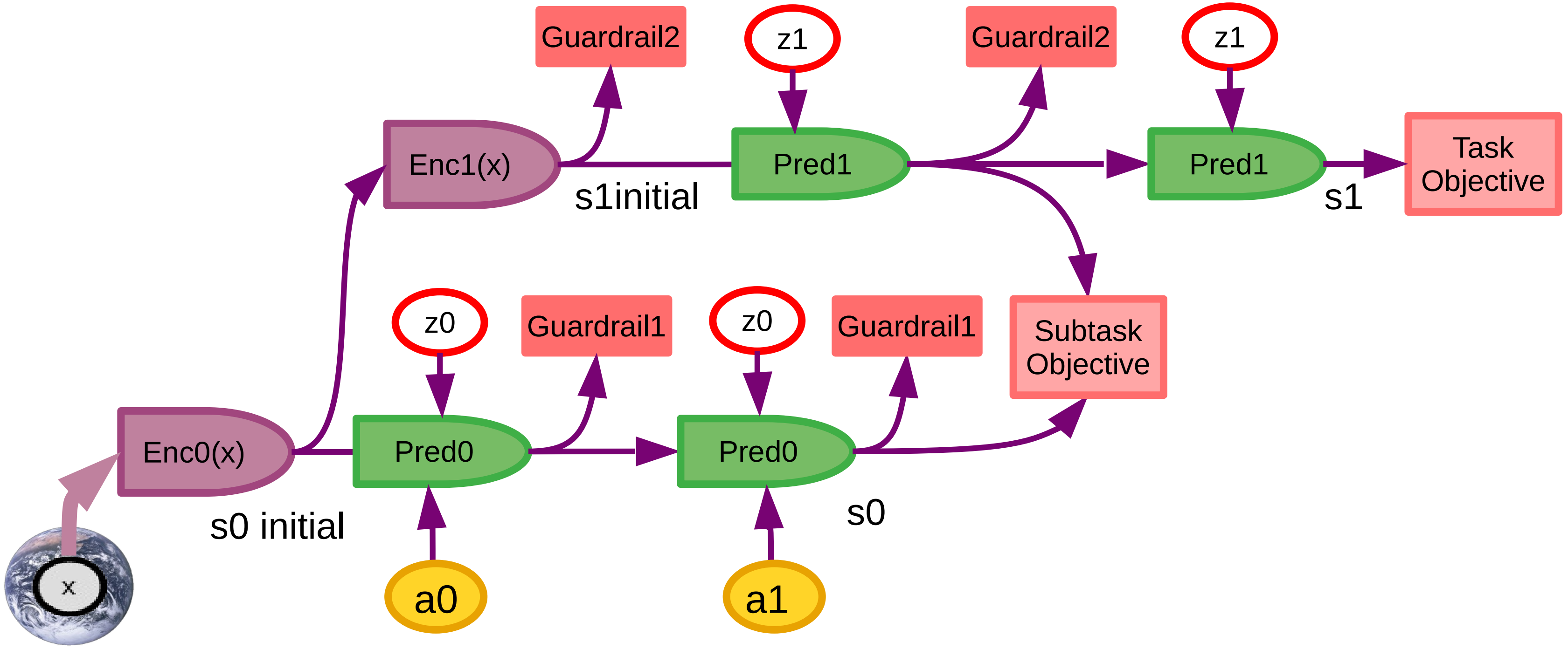
Objective-Driven AI: Non-Deterministic World Model

- **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



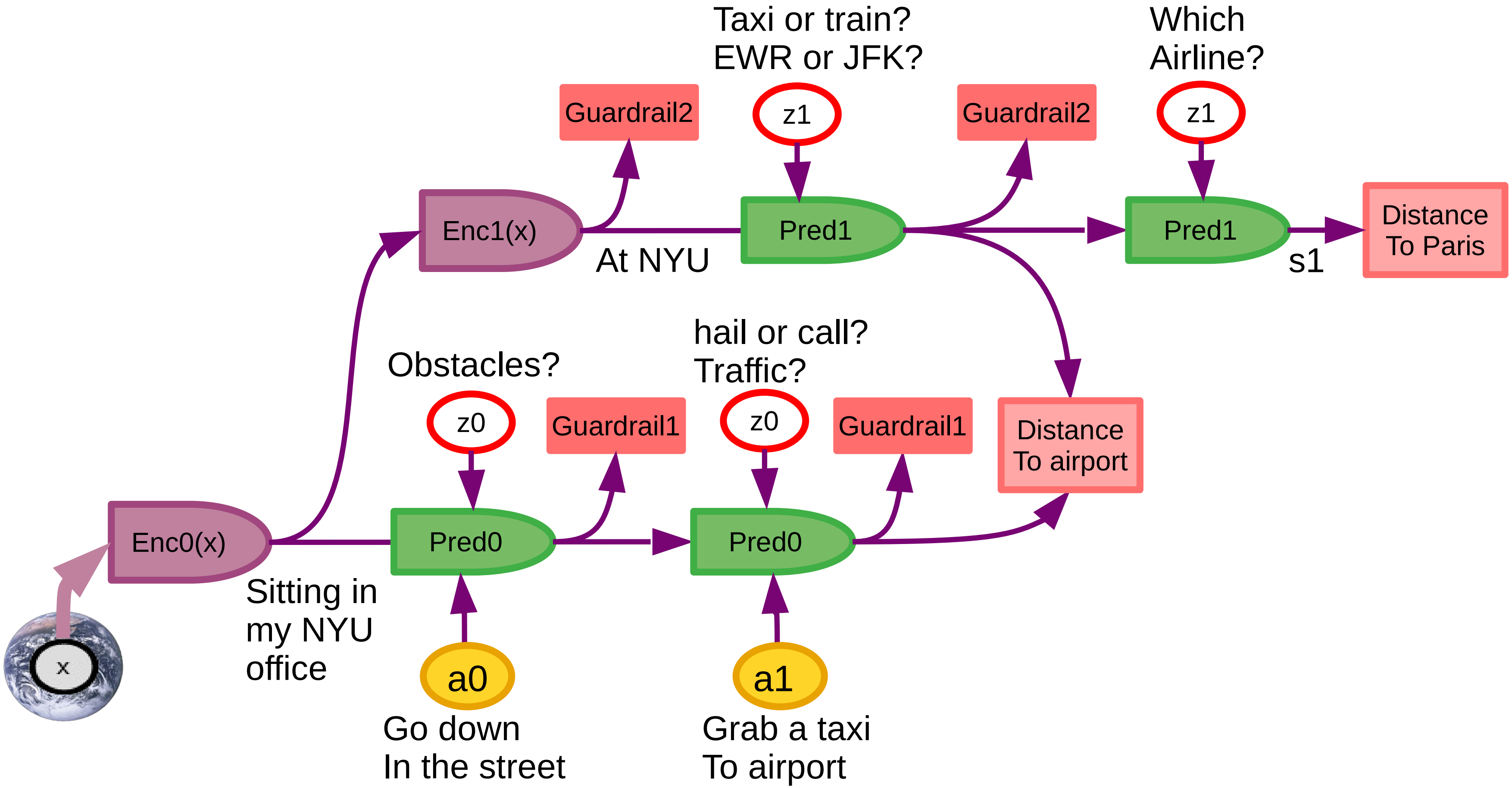
Objective-Driven AI: Hierarchical Planning

- **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



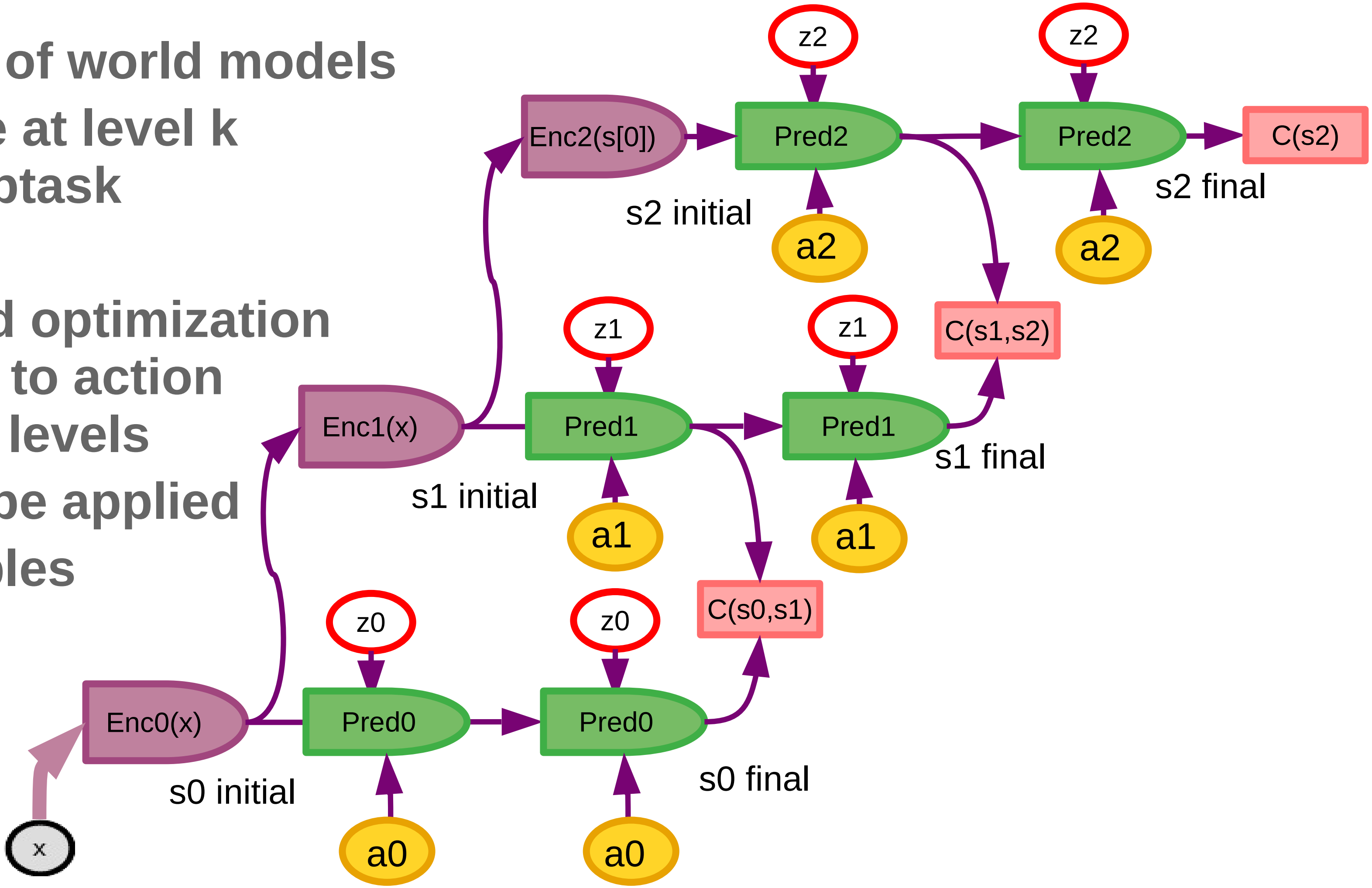
Objective-Driven AI: Hierarchical Planning

- **Hierarchical Planning: going from NYU to Paris**



Objective-Driven AI: Hierarchical Planning

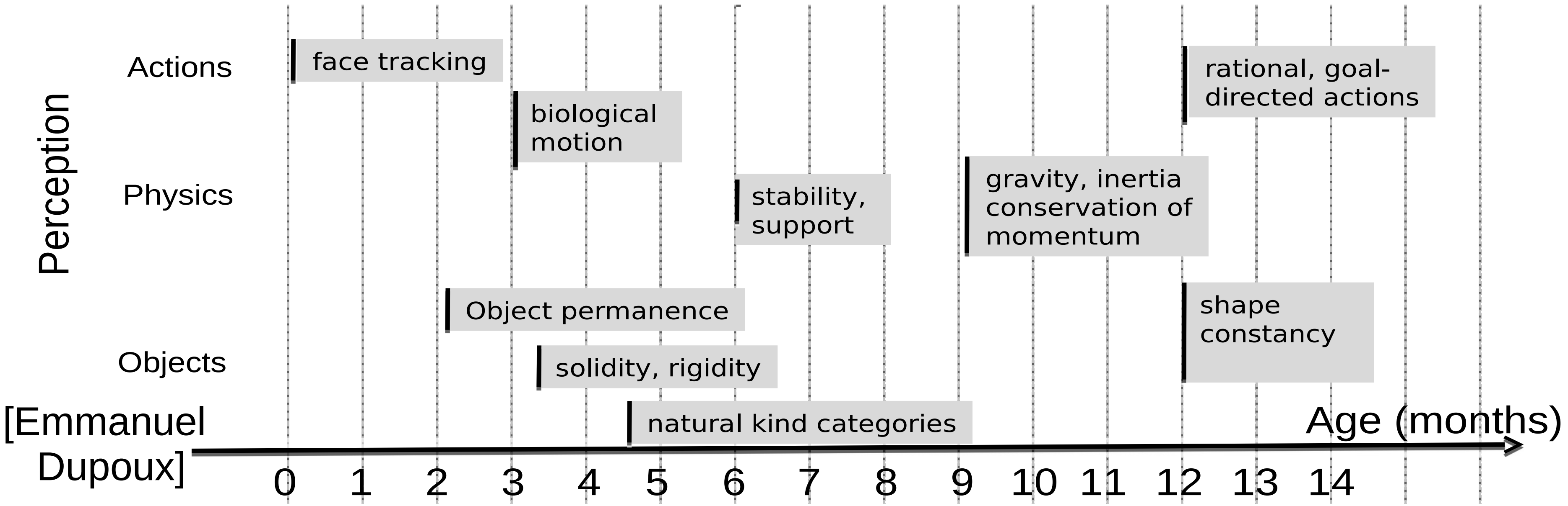
- Multiple levels of world models
- Predicted state at level k determines subtask for level k-1
- Gradient-based optimization can be applied to action variables at all levels
- Sampling can be applied to latent variables at all levels.



How could Machines Learn World Models from Sensory Input?

with
Self-Supervised Learning

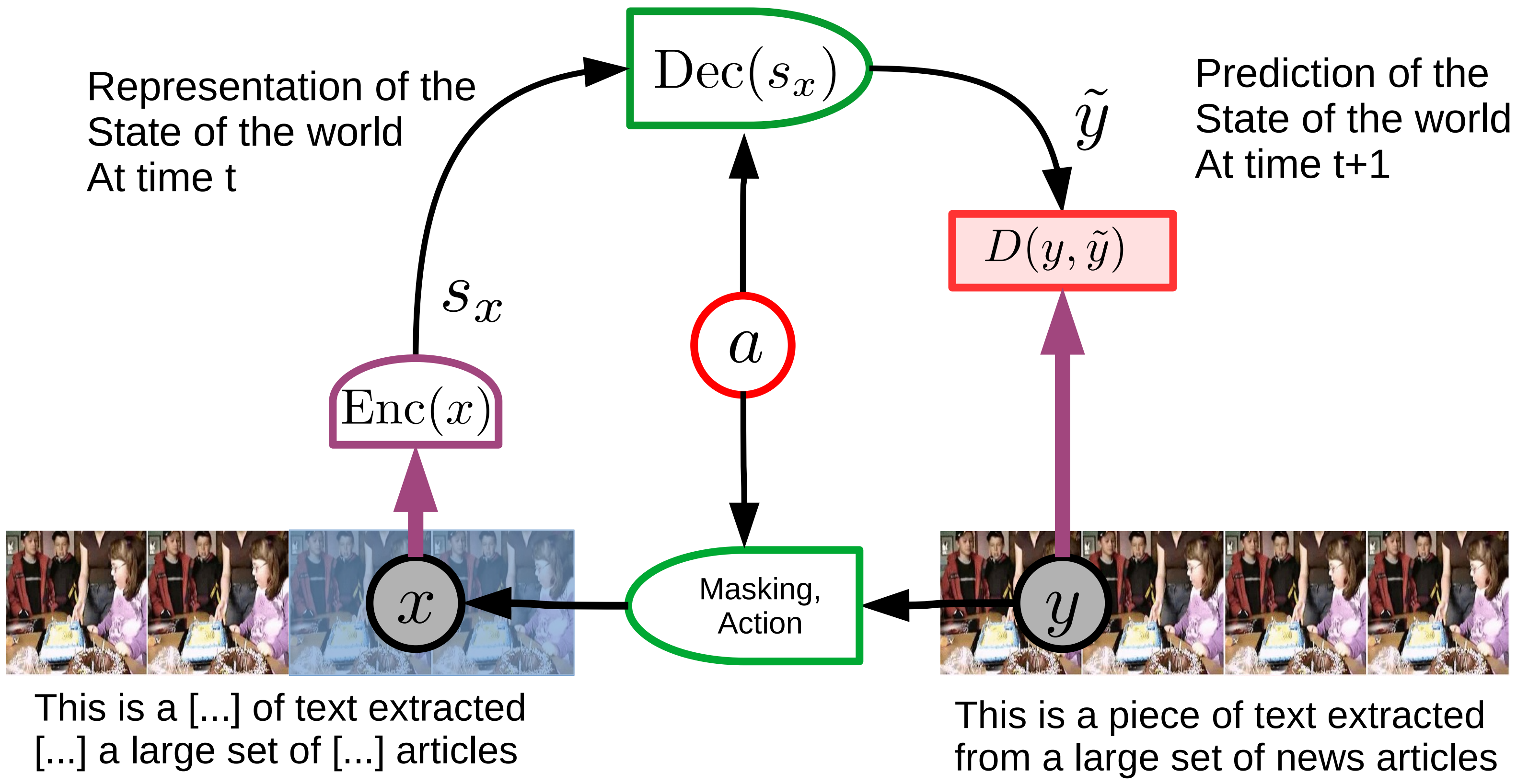
How could machines learn like animals and humans?



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

Generative World Models with Self-Supervised Training?

- **Generative world model architecture**

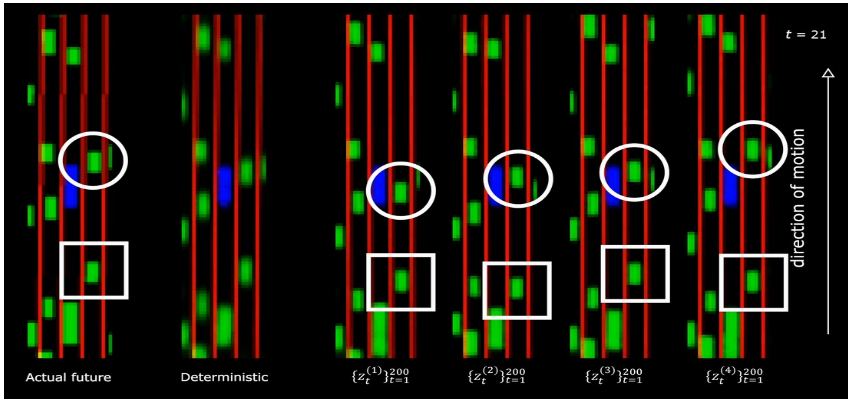


Generative Architectures DO NOT Work for Images

- **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**

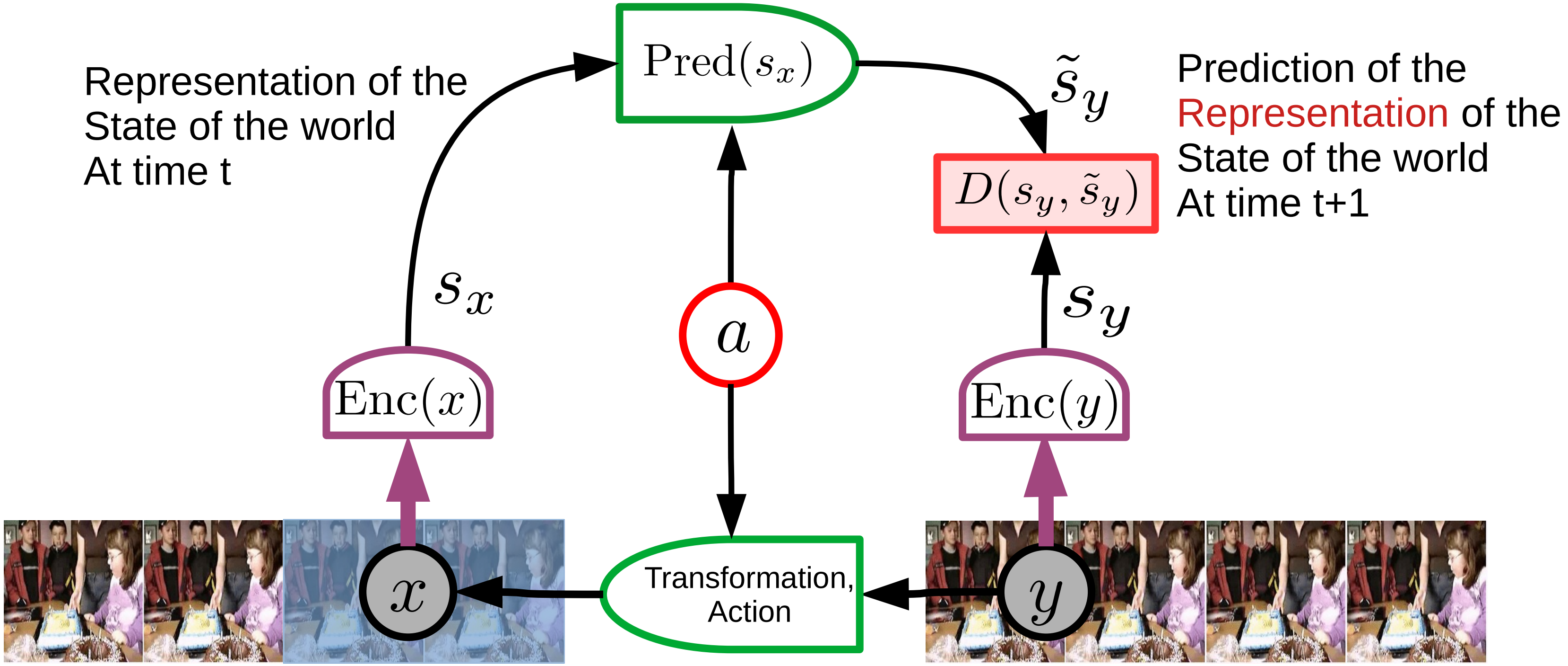
[Mathieu, Couprie, LeCun ICLR 2016]



[Henaff, Canziani, LeCun ICLR 2019]

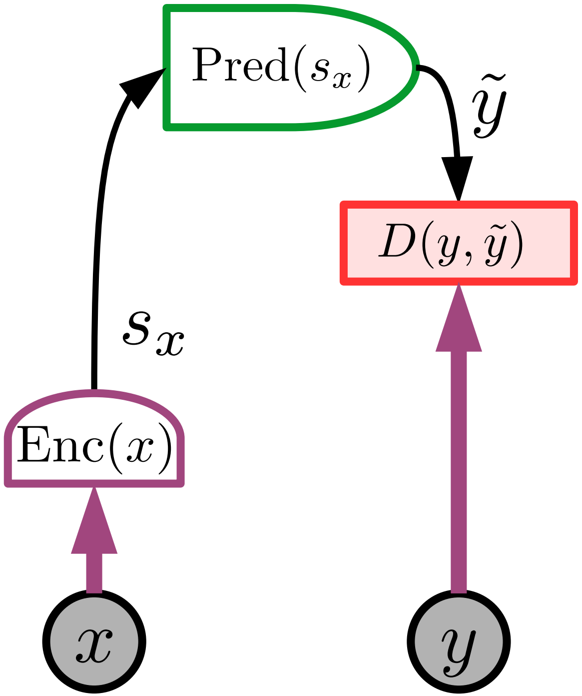
Joint Embedding World Model: Self-Supervised Training

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

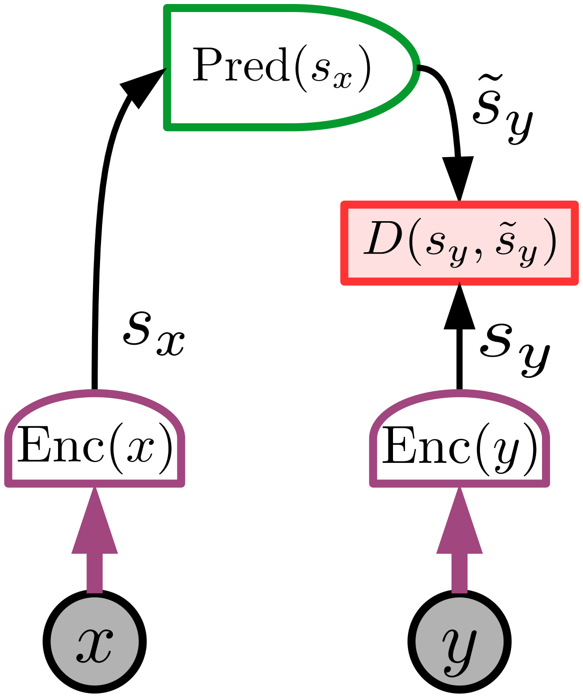


Architectures: Generative vs Joint Embedding

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



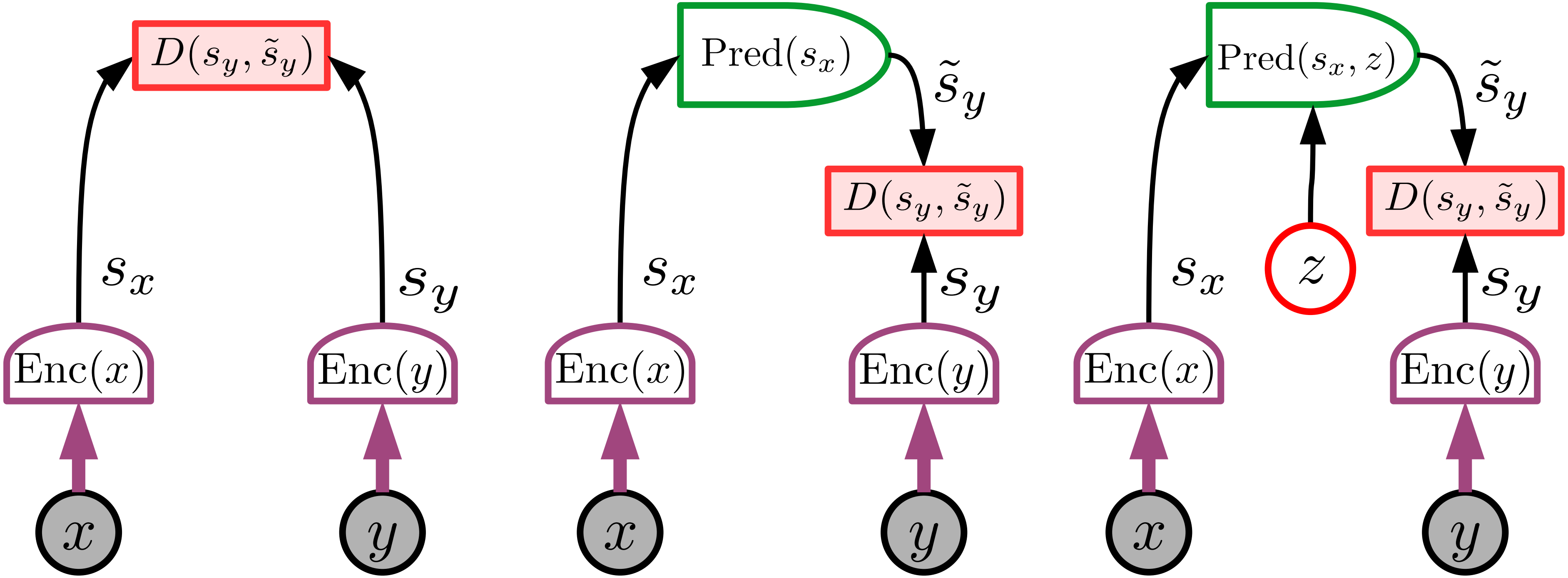
a) Generative Architecture
Examples: VAE, MAE...



b) Joint Embedding Architecture

Joint Embedding Architectures

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



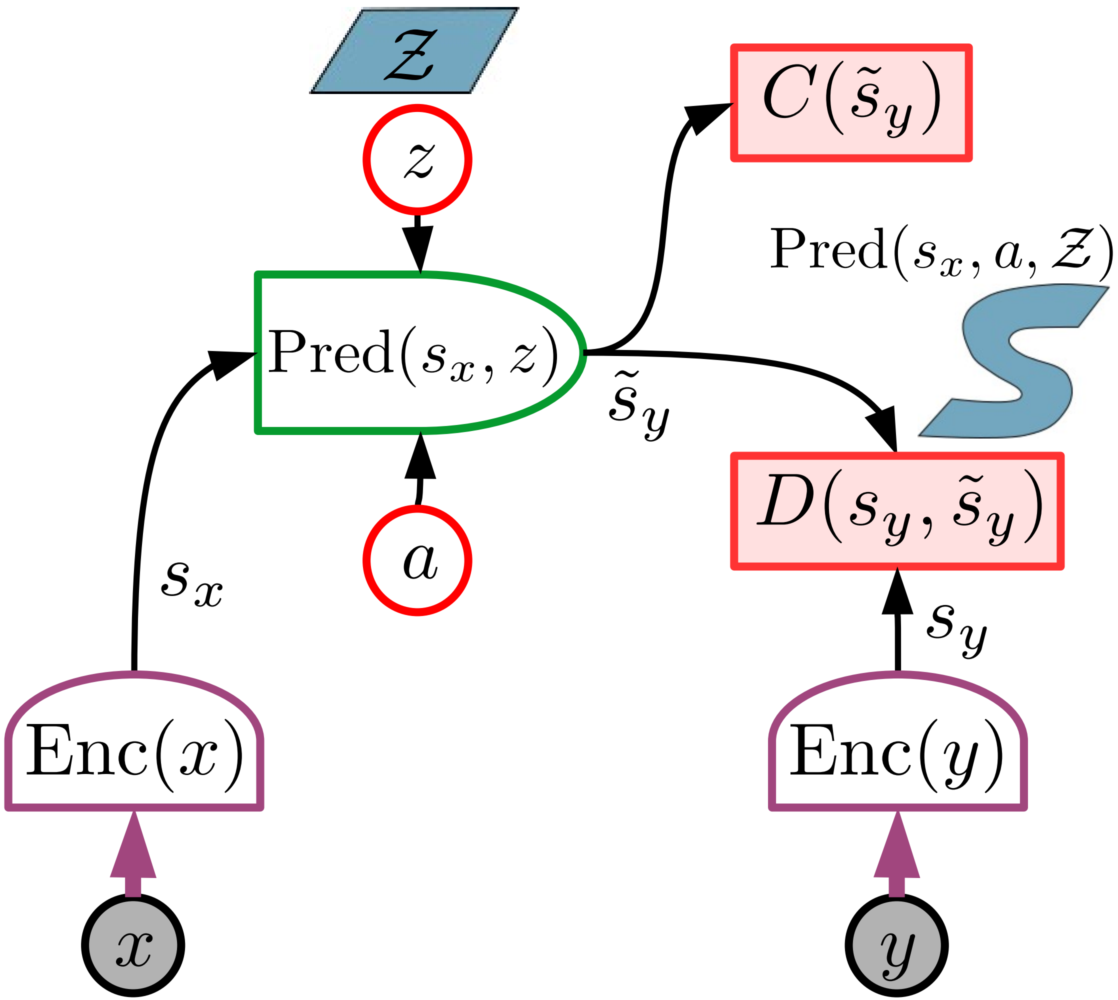
a) Joint Embedding Architecture (JEA)
Examples: Siamese Net, Pirl, MoCo, SimCLR, BarlowTwins, VICReg,

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

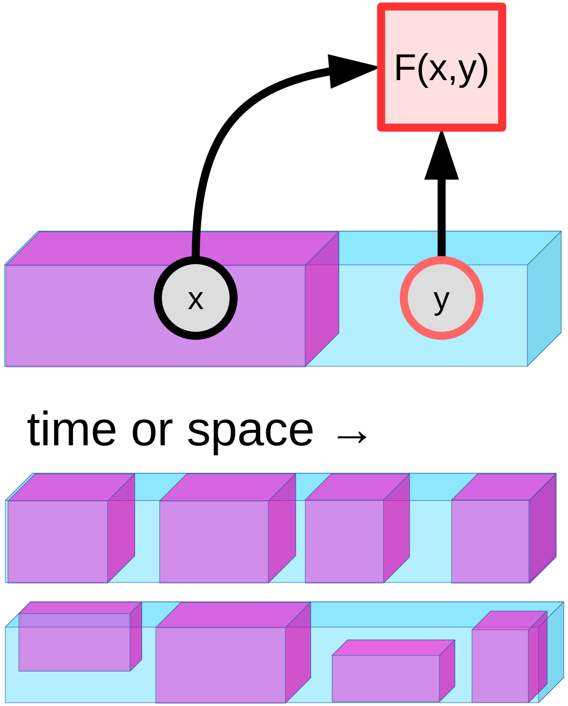


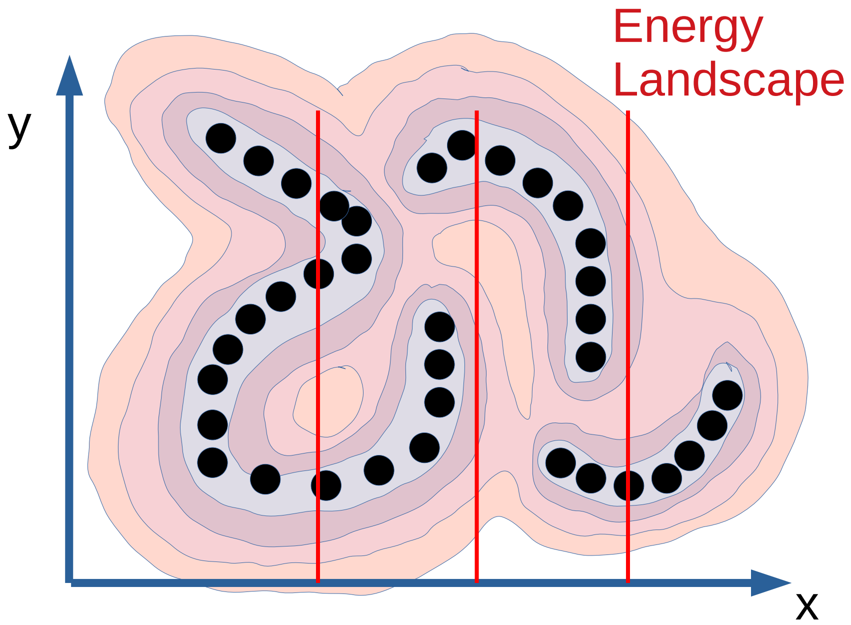
Energy-Based Models

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



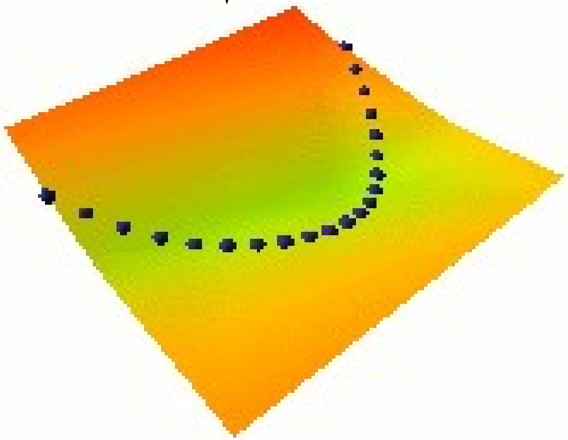


$$\check{y} = \mathrm{argmin}_y F(x,y)$$

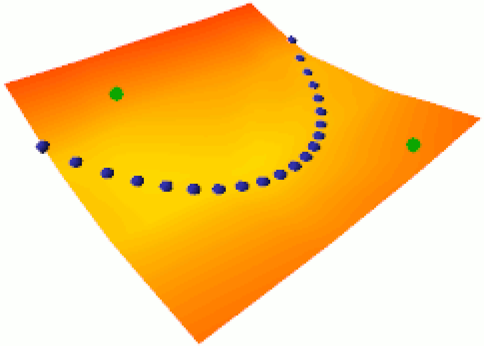
Training Energy-Based Models: Collapse Prevention

- **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.

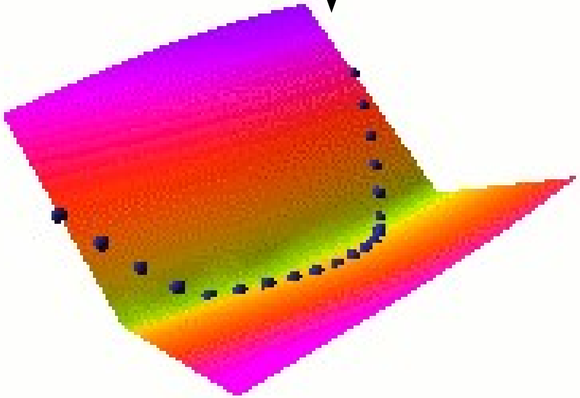
Collapse!



Contrastive Method

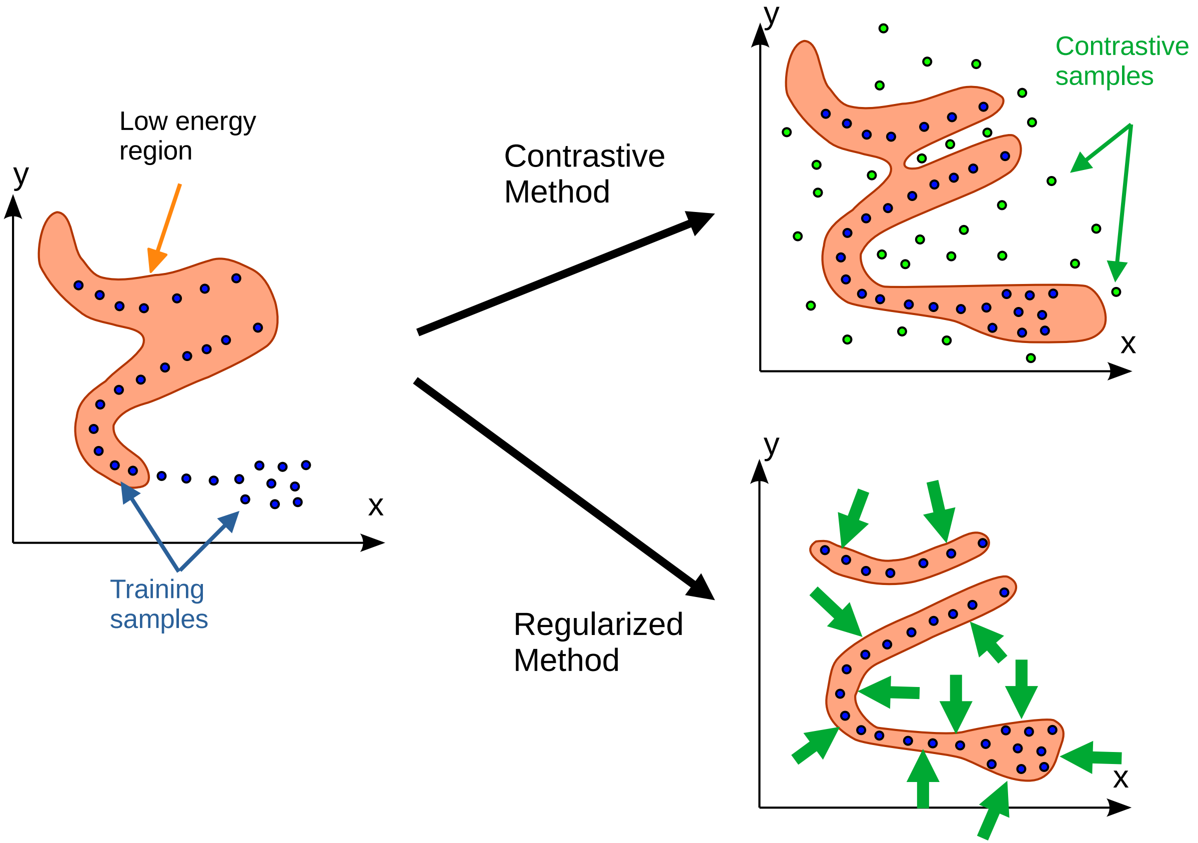


Regularized Methods



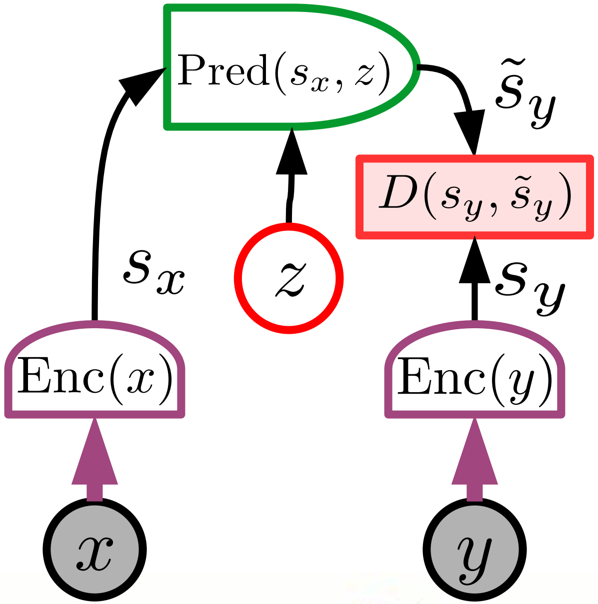
EBM Training: two categories of methods

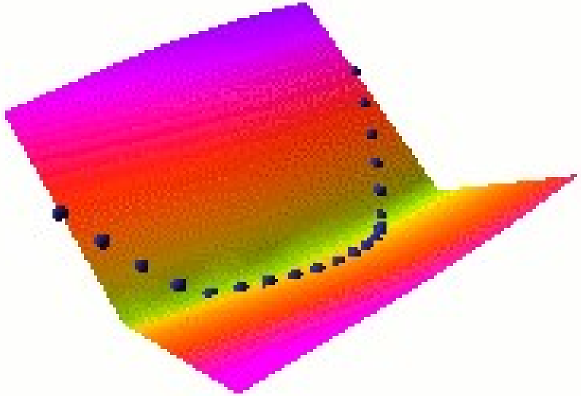
- **Contrastive methods**
  - Push down on energy of training samples
  - Pull up on energy of suitably-generated contrastive samples
  - Scales very badly with dimension
- **Regularized Methods**
  - Regularizer minimizes the volume of space that can take low energy



Recommendations:

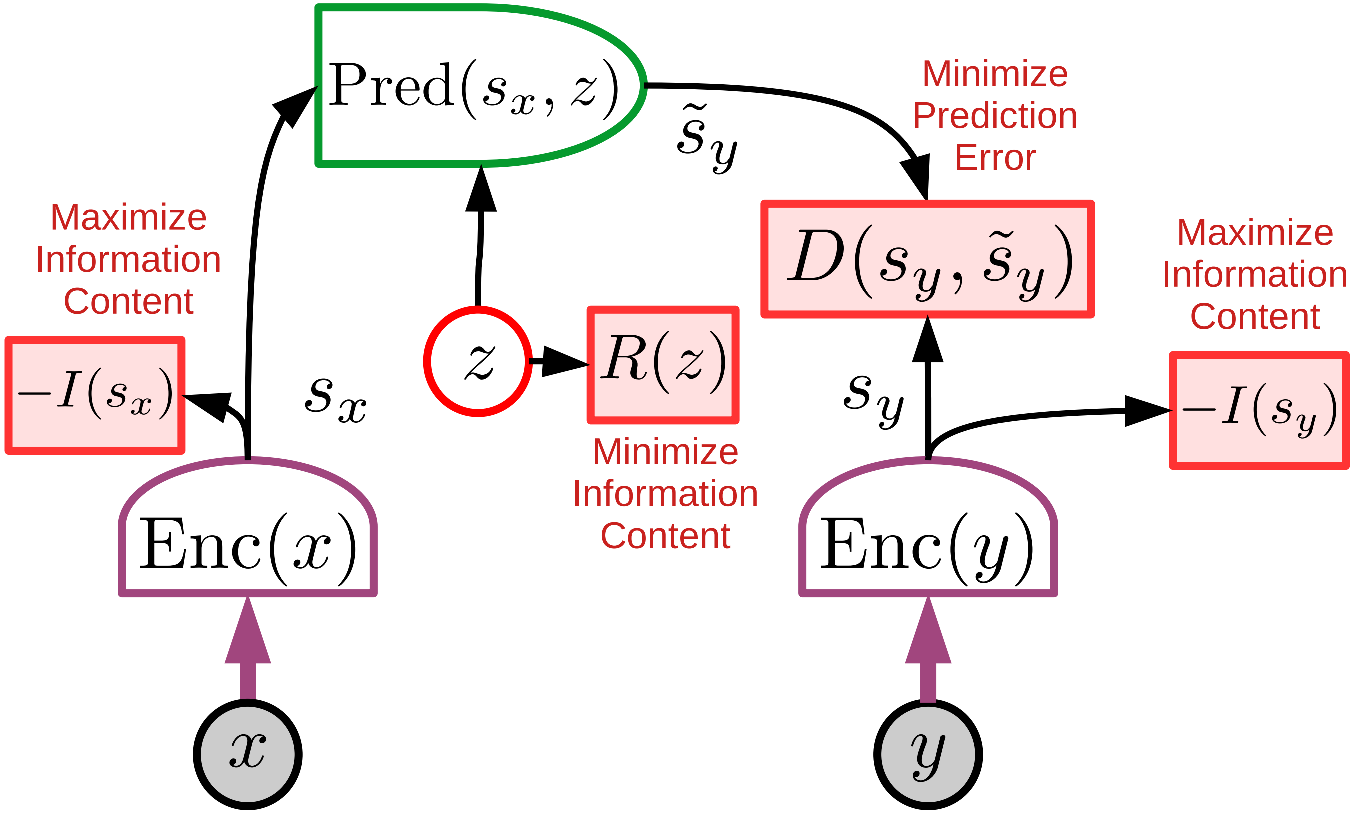
- **Abandon generative models**
  - in favor joint-embedding architectures
- **Abandon probabilistic model**
  - in favor of energy-based models
- **Abandon contrastive methods**
  - in favor of regularized methods
- **Abandon Reinforcement Learning**
  - In favor of model-predictive control
  - Use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





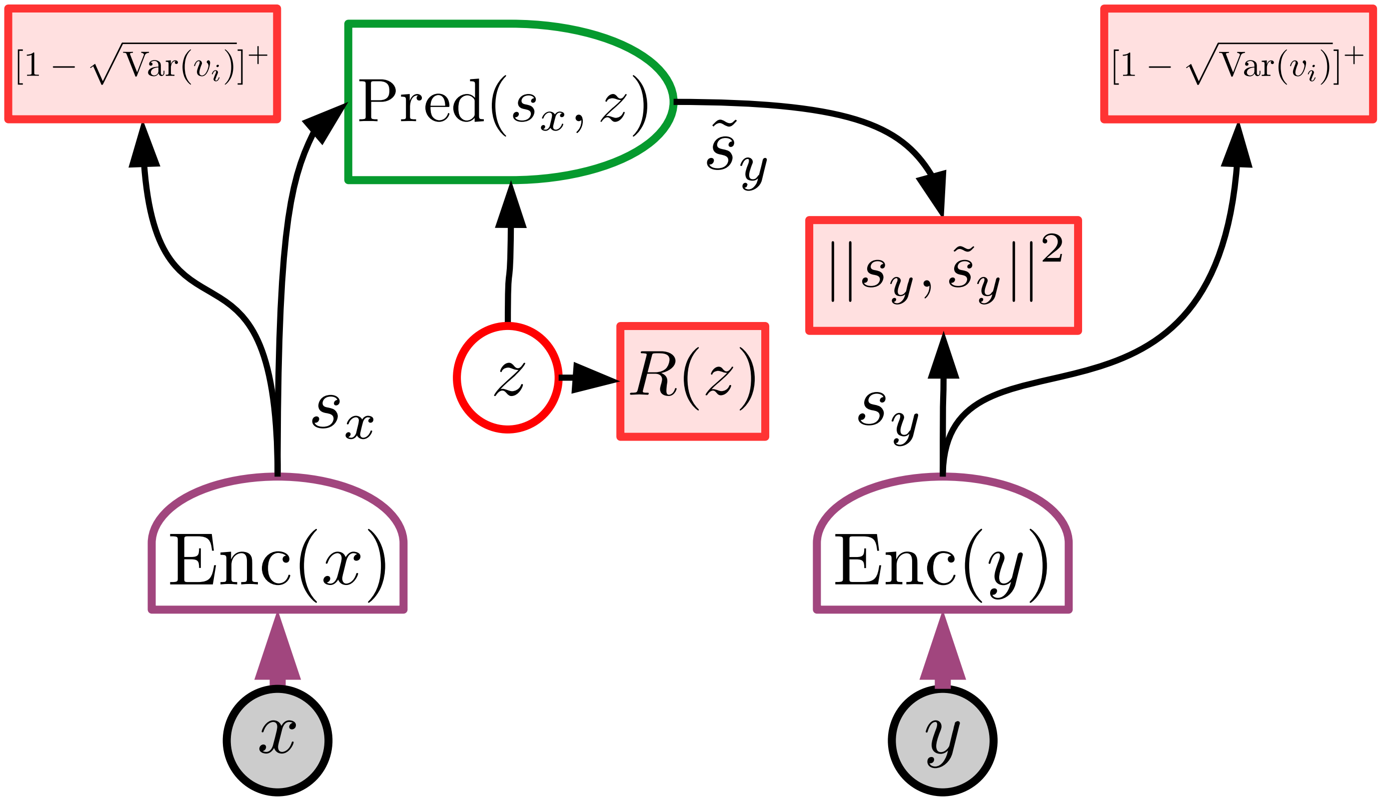
Training a JEPA with Regularized Methods

- **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

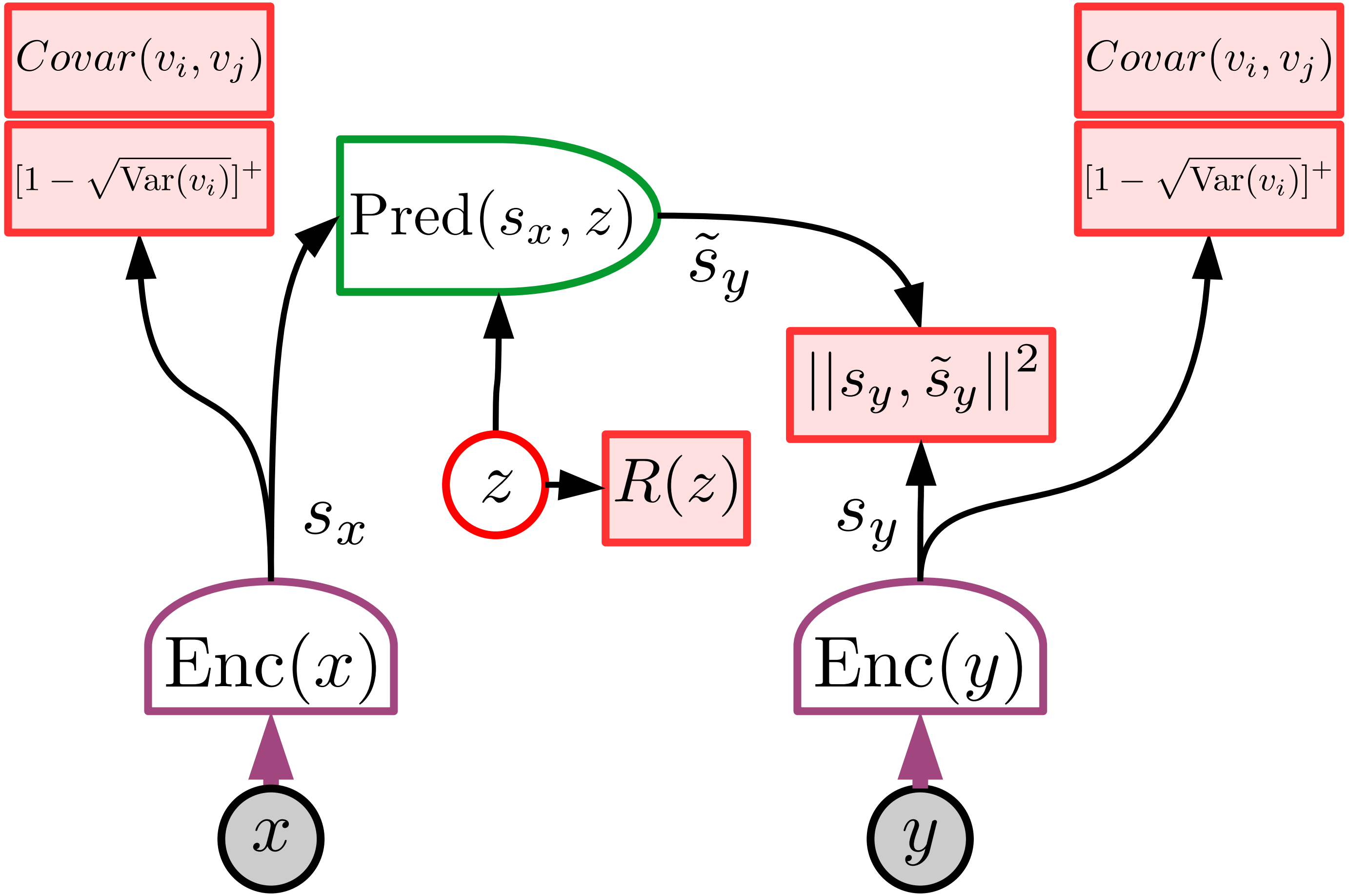
- **Variance:**
  - Maintains variance of components of representations
- **Invariance:**
  - Minimizes prediction error.



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.



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]

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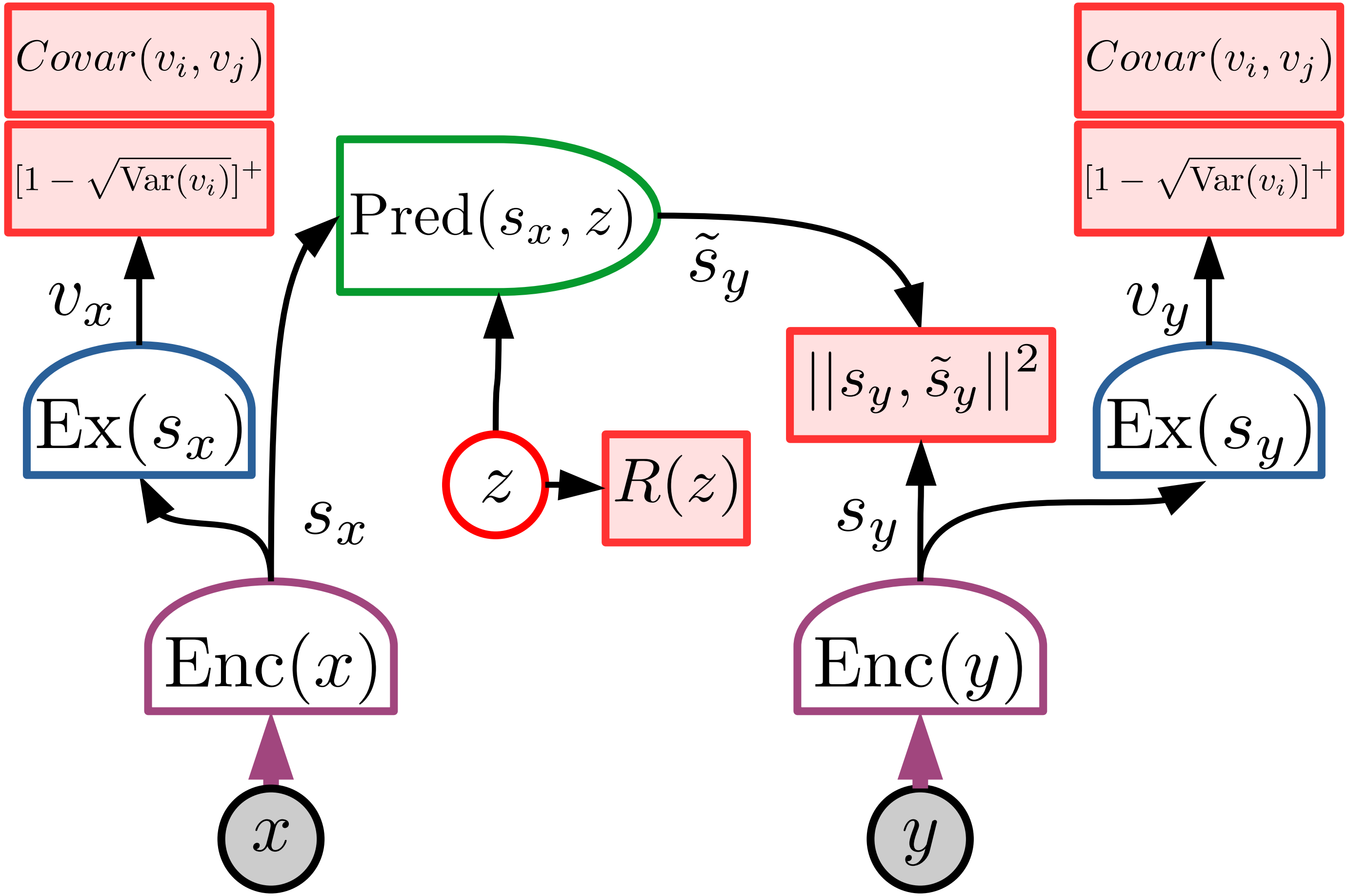
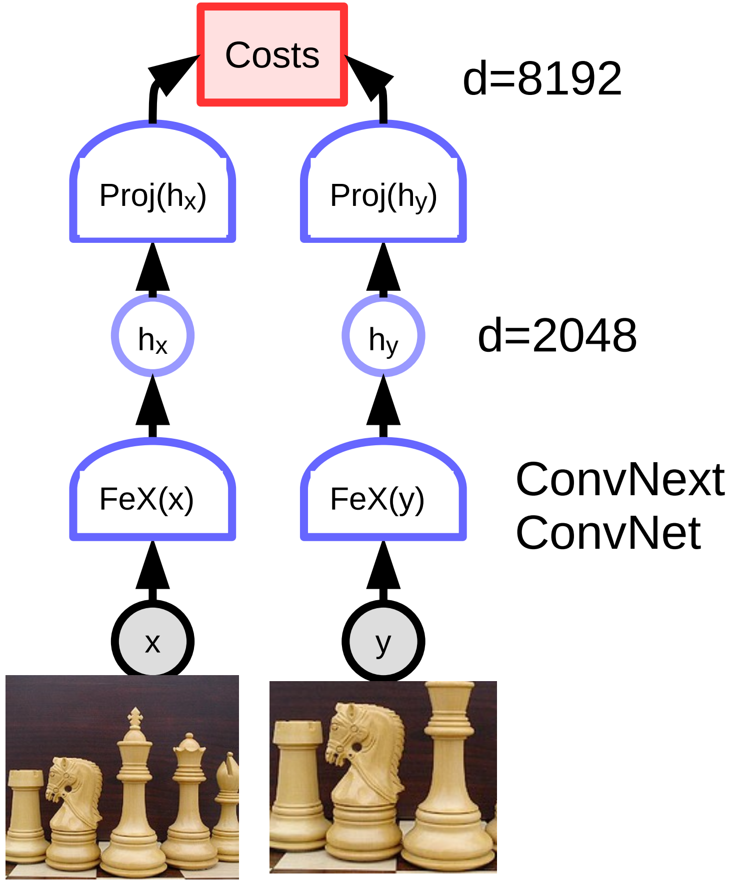


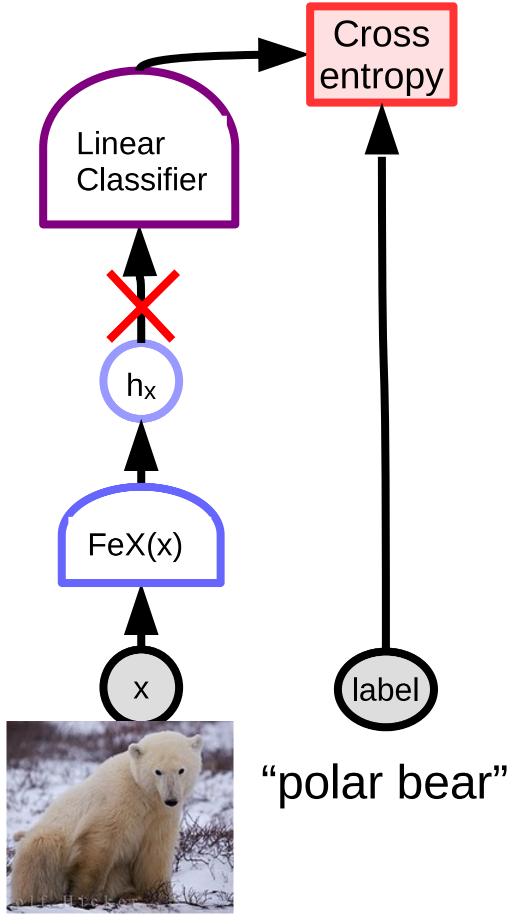
Barlow Twins [Zbontar et al. ArXiv:2103.03230], VICReg [Bardes, Ponce, LeCun arXiv:2105.04906, ICLR 2022], VICRegL [Bardes et al. NeurIPS 2022], MCR2 [Yu et al. NeurIPS 2020][Ma, Tsao, Shum, 2022]

SSL-Pretrained Joint Embedding for Image Recognition

JEA pretrained with VICReg



Training a supervised linear head



VICReg: Results with linear head and semi-supervised.

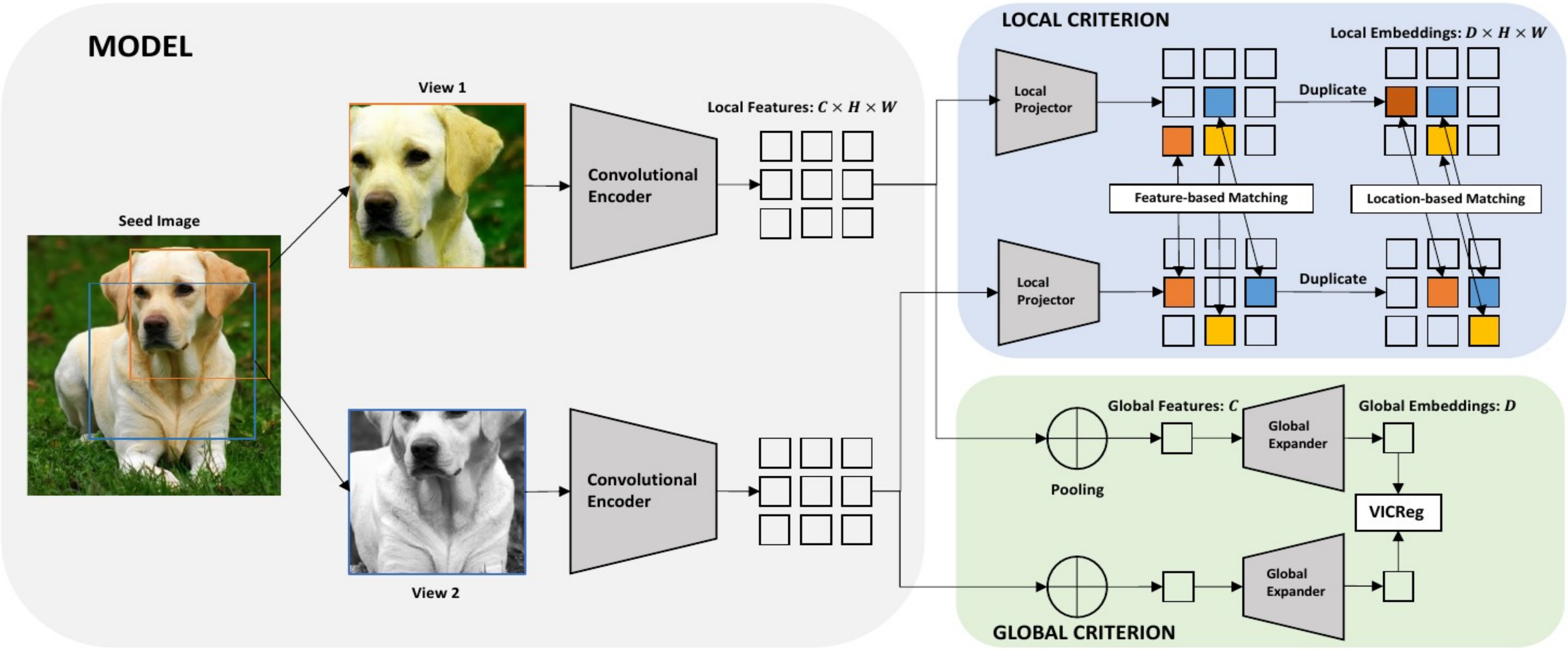
Method	Linear Top-1	Linear Top-5	Semi-supervised Top-1 1%	Semi-supervised Top-1 10%	Semi-supervised Top-5 1%	Semi-supervised Top-5 10%
Supervised	76.5	-	25.4	56.4	48.4	80.4
MoCo He et al. (2020)	60.6	-	-	-	-	-
PIRL Misra & Maaten (2020)	63.6	-	-	-	57.2	83.8
CPC v2 Hénaff et al. (2019)	63.8	-	-	-	-	-
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

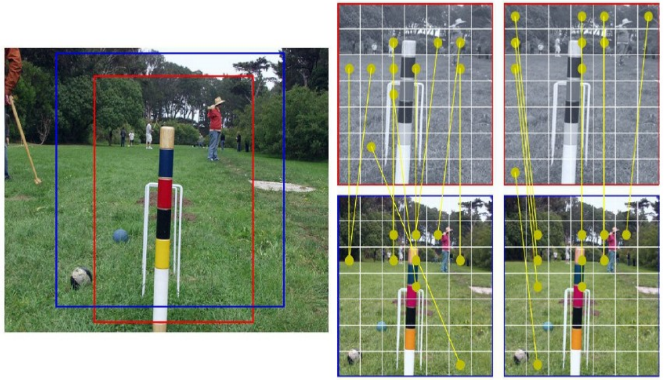
VICRegL: local matching latent variable for segmentation

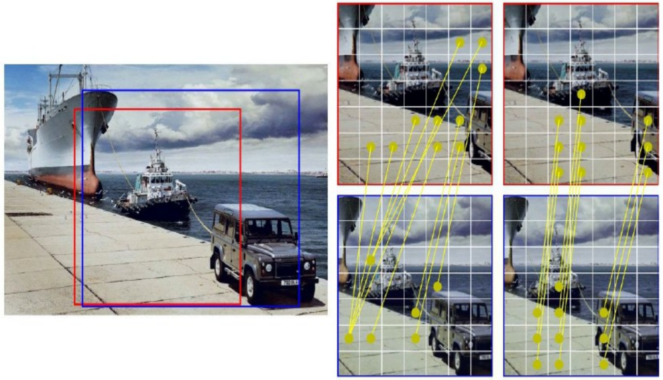
- **Latent variable optimization:**
  - Finds a pairing between local feature vectors of the two images
  - [Bardes, Ponce, LeCun, NeurIPS 2022, arXiv:2210.01571]



VICRegL: local matching latent variable for segmentation

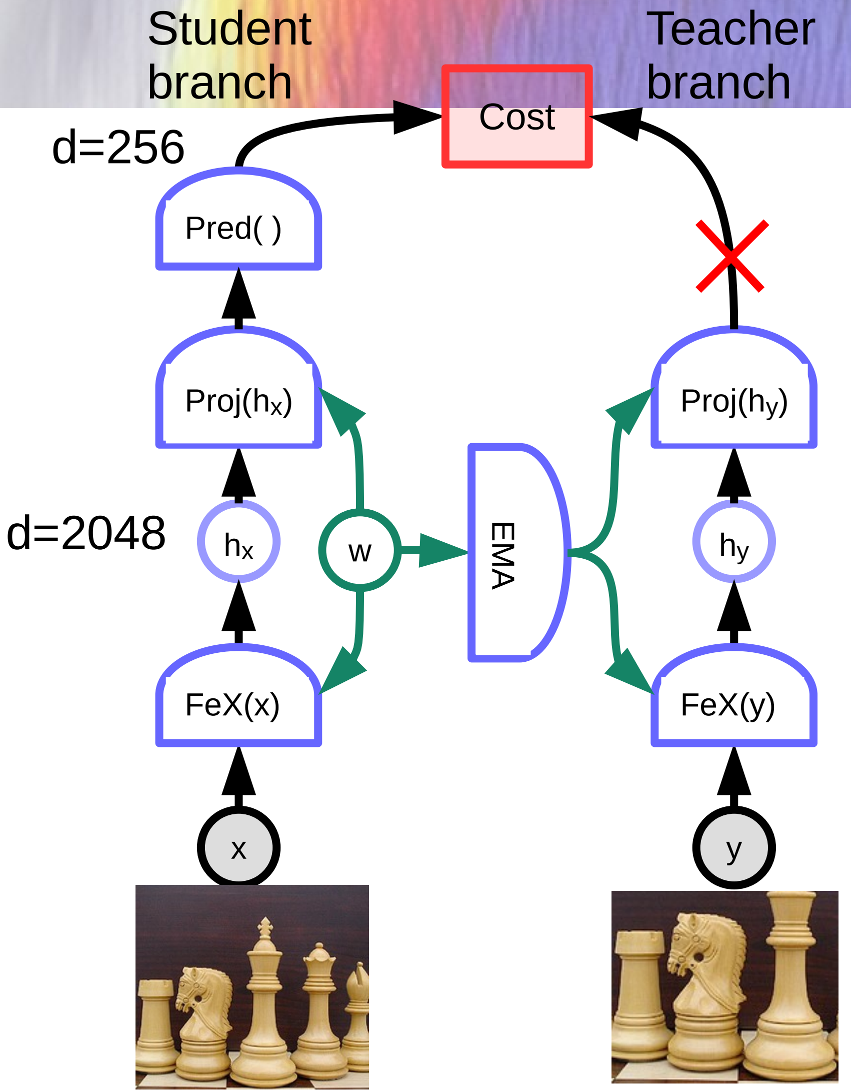
Method	Epochs	Linear Cls. (%) ImageNet Frozen	Linear Seg. (mIoU) Pascal VOC Frozen	Pascal VOC Fine-Tuned	Cityscapes Frozen
Global features					
MoCo v2 [Chen et al., 2020b]	200	67.5	35.6	64.8	14.3
SimCLR [Chen et al., 2020a]	400	68.2	45.9	65.4	17.9
BYOL [Grill et al., 2020]	300	**72.3**	47.1	65.7	22.6
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**





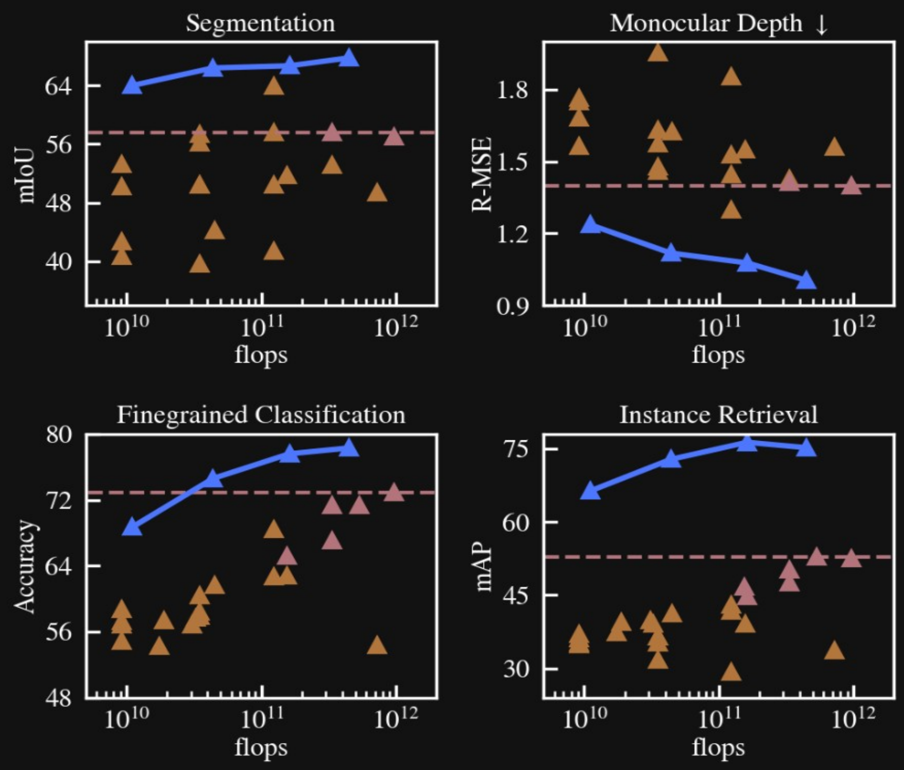
Distillation Methods

- **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



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



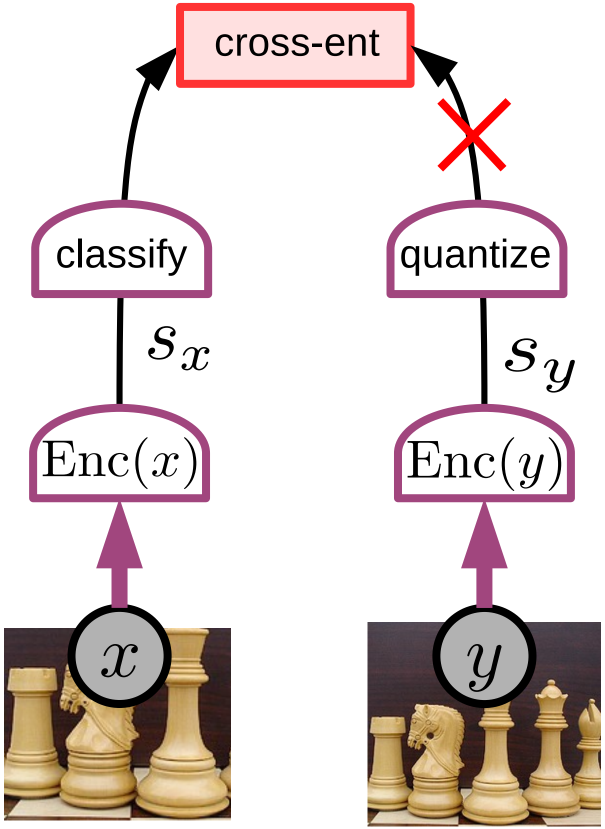
The DINOv2 family of models **drastically improves** over the previous state of the art in self-supervised learning (SSL), and **reaches performance comparable** with weakly-supervised features (WSL).

DINOv2: image foundation model

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

DINOv2: Joint Embedding Architecture

- **SSL by distillation**



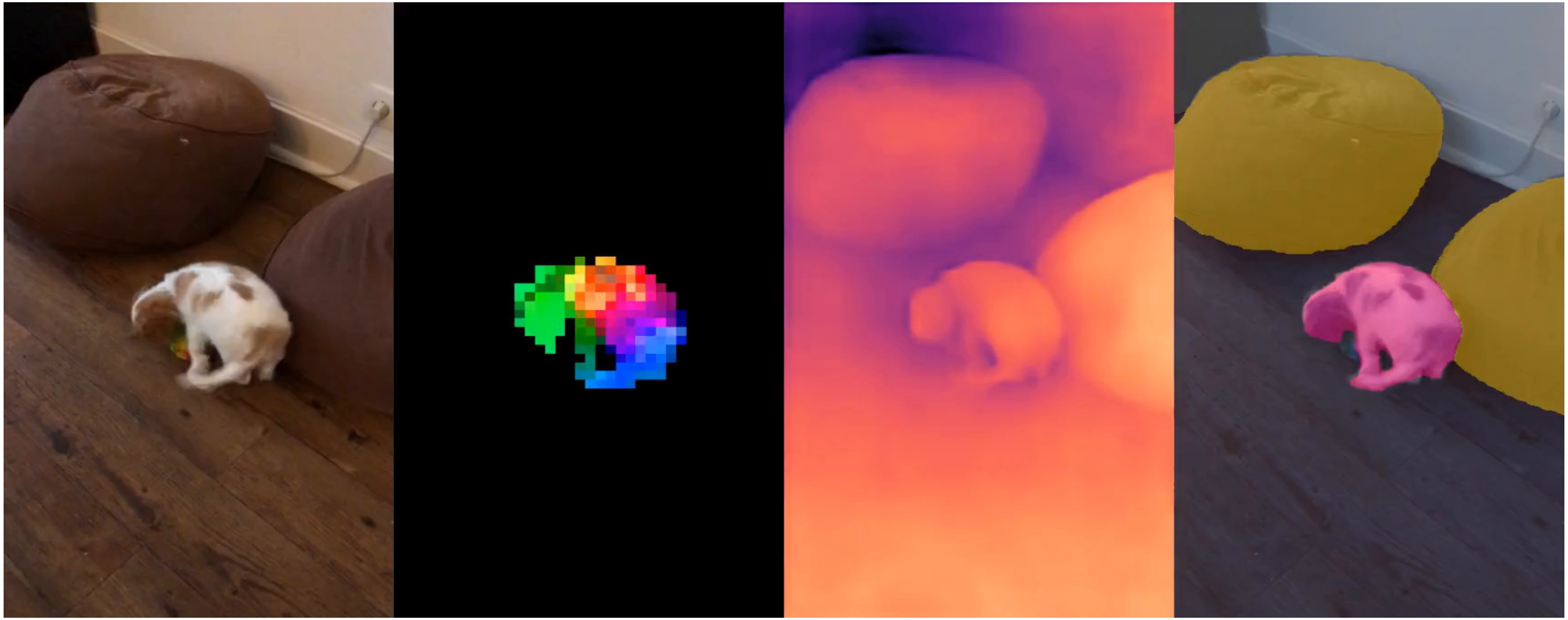
Method	Arch.	Data	Text sup.	kNN val	linear val	linear ReaL	linear V2
Weakly supervised							
CLIP	ViT-L/14	WIT-400M	✓	79.8	84.3	88.1	75.3
CLIP	ViT-L/14$_{336}$	WIT-400M	✓	80.5	85.3	88.8	75.8
SWAG	ViT-H/14	IG3.6B	✓	82.6	85.7	88.7	77.6
OpenCLIP	ViT-H/14	LAION	✓	81.7	84.4	88.4	75.5
OpenCLIP	ViT-G/14	LAION	✓	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

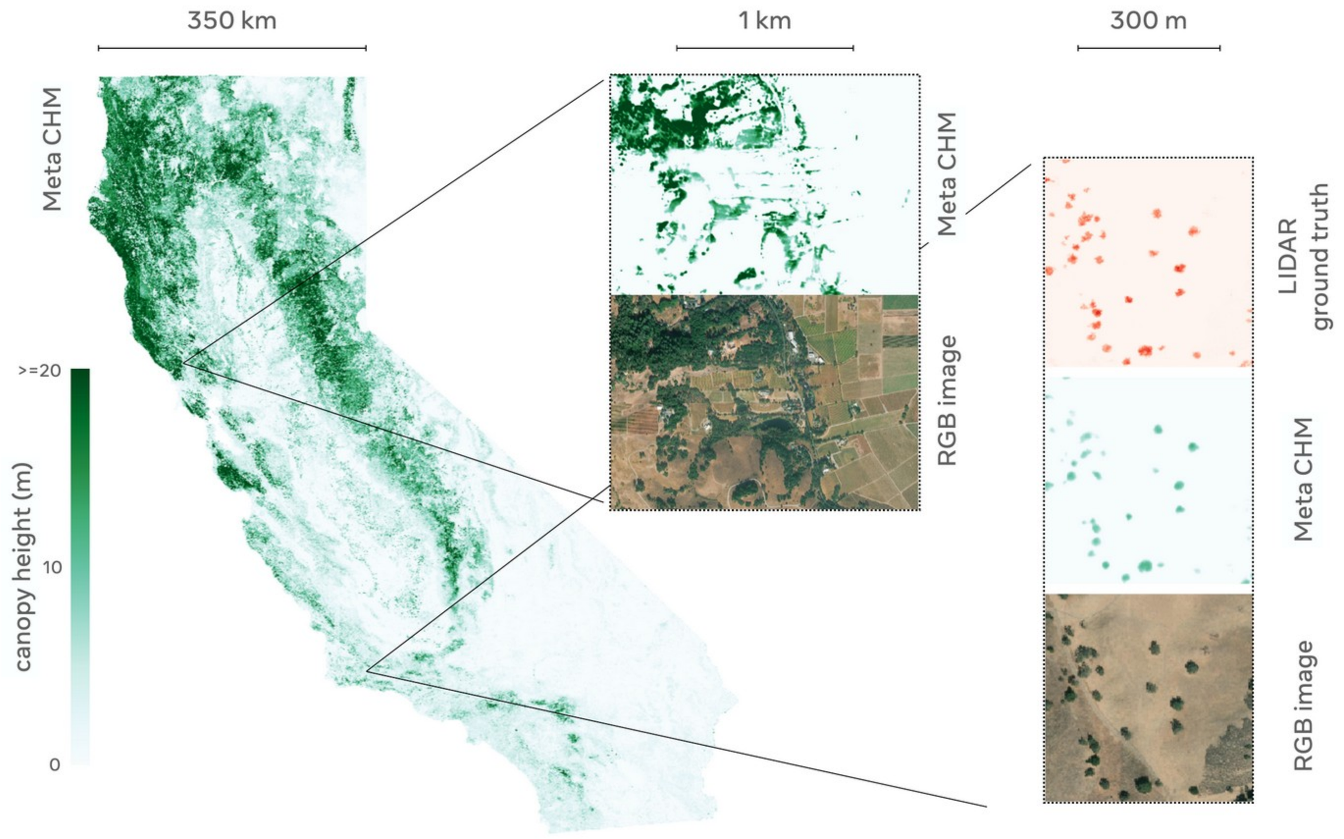
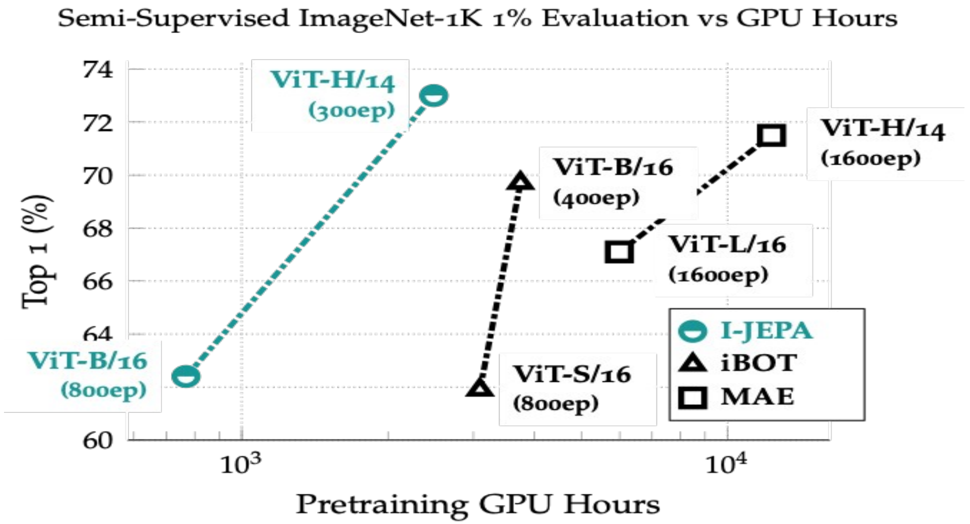
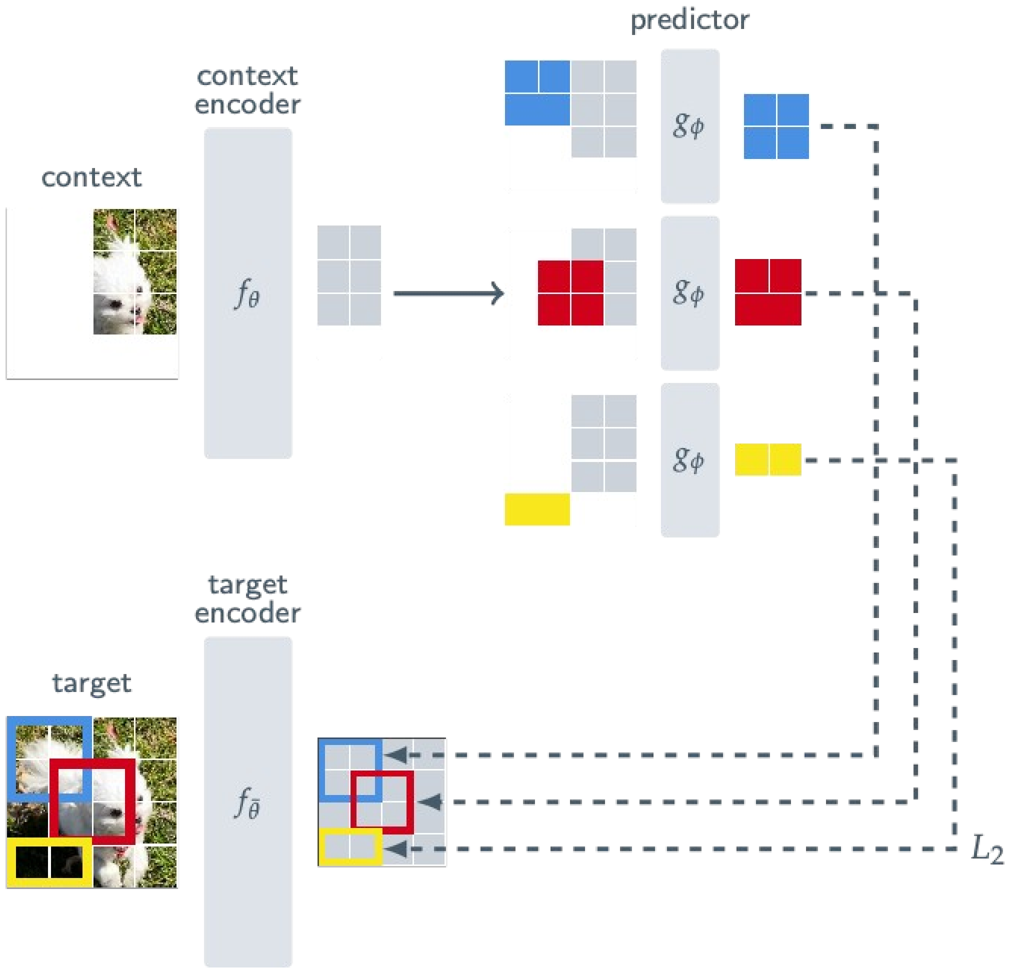


Figure 1: Canopy Height Map (CHM) for California, with inset showing zoomed-in region with input RGB imagery and LIDAR ground truth

Image-JEPA: uses masking & transformer architectures

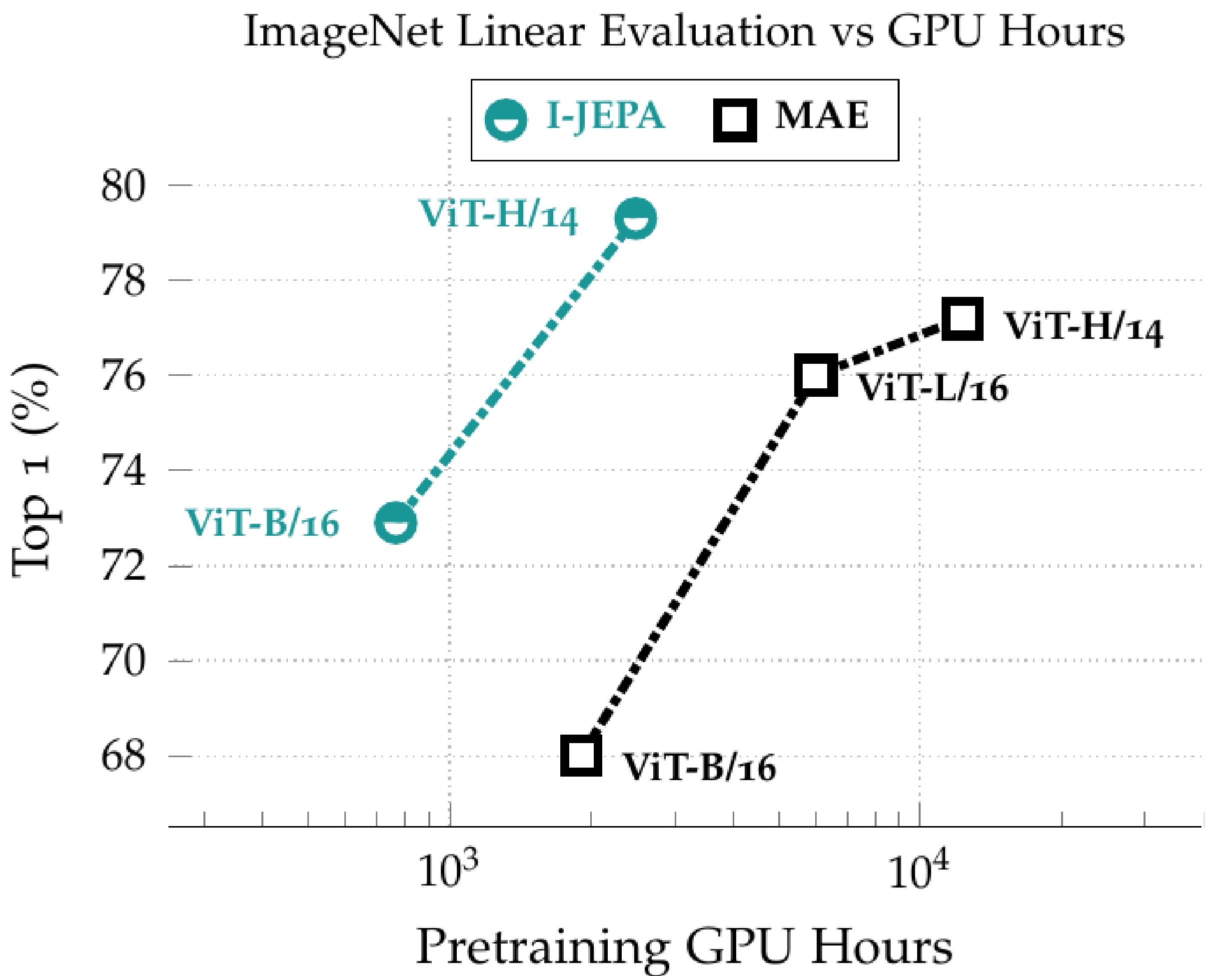
- **"SSL from images with a JEPA"**
  - [M. Assran et al arxiv:2301.08243]
- **Jointly embeds a context and a number of neighboring patches.**
  - Uses predictors
  - Uses only masking





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.**

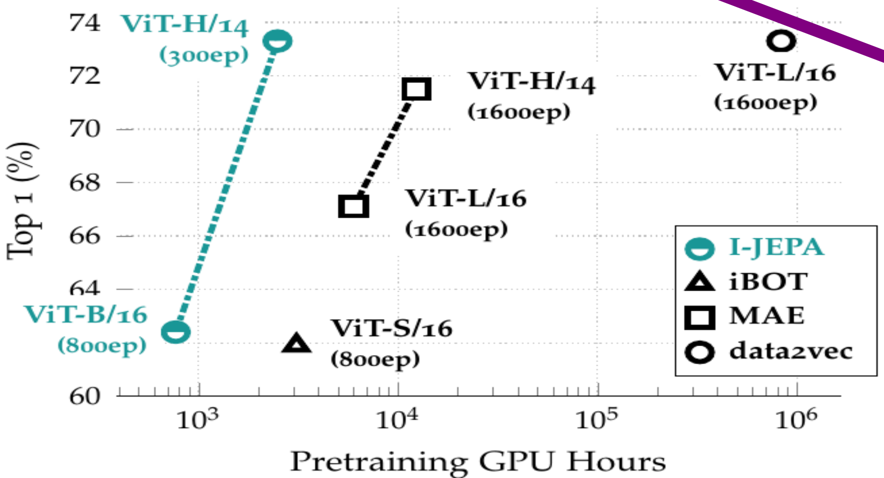
Targets	Arch.	Epochs	Top-1
Target-Encoder Output	ViT-L/16	500	**66.9**
Pixels	ViT-L/16	800	40.7

- **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**

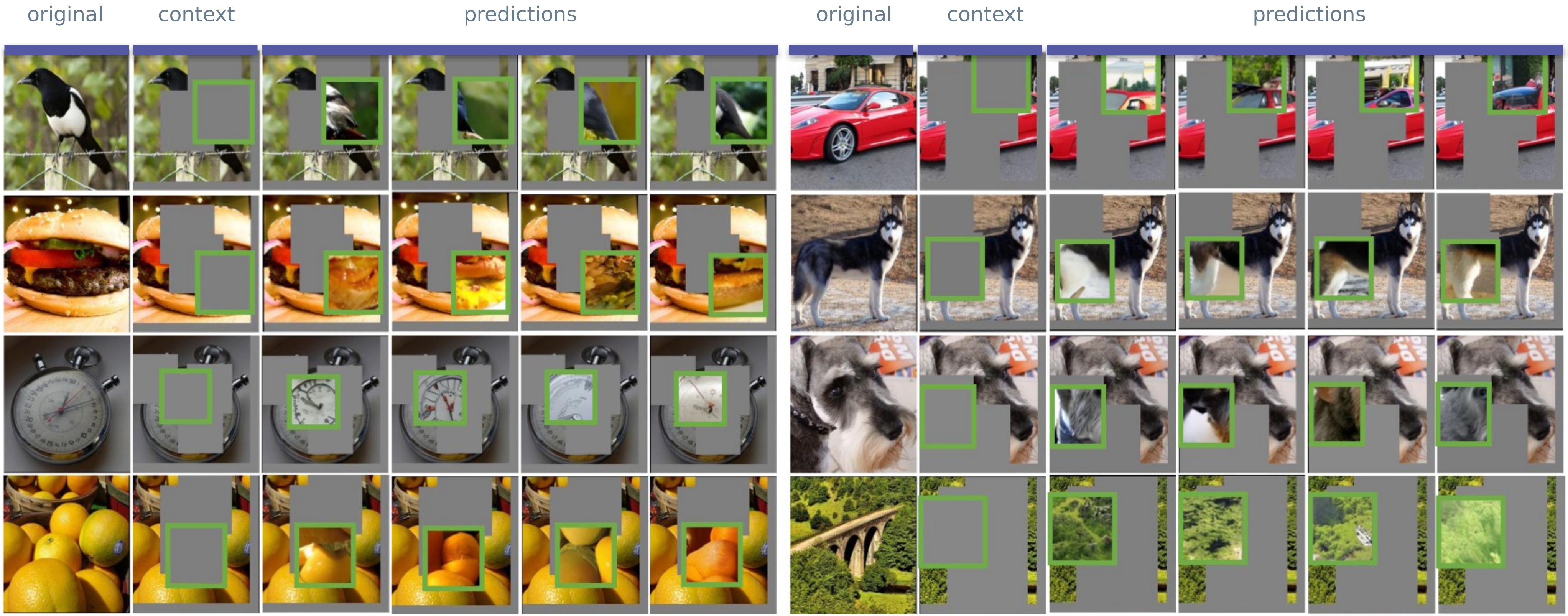
I-JEPA Results on ImageNet with 1% training

- **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**

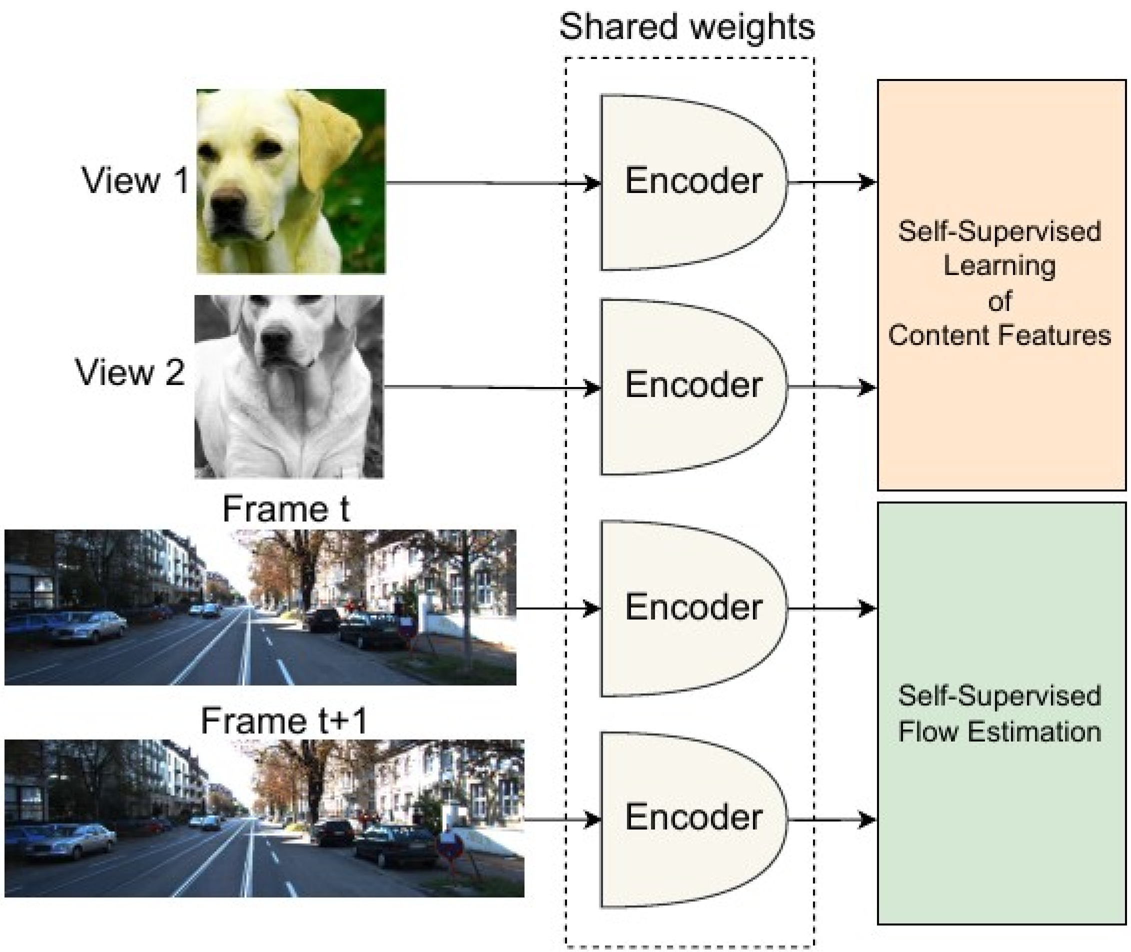
I-JEPA: Visualizing Predicted Representations



MC-JEPA: Motion & Content JEPA

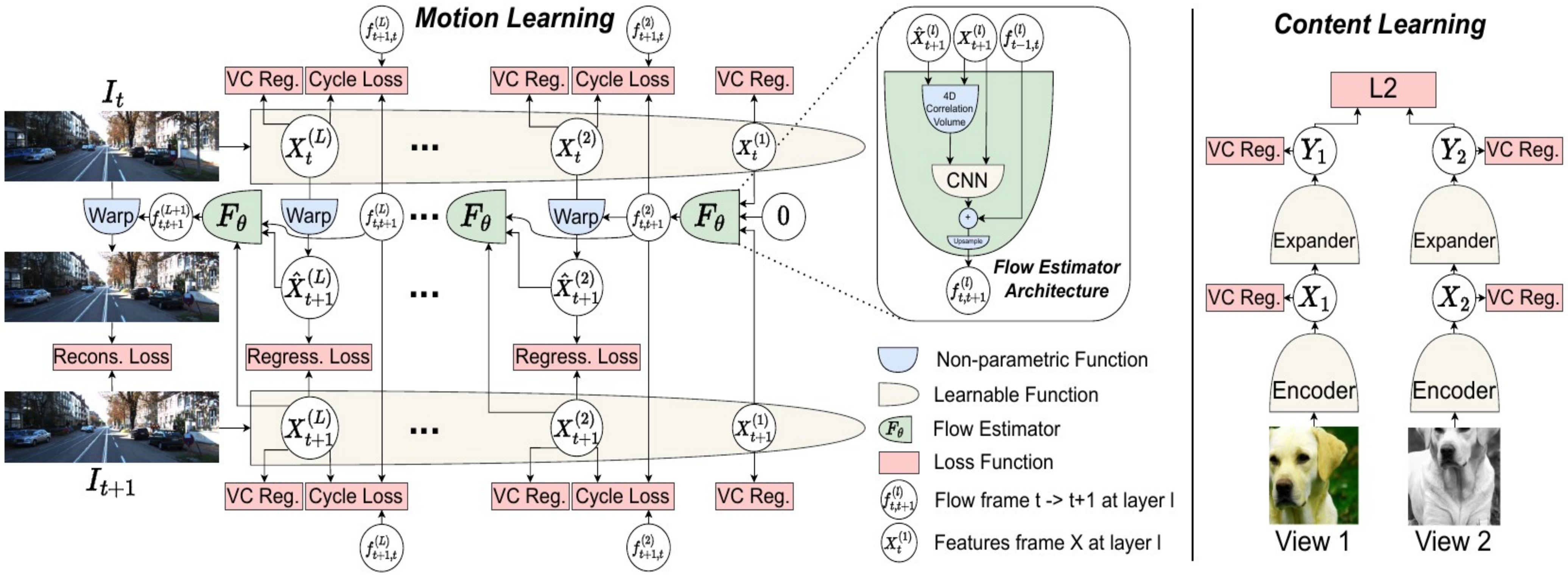
[Bardes, Ponce, LeCun 23]

- **Simultaneous SSL for**
  - Image recognition
  - Motion estimation
- **Trained on**
  - ImageNet 1k
  - Various video datasets
- **Uses VCReg to prevent collapse**
  - ConvNext-T backbone

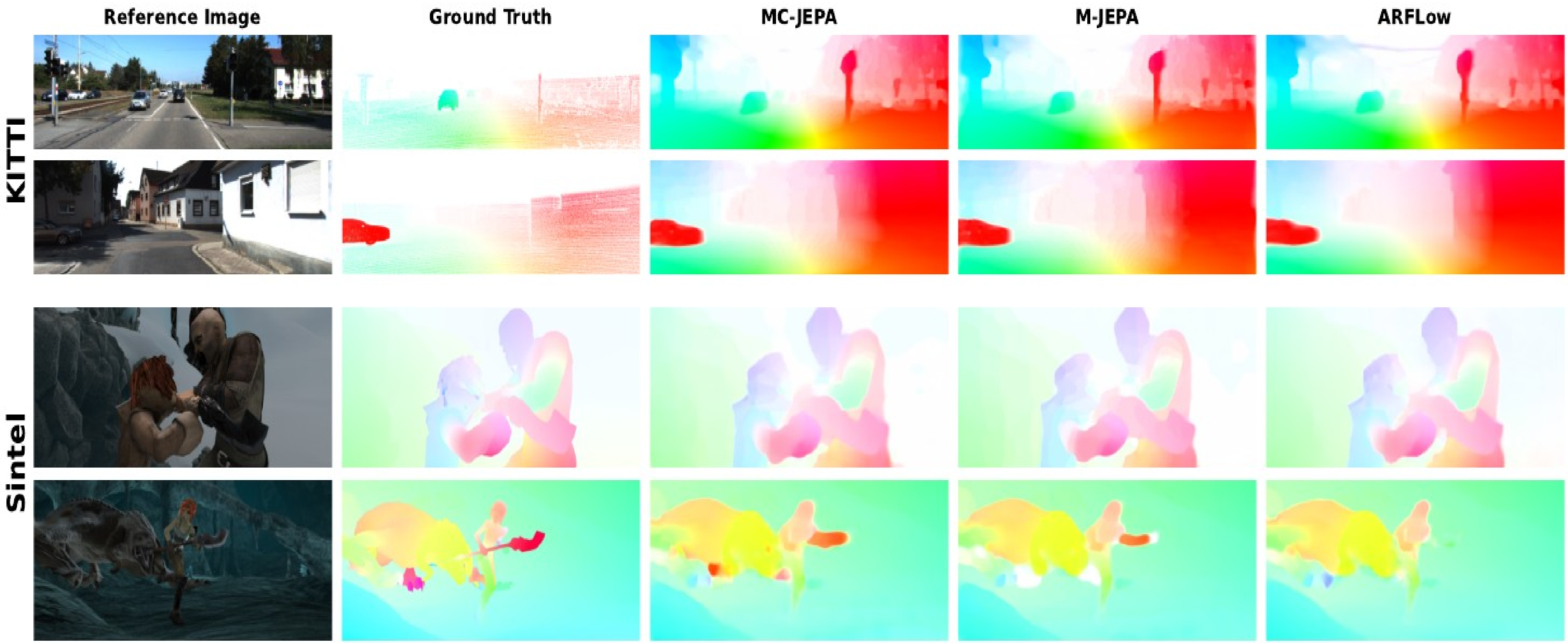


MC-JEPA: Motion & Content JEPA

- Motion estimation architecture uses a top-down hierarchical predictor that “warp” feature maps.



MC-JEPA: Optical Flow Estimation Results



Problems to Solve

- **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 industrial policy?

- **AI systems will become a common platform**
- **The platforms (foundation models) will need to be open**
  - 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.
  - Move as much as possible to the edge.

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.

Why the doomers are wrong

- **The speculations about the probability of human extinction p(doom) are just that: speculations.**
- **There are infinite ways to build dangerous and unreliable AI, and only a few ways to do it right. But a few good ways is all we need.**
  - There are infinite ways to build unreliable turbojets,…
  - … but safe and reliable turbojets do exist. They are the ones we use.
  - All doom scenarios assume that there is no way to build safe AI systems
  - Some scenarios assume that the slightest mistake will spell doom.
  - But this is not how technology development works.
- **Developing safe and reliable AI systems will take time**
  - Safer AI is simply better AI with the proper objectives and guardrails.
  - This will take years (decades?) of careful engineering
  - Just like the design of safe, reliable, and efficient turbojets.

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