FACEBOOK AI   NEW YORK UNIVERSITY

What DL Hardware Will We Need?

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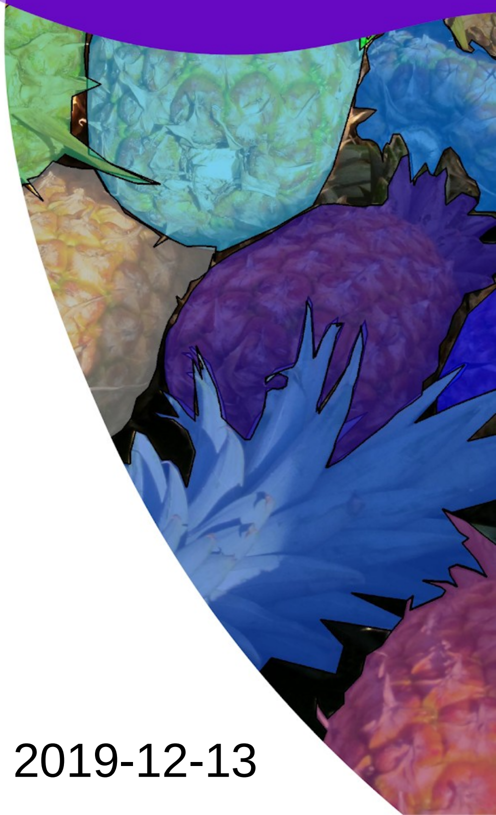
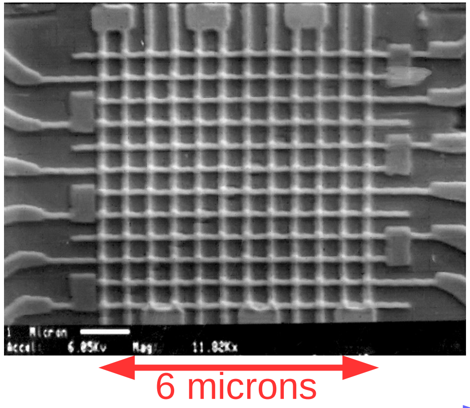


EMC^2, 2019-12-13

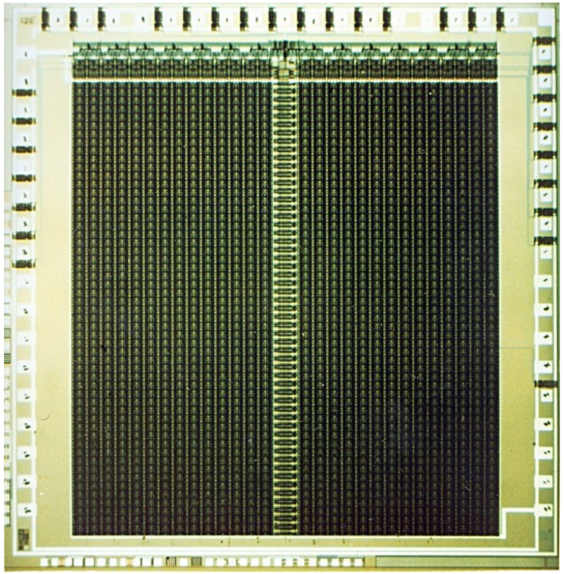
Y. LeCun

1986-1996 Neural Net Hardware at Bell Labs, Holmdel

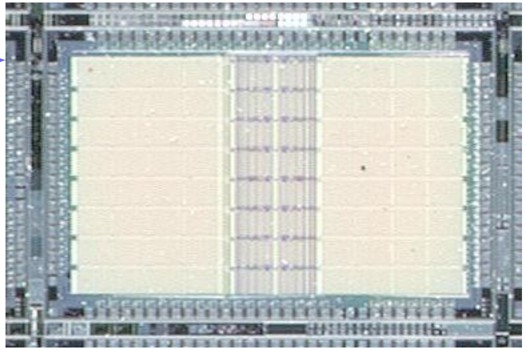
- **1986: 12x12 resistor array**
  - Fixed resistor values
  - E-beam lithography: 6x6microns



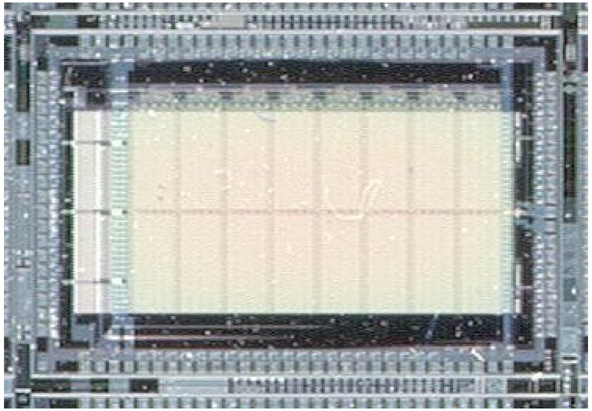
- **1988: 54x54 neural net**
  - Programmable ternary weights
  - On-chip amplifiers and I/O



- **1991: Net32k: 256x128 net**
  - Programmable ternary weights
  - 320GOPS, 1-bit convolver.



- **1992: ANNA: 64x64 net**
  - ConvNet accelerator: 4GOPS
  - 6-bit weights, 3-bit activations

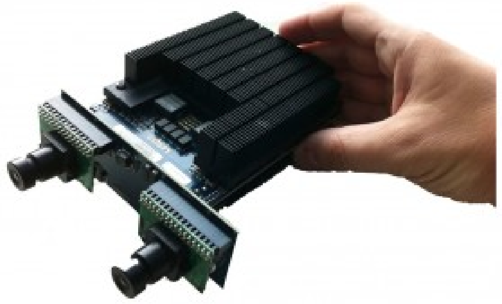


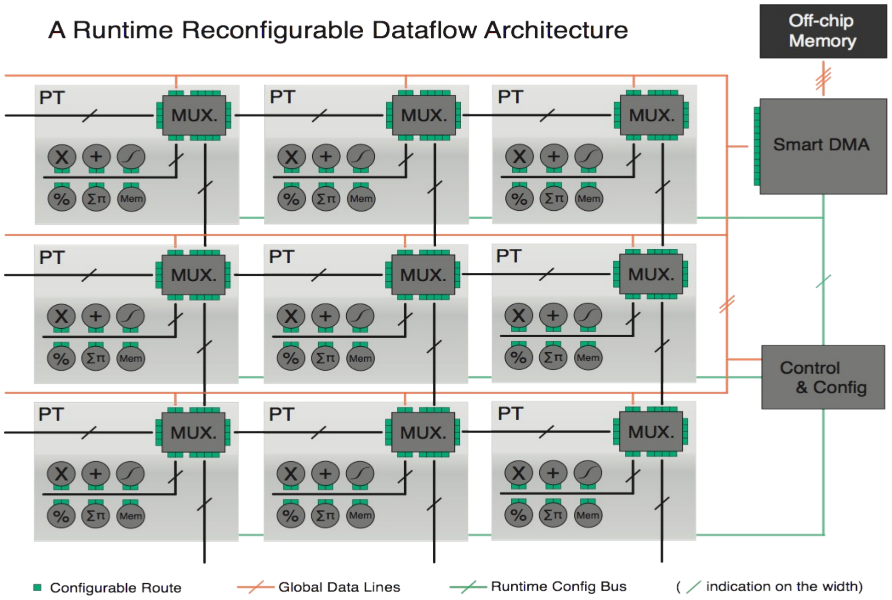
LeNet character recognition demo 1992

- Running on an AT&T DSP32C (floating-point DSP, 20 MFLOPS)

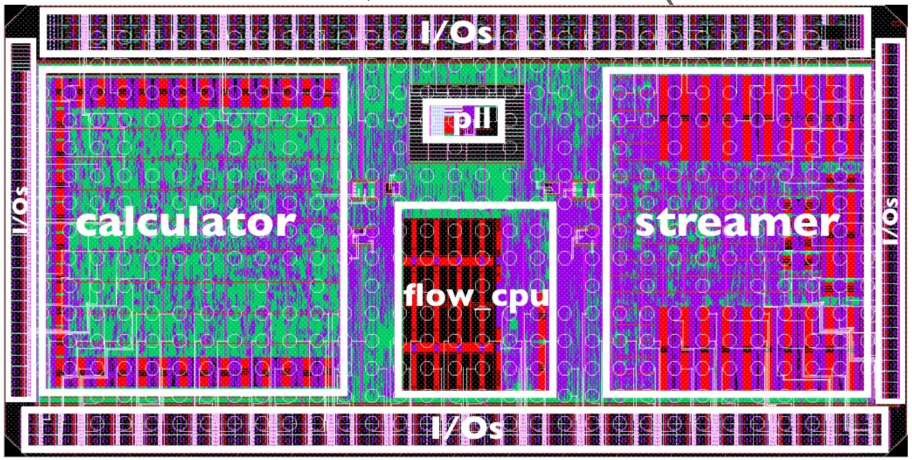
FPGA ConvNet Accelerator: NewFlow [Farabet 2011]

- **NeuFlow: Reconfigurable Dataflow architecture**
  - Implemented on Xilinx Virtex6 FPGA
  - 20 configurable tiles. 150GOPS, 10 Watts
  - Semantic Segmentation: 20 frames/sec at 320x240
  - **Exploits the structure of convolutions**

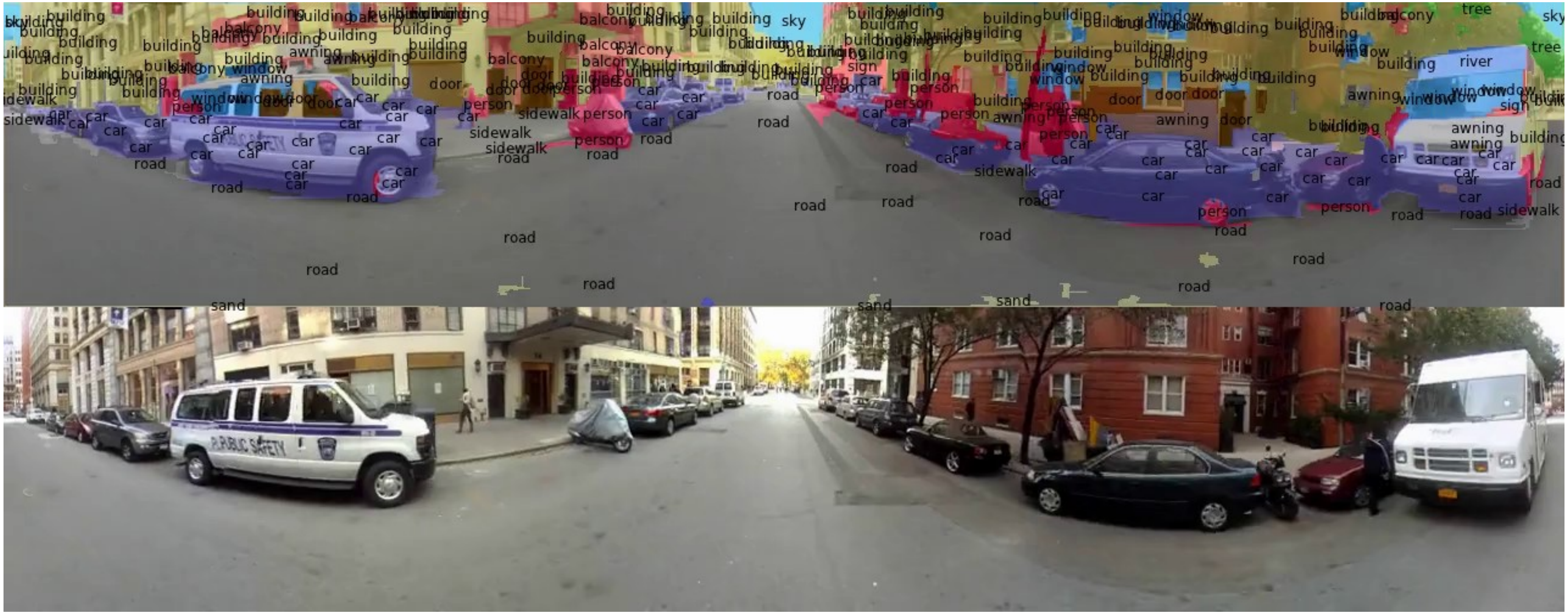




- **NeuFlow ASIC** [Pham 2012]
  - 150GOPS, 0.5 Watts (simulated)



Semantic Segmentation with ConvNets [Farabet 2012]



Lessons learned #1

- ***1.1: It's hard to succeed with exotic hardware***
  - *Hardwired analog → programmable hybrid → digital*
- ***1.2: Hardware limitations influence research directions***
  - *It constrains what algorithm designers will let themselves imagine*
- ***1.3: Good software tools shape research and give superpowers***
  - *But require a significant investment*
  - *Common tools for Research and Development facilitates productization*
- ***1.4: Hardware performance matters***
  - *Fast turn-around is important for R&D*
  - *But high-end production models always take 2-3 weeks to train*
- ***1.5: When hardware is too slow, software is not readily available, or experiments are not easily reproducible, good ideas can be abandoned.***

Lessons learned #2

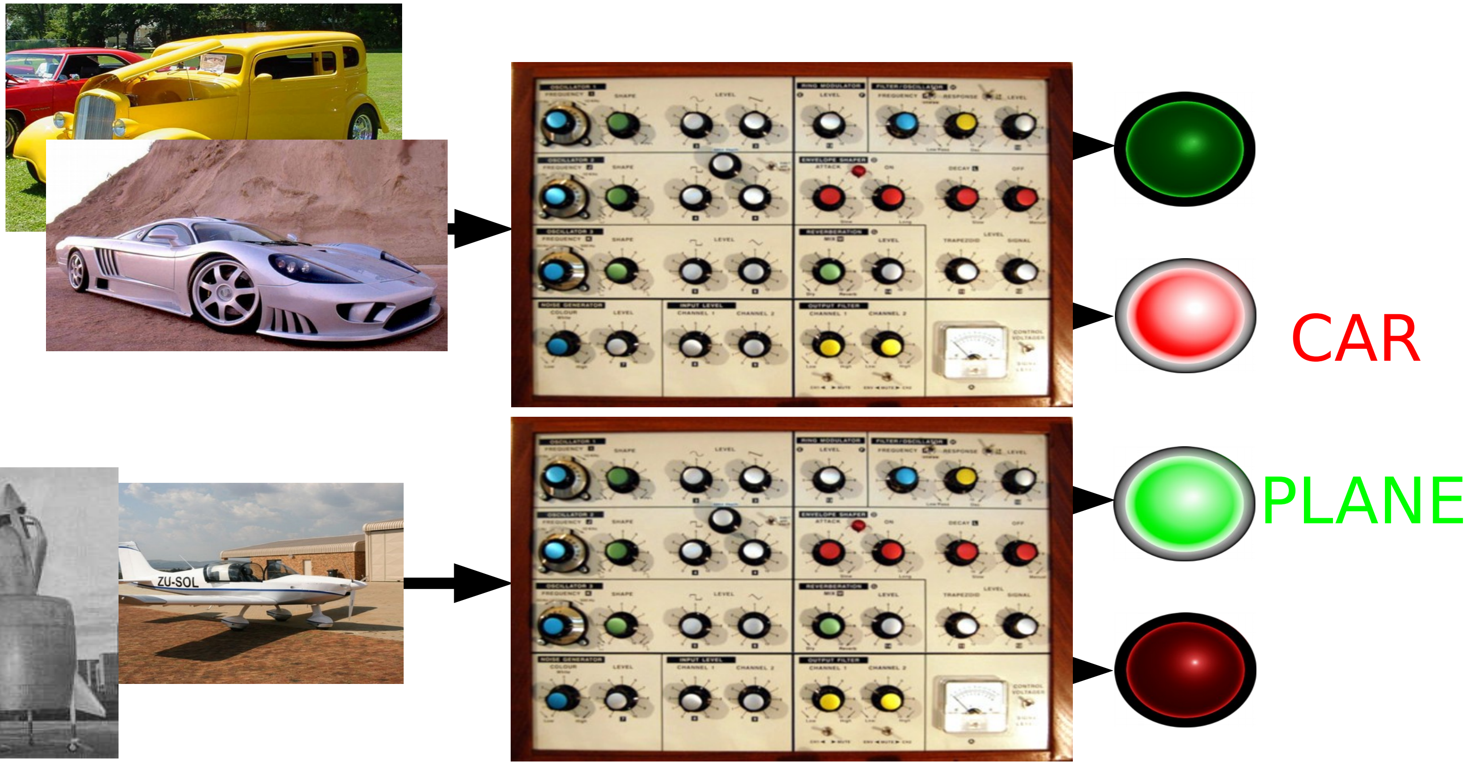
- ***2.1: Good results are not enough***
  - *Making them easily reproducible also makes them credible.*
- ***2.2: Hardware progress enables new breakthroughs***
  - *General-Purpose GPUs should have come 10 years earlier!*
  - *But can we please have hardware that doesn't require batching?*
- ***2.3: Open-source software platforms disseminate ideas***
  - *But making platforms that are good for research and production is hard.*
- ***2.4: Convolutional Nets will soon be everywhere***
  - *Hardware should exploit the properties of convolutions better*
  - *There is a need for low-cost, low-power ConvNet accelerators*
  - *Cars, cameras, vacuum cleaners, lawn mowers, toys, maintenance robots...*

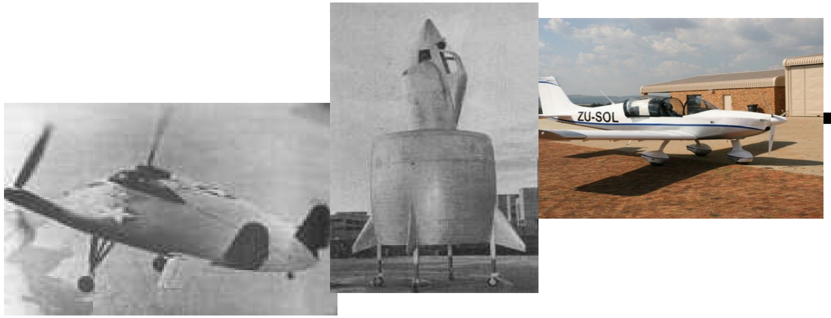
What will be the killer app of embedded DL hardware?

- **AR glasses!**
  - Yes, Facebook is working on AR glasses
  - Yes, obviously, Facebook is working on DL hardware for AR glasses
- **DL-based functions in AR glasses:**
    - Position tracking / SLAM / 3D reconstruction
    - hand pose tracking, gesture recognition
    - Recognition: landmarks, products, faces, plants, birds, insects...
    - OCR, ASR, TTS
    - Translation (from speech and OCR'ed text)
    - …
  - All of this on a tiny device that needs to run all day.

Supervised Learning works (but requires many labeled samples)

- **Training a machine by showing examples instead of programming it**
- **When the output is wrong, tweak the parameters of the machine**
- **Works well for:**
  - Speech→words
  - Image→categories
  - Portrait→ name
  - Photo→caption
  - Text→topic
  - ….



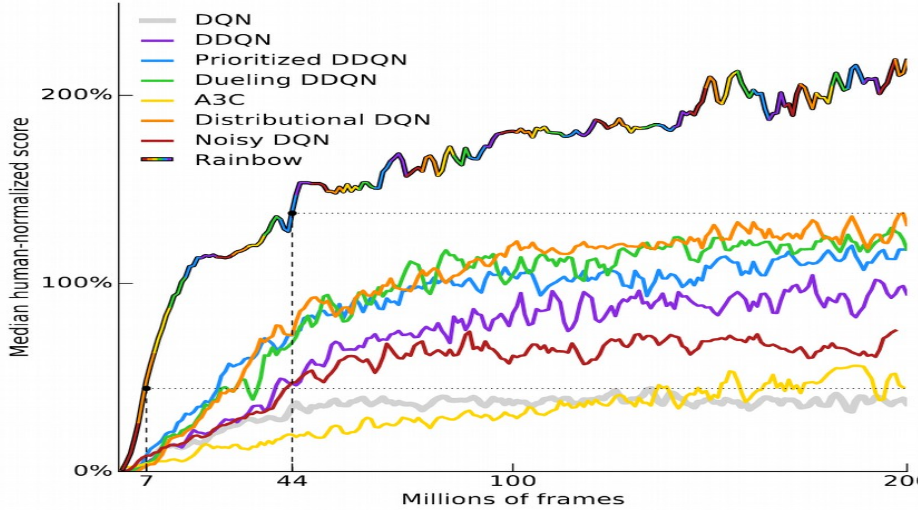


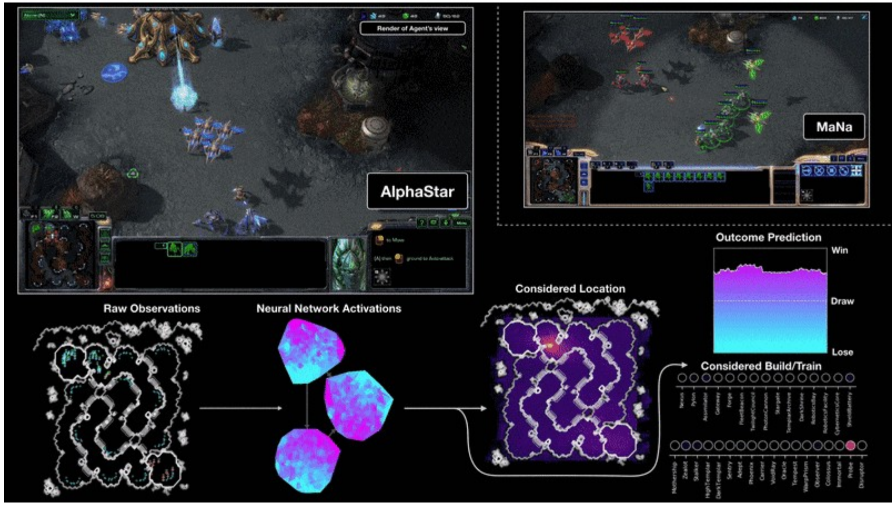
Detectron2

- Panoptic instance segmentation, (dense) body pose estimation
- Open source: https://github.com/facebookresearch/detectron2

Reinforcement Learning: works great for games and simulations.

- **57 Atari games: takes 83 hours equivalent real-time (18 million frames) to reach a performance that humans reach in 15 minutes of play.**
  - [Hessel ArXiv:1710.02298]
- **Elf OpenGo v2: 20 million self-play games. (2000 GPU for 14 days)**
  - [Tian arXiv:1902.04522]
- **StarCraft: AlphaStar 200 years of equivalent real-time play**
  - [Vinyals blog post 2019]
- **OpenAI single-handed Rubik's cube**
  - 10,000 years of simulation





But RL Requires too many trials in the real world

- **Pure RL requires too many trials to learn anything**
  - it's OK in a game
  - it's not OK in the real world
- **RL works in simple virtual world that you can run faster than real-time on many machines in parallel.**

- **Anything you do in the real world can kill you**
- **You can't run the real world faster than real time**

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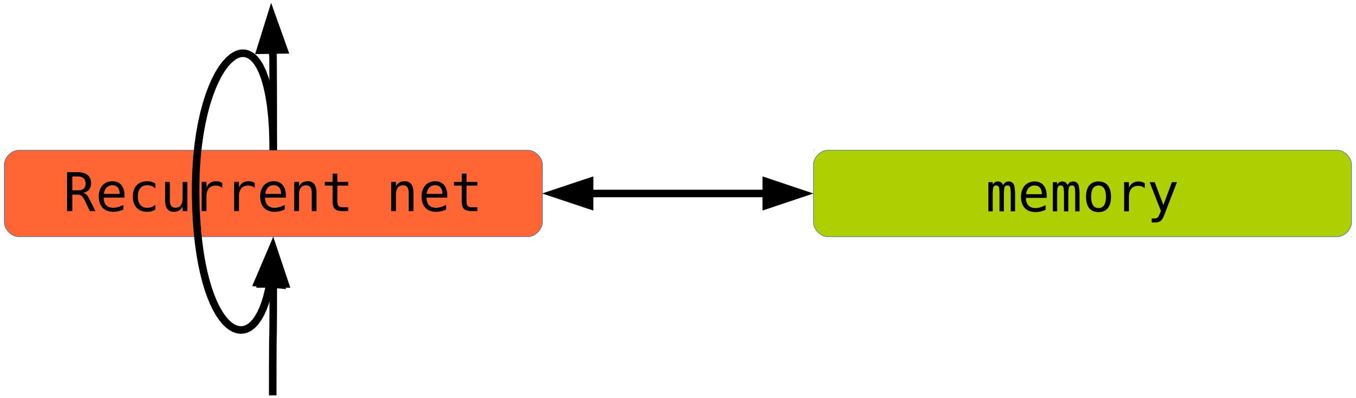
New Deep Learning Architectures

Attention,
Dynamic architectures,
hyper networks.

Memory-Augmented Networks

- **Recurrent networks cannot remember things for very long**
  - The cortex only remember things for 20 seconds
- **We need a "hippocampus" (a separate memory module)**
  - LSTM [Hochreiter 1997], registers
  - **Memory networks** [Weston et 2014] (FAIR), associative memory
  - **Stacked-Augmented Recurrent Neural Net** [Joulin & Mikolov 2014] (FAIR)
  - **Neural Turing Machine** [Graves 2014],
  - **Differentiable Neural Computer** [Graves 2016]

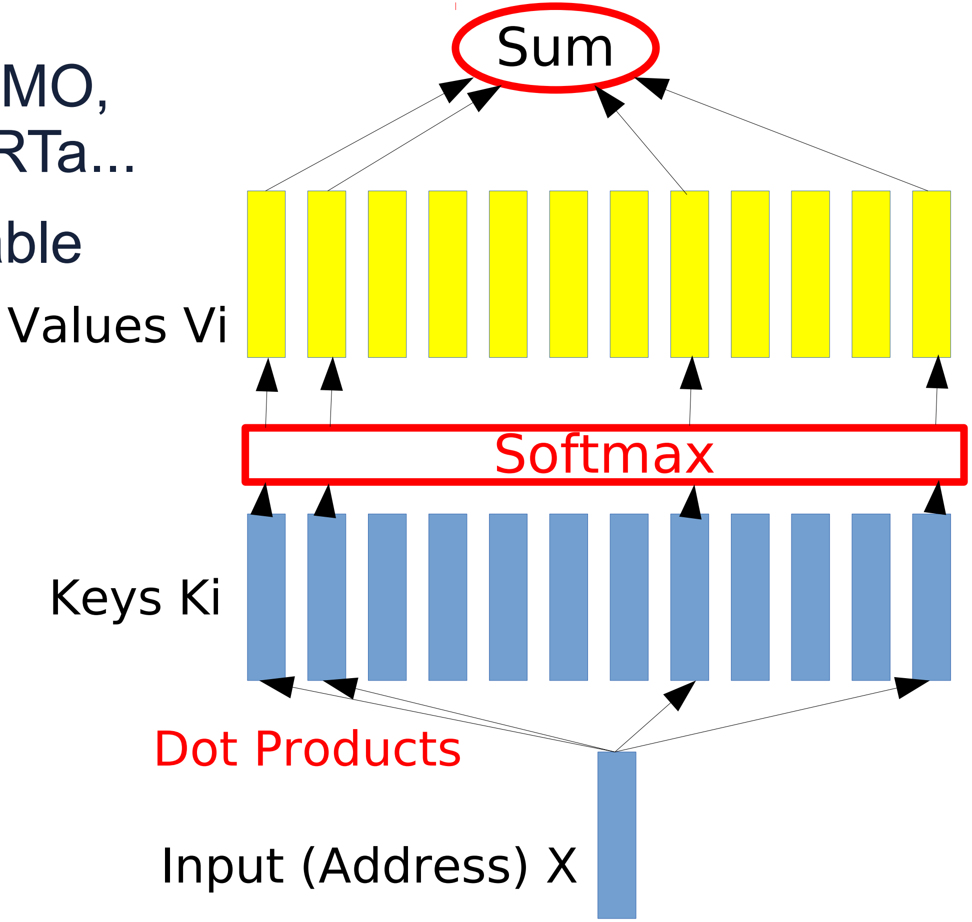


Differentiable Associative Memory == “soft RAM”

- Used very widely in NLP
- MemNN, Transformer Network, ELMO, GPT, BERT, GPT2, GloMO, RoBERTa...
- Essentially a “soft” RAM or hash table

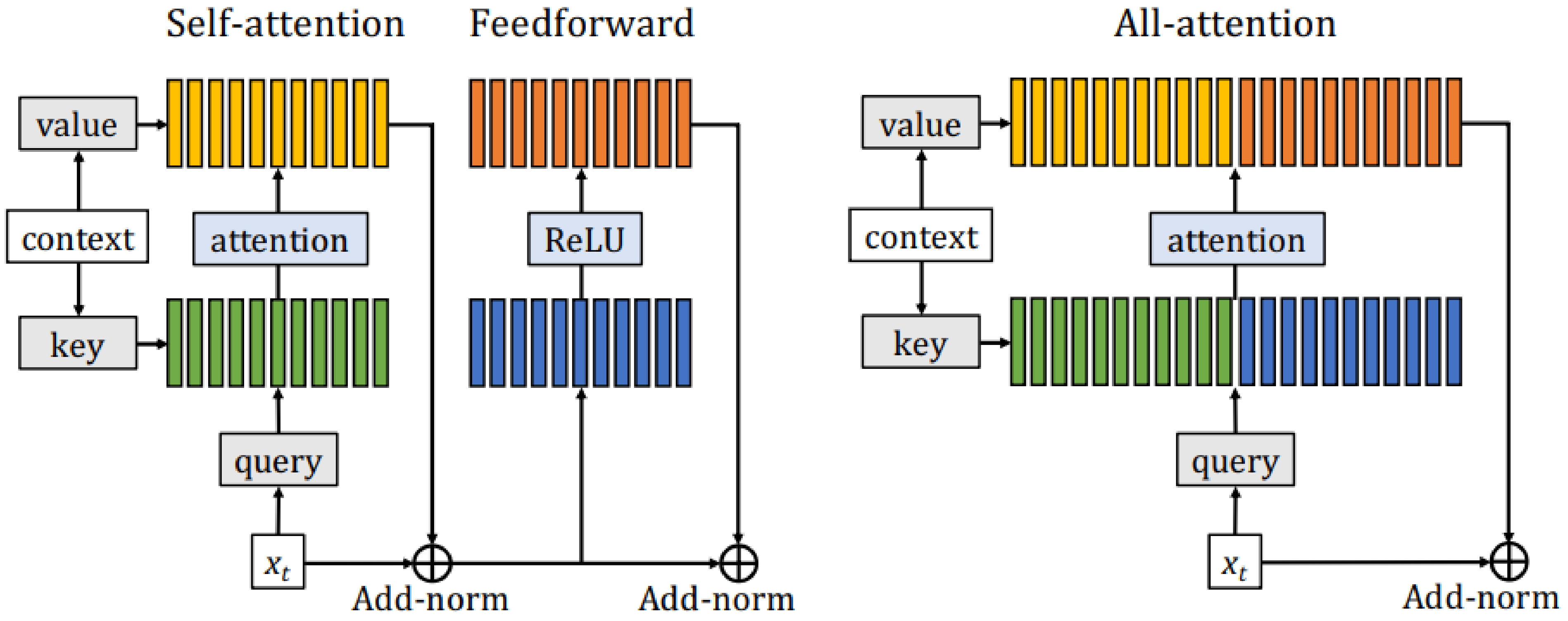
$$C_i = \frac{e^{K_i^T X}}{\sum_j e^{K_j^T X}}$$

$$Y = \sum_i C_i V_i$$



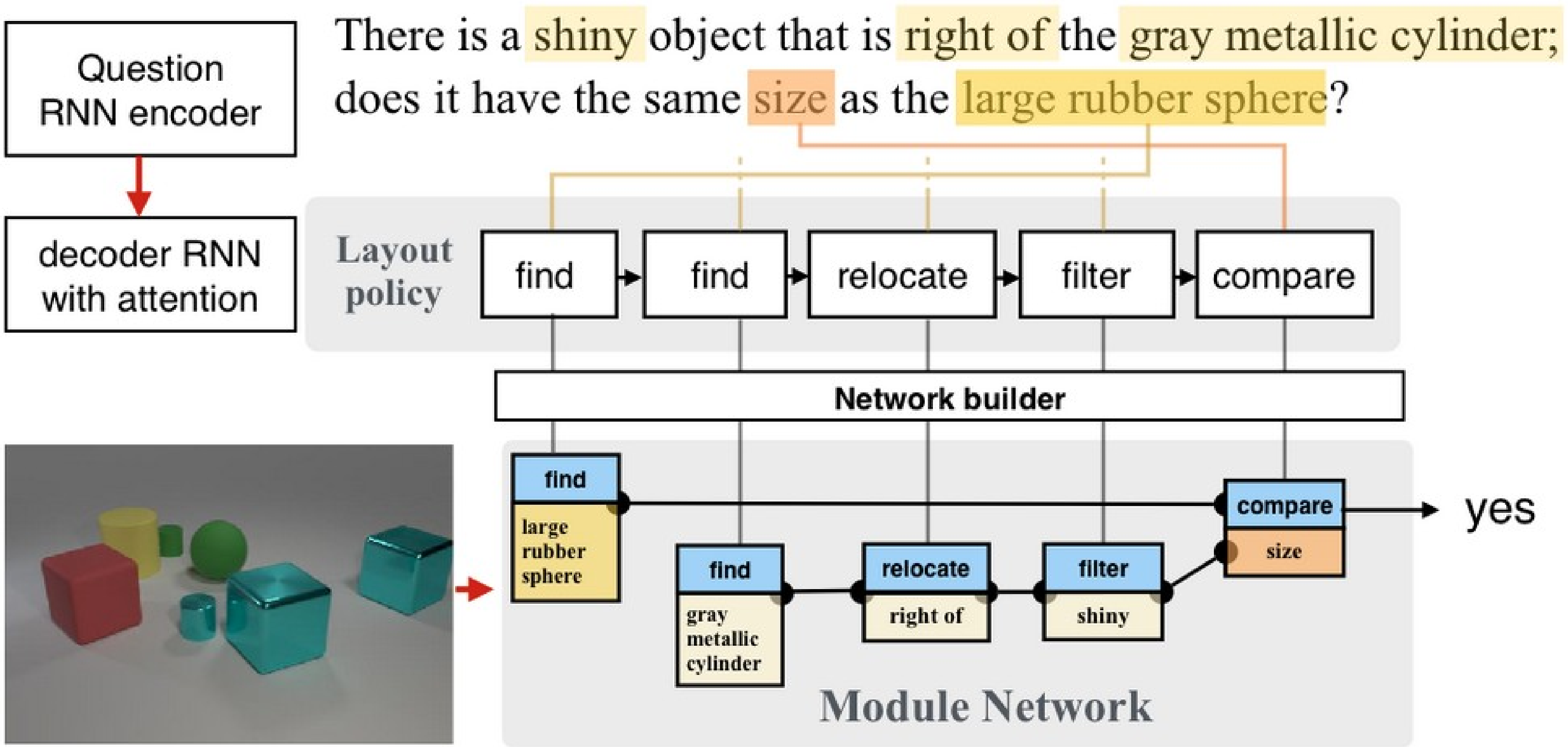
All-Attention Circuit with persistent memory

- **[Sukhbaatar arXiv:1907.01470]**



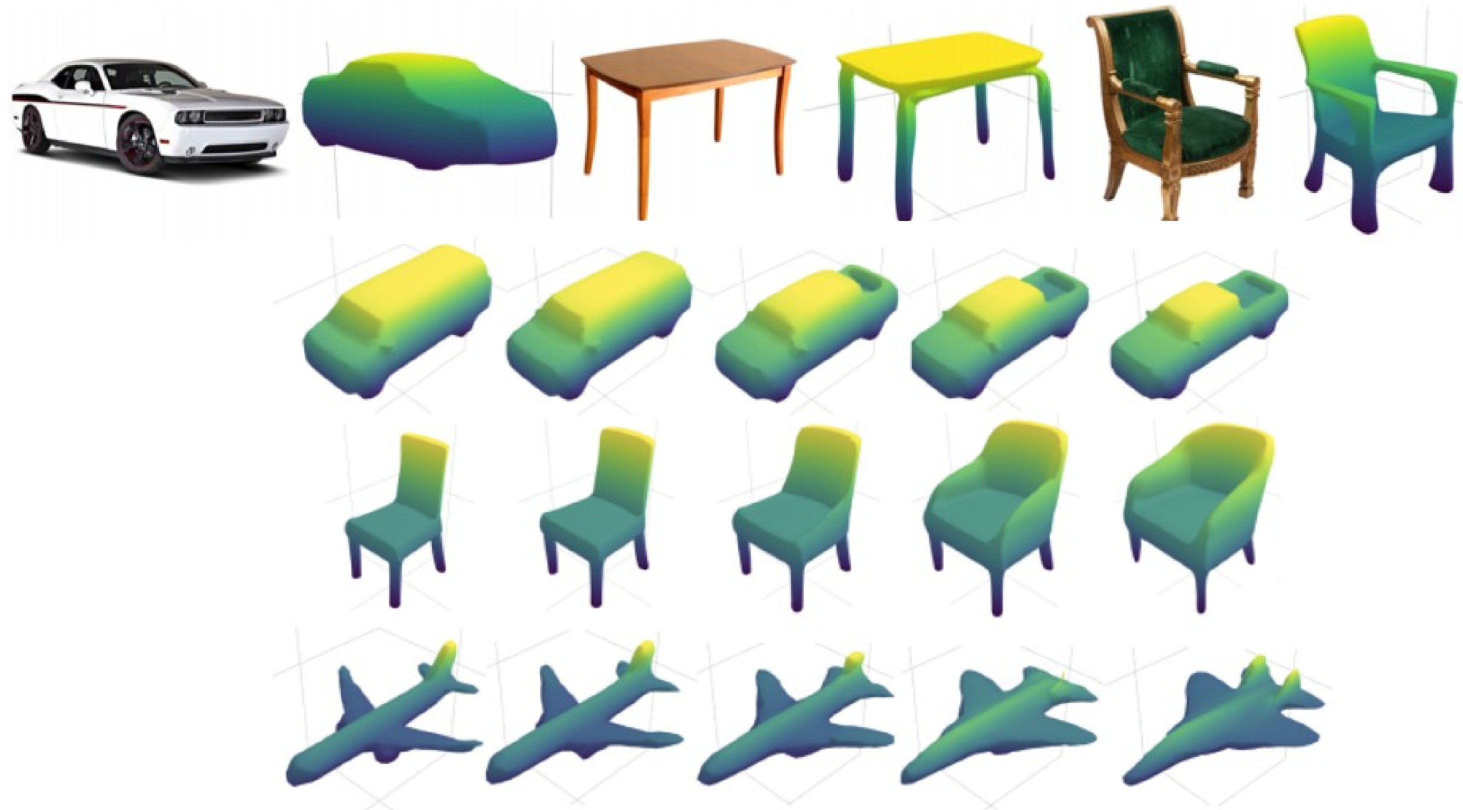
Learning to synthesize neural programs for visual reasoning

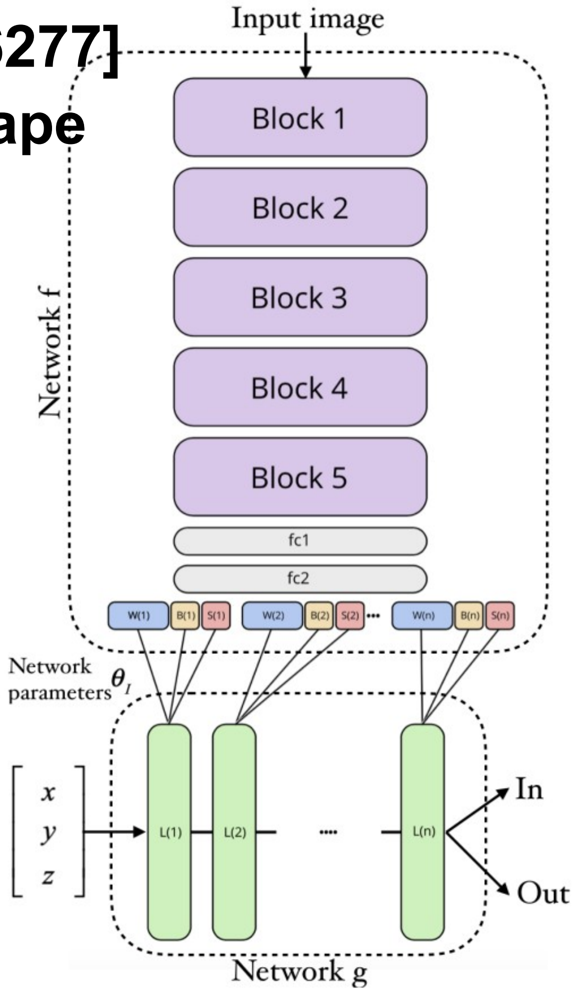
https://research.fb.com/visual-reasoning-and-dialog-towards-natural-language-conversations-about-visual-data/



Networks produced by other networks

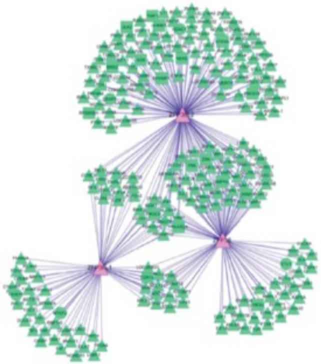
- **2D image to 3D model [Ltitwin & Wolf arXiv:1908.06277]**
- **Net1 → weights of Net2: implicit function for 3D shape**



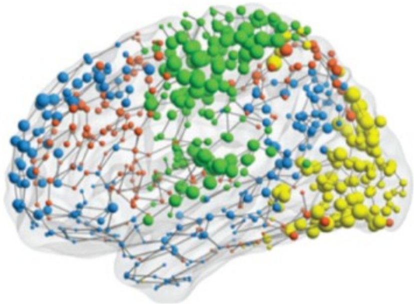


ConvNets on Graphs (fixed and data-dependent)

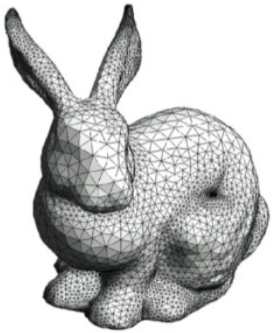
Social networks



Regulatory networks



Functional networks



3D shapes

- **Graphs can represent: Natural language, social networks, chemistry, physics, communication networks...**

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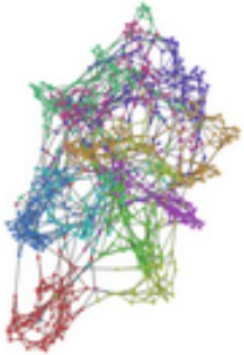
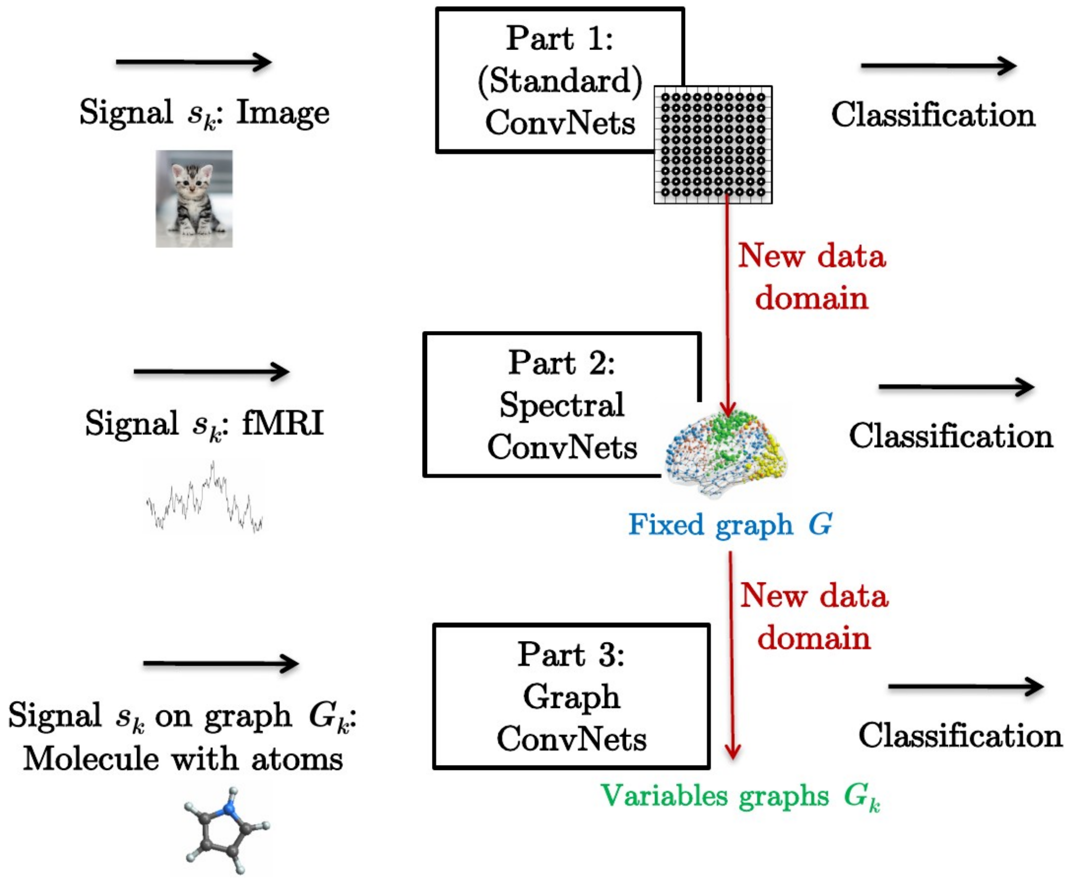


Graphs/
Networks

- **Review paper: "Geometric deep learning: going beyond euclidean data", MM Bronstein, J Bruna, Y LeCun, A Szlam, P Vandergheynst, IEEE Signal Processing Magazine 34 (4), 18-42, 2017 [ArXiv:1611.08097]**

Spectral ConvNets / Graph ConvNets

- **Regular grid graph**
  - Standard ConvNet
- **Fixed irregular graph**
  - Spectral ConvNet
- **Dynamic irregular graph**
  - Graph ConvNet



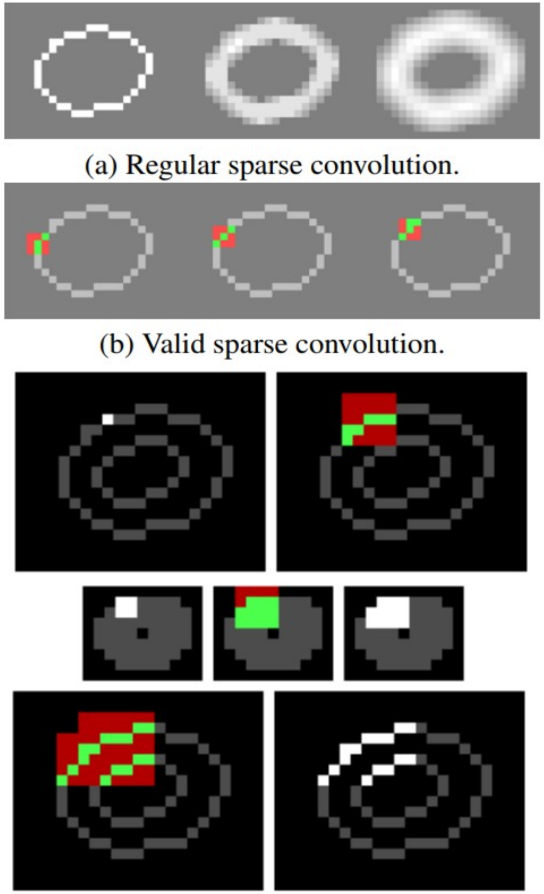
IPAM workshop:

http://www.ipam.ucla.edu/programs/workshops/new-deep-learning-techniques/

Sparse ConvNets: for sparse voxel-based 3D data

- **ShapeNet competition results ArXiv:1710.06104]**
- **Winner: Submanifold Sparse ConvNet**
  - [Graham & van der Maaten arXiv 1706.01307]
  - PyTorch: https://github.com/facebookresearch/SparseConvNet

method	mean
SSCN	**86.00**
PdNet	85.49
DCPN	84.32
PCNN	82.29
PtAdLoss	77.96
KDTNet	65.80
DeepPool	42.79
NN	77.57
[19]	84.74



(a) Regular sparse convolution.

(b) Valid sparse convolution.

:) Block with a strided, a valid, and a de-convolution.

Lessons learned #3

- ***3.1: Dynamic networks are gaining in popularity (e.g. for NLP)***
  - *Dynamicity breaks many assumptions of current hardware*
  - *Can't optimize the compute graph distribution at compile time.*
  - *Can't do batching easily!*
- ***3.2: Large-Scale Memory-Augmented Networks...***
  - *...Will require efficient associative memory/nearest-neighbor search*
- ***3.3: Graph ConvNets are very promising for many applications***
  - *Say goodbye to matrix multiplications?*
  - *Say goodbye to tensors?*
- ***3.4: Large Neural Nets may have sparse activity***
  - *How to exploit sparsity in hardware?*

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How do humans and animals learn so quickly?

Not supervised.
Not Reinforced.

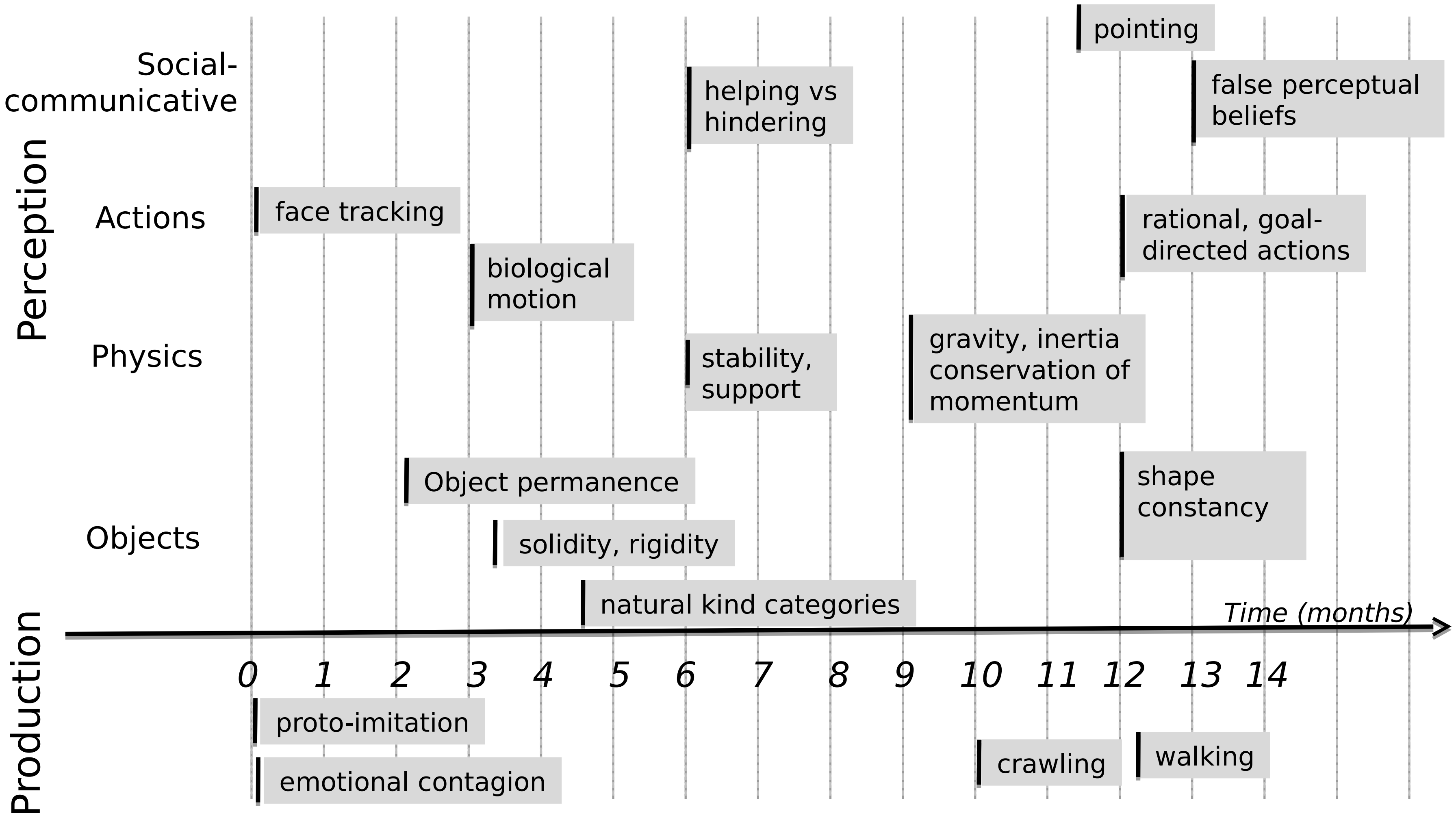
Babies learn how the world works by observation

- **Largely by observation, with remarkably little interaction.**

Photos courtesy of Emmanuel Dupoux

Y. LeCun

Early Conceptual Acquisition in Infants [from Emmanuel Dupoux]



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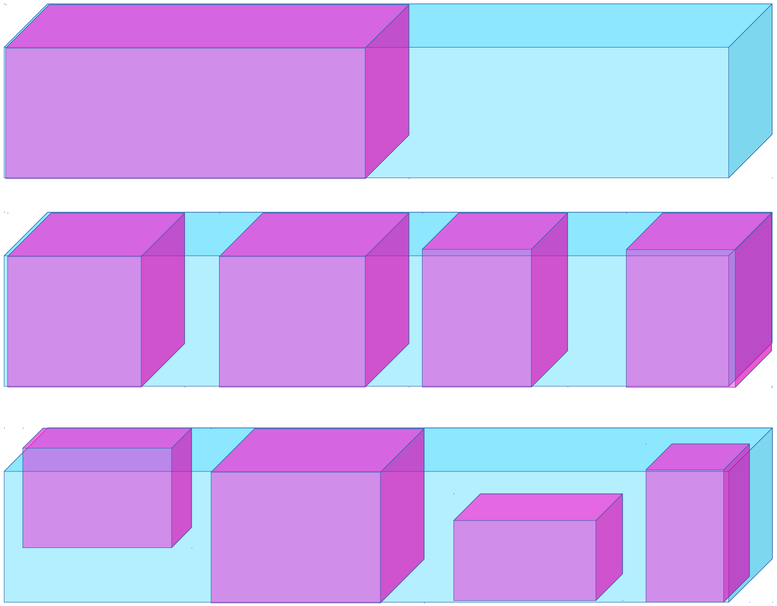
Self-Supervised Learning

Predict everything
from everything else

Self-Supervised Learning = Filling in the Blanks

- **Predict any part of the input from any other part.**
- **Predict the future from the past.**
- **Predict the masked from the visible.**
- **Predict the any occluded part from all available parts.**

time or space →



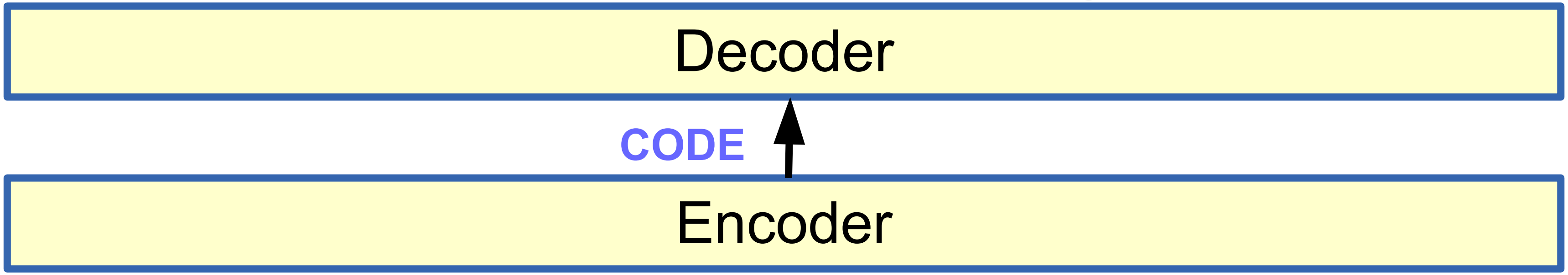
- **Pretend there is a part of the input you don't know and predict that.**
- **Reconstruction = SSL when any part could be known or unknown**

Y. LeCun

Self-Supervised Learning: filling in the bl_nks

- **Natural Language Processing: works great!**

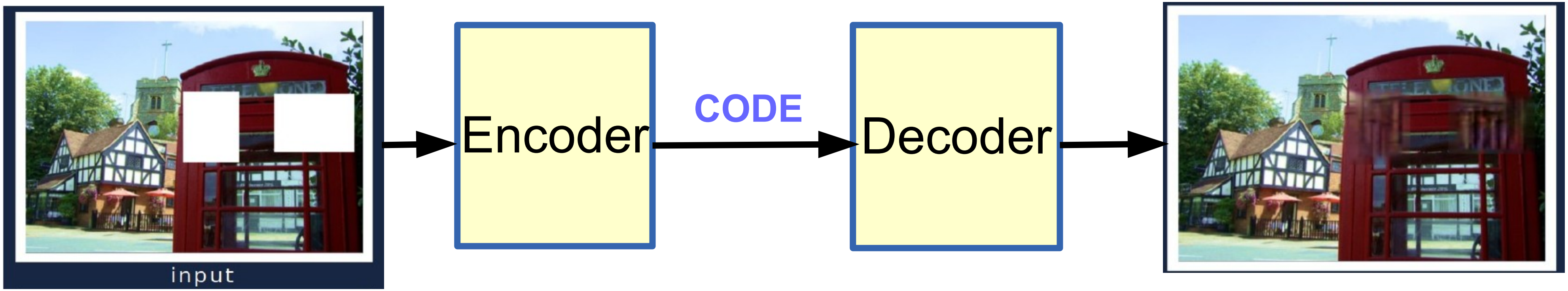
OUTPUT: This is a **piece** of text extracted **from** a large set of **news** articles



INPUT: This is a [......] of text extracted [.....] a large set of [......] articles

- **Image Recognition / Understanding: works so-so**

[Pathak et al 2014]



Learning Representations through Pretext SSL Tasks

- **Text / symbol sequences (discrete, works great!)**
  - Future word(s) prediction (NLM)
  - Masked words prediction (BERT et al.)
- **Image (continuous)**
  - Inpainting, colorization, super-resolution
- **Video (continuous)**
  - Future frame(s) prediction
  - Masked frames prediction
- **Signal / Audio (continuous)**
  - Restoration
  - Future prediction

Self-Supervised Learning works **very** well for text

- **Word2vec**
  - [Mikolov 2013]
- **FastText**
  - [Joulin 2016] (FAIR)
- **BERT**
  - Bidirectional Encoder Representations from Transformers
  - [Devlin 2018]
- **Cloze-Driven Auto-Encoder**
  - [Baevski 2019] (FAIR)
- **RoBERTa** [Ott 2019] (FAIR)

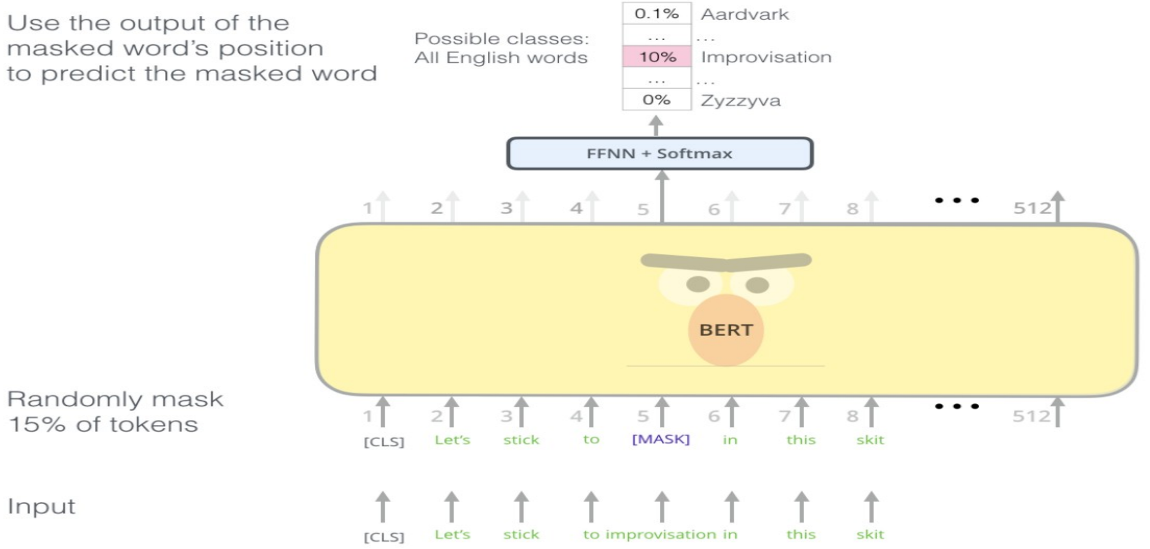
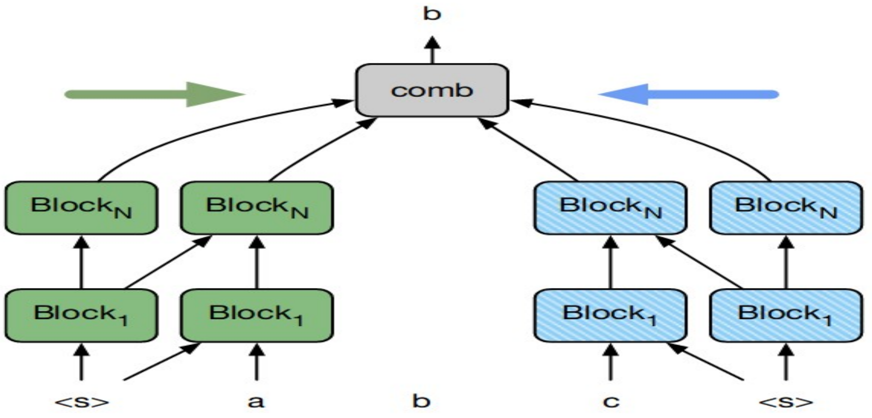


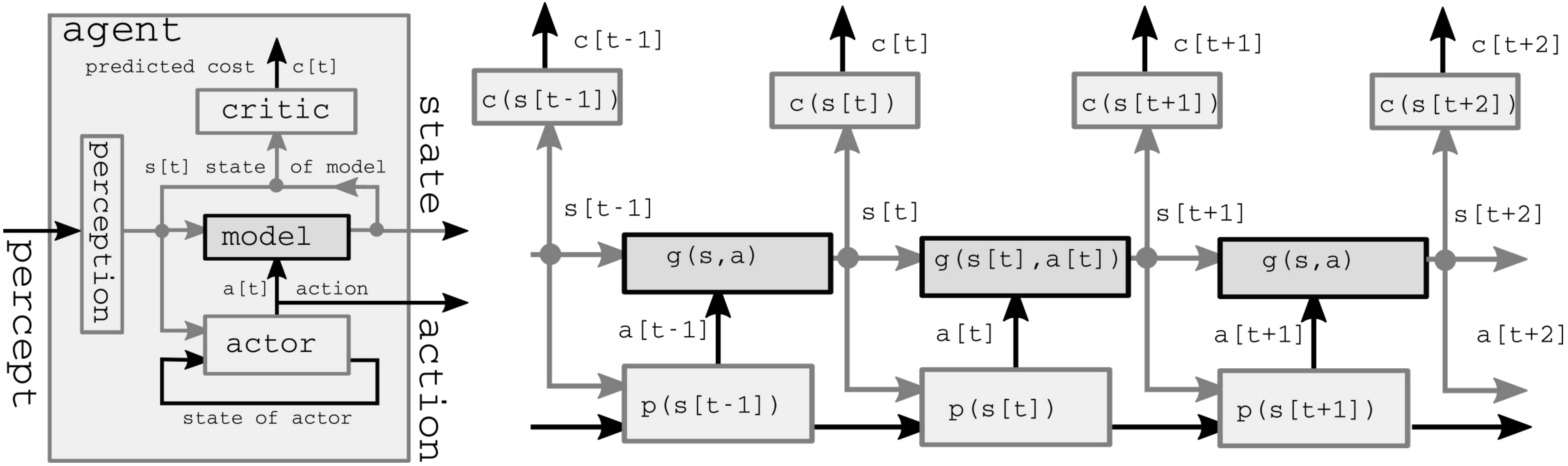
Figure credit: Jay Alammar http://jalammar.github.io/illustrated-bert/



SSL works less well for images and video

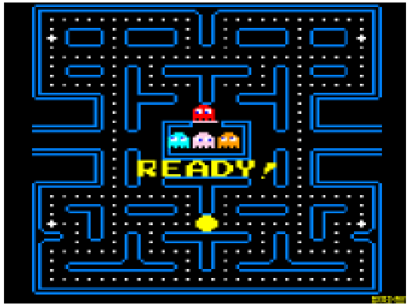
Learning World Models for Autonomous AI Agents

- **Learning forward models for control**
  - s[t+1] = g(s[t], a[t], z[t])
  - Model-predictive control, model-predictive policy learning, model-based RL
  - Robotics, games, dialog, HCI, etc



Three Types of Learning

- **Reinforcement Learning**
  - The machine predicts a scalar reward given once in a while.
  - **weak feedback**



- **Supervised Learning**
  - The machine predicts a category or a few numbers for each input
  - **medium feedback**

- **Self-supervised Learning**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **A lot of feedback**

How Much Information is the Machine Given during Learning?

- **"Pure" Reinforcement Learning (cherry)**
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning (icing)**
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- **Self-Supervised Learning (cake génoise)**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

The Next AI Revolution

With thanks to Alyosha Efros and Gil Scott Heron

Get the T-shirt!

Jitendra Malik: "Labels are the opium of the machine learning researcher"

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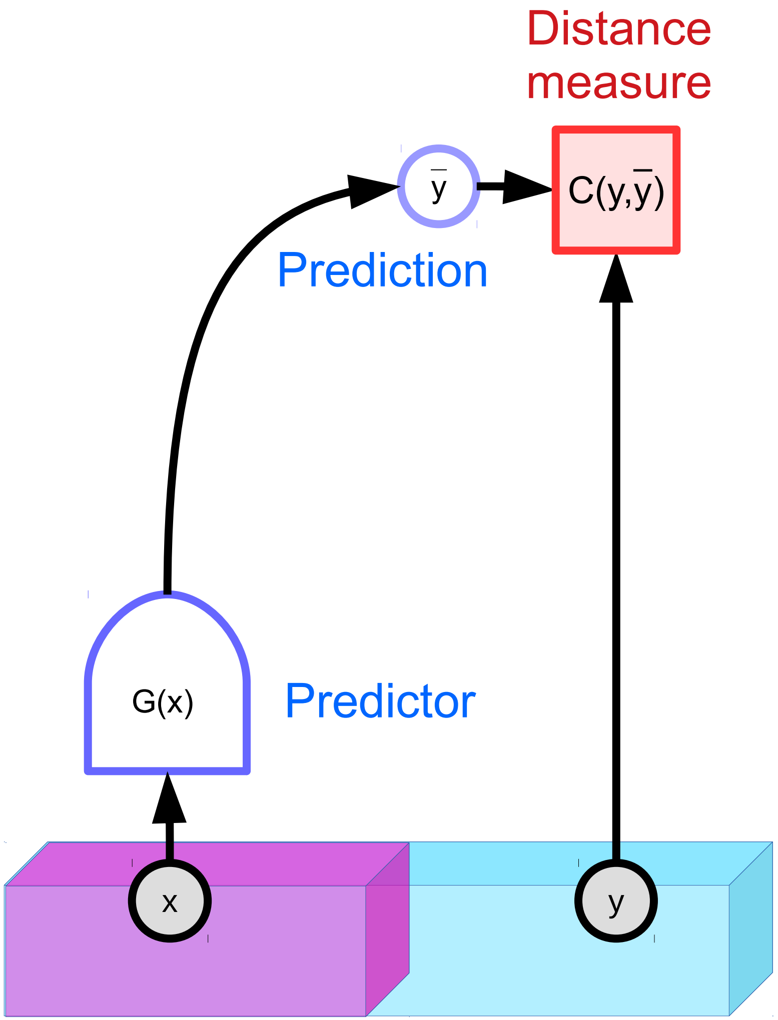
Energy-Based Models

Learning to deal with uncertainty while eschewing probabilities

Problem: uncertainty!

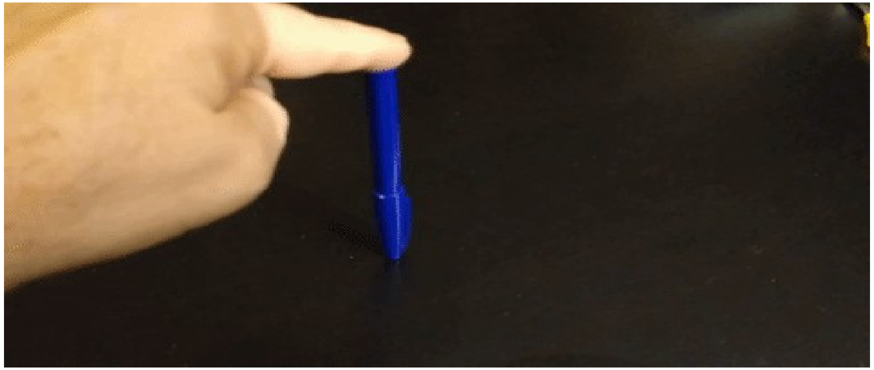
- There are **many** plausible words that complete a text.
- There are **infinitely many** plausible frames to complete a video.
- **Deterministic predictors don't work!**
- **How to deal with uncertainty in the prediction?**



$$E(x,y)=C(y,G(x))$$

The world is not entirely predictable / stochastic

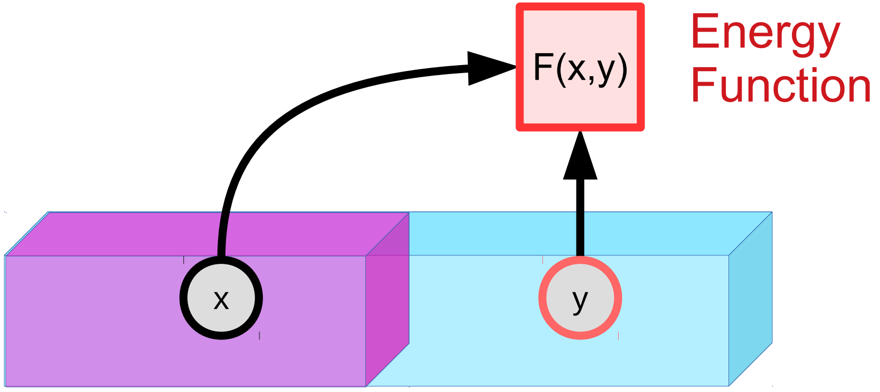
- **Video prediction:**
  - A deterministic predictor with L2 distance will predict the average of all plausible futures.
- **Blurry prediction!**



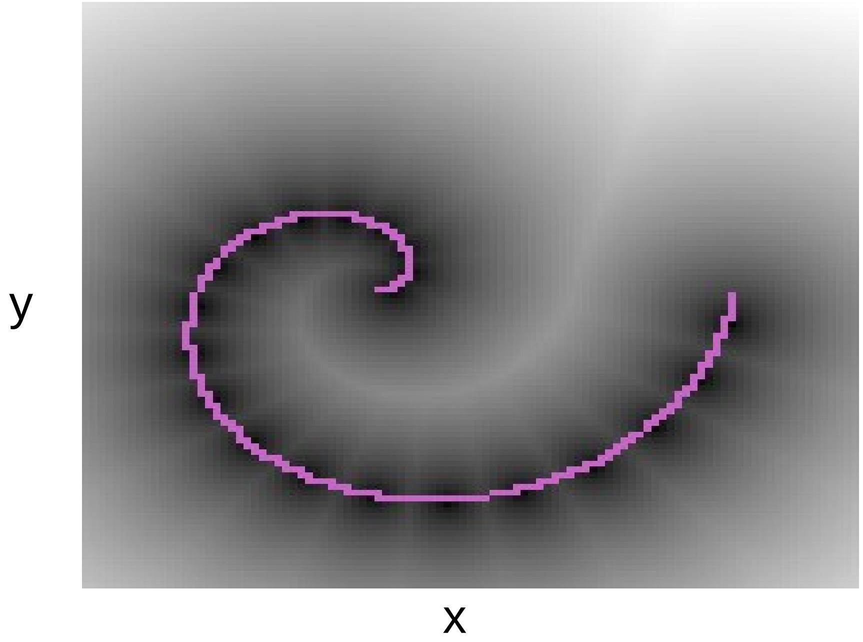
Energy-Based Model

Y. LeCun

- **Scalar-valued energy function: F(x,y)**
  - measures the compatibility between x and y
  - Low energy: y is good prediction from x
  - High energy: y is bad prediction from x
  - Inference: $\check{y} = argmin_y F(x, y)$



Dark = low energy (good)
Bright = high energy (bad)
Purple = data manifold



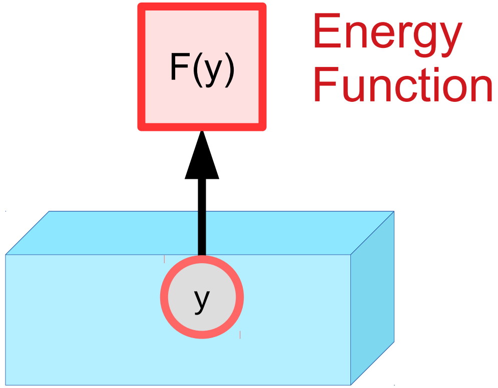
[Figure from M-A Ranzato's PhD thesis]

Y. LeCun

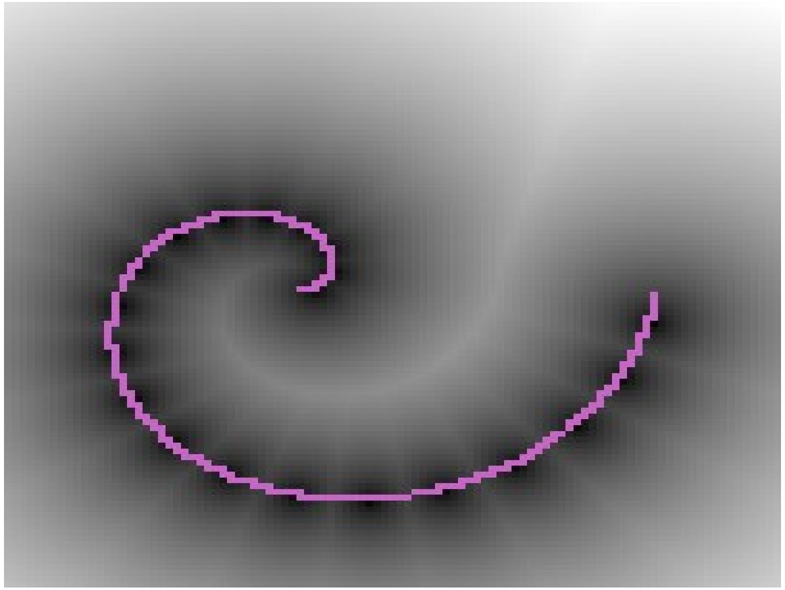
Energy-Based Model: unconditional version

- **Scalar-valued energy function: F(y)**
  - measures the compatibility between the components of y
  - If we don't know in advance which part of y is known and which part is unknown
  - Example: auto-encoders, generative models (energy = -log likelihood)

Dark = low energy (good)
Bright = high energy (bad)
Purple = data manifold



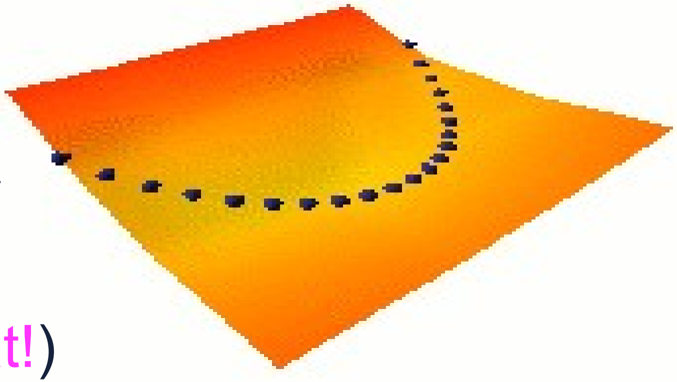
y2



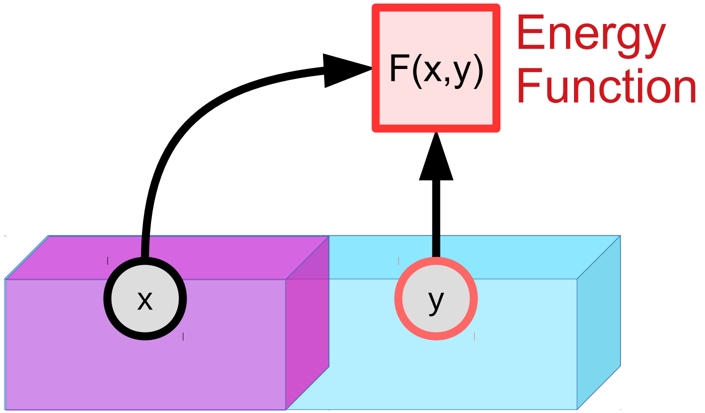
y1

Training an Energy-Based Model

- **Parameterize F(x,y)**
- **Get training data (x[i], y[i])**
- **Shape F(x,y) so that:**
  - F(x[i], y[i]) is strictly smaller than F(x[i], y) for all y different from y[i]
  - F is smooth (probabilistic methods break that!)



- **Two classes of learning methods:**
  - 1. **Contrastive methods**: push down on F(x[i], y[i]), push up on other points F(x[i], y')
  - 2. **Architectural Methods**: build F(x,y) so that the volume of low energy regions is limited or minimized through regularization



Seven Strategies to Shape the Energy Function

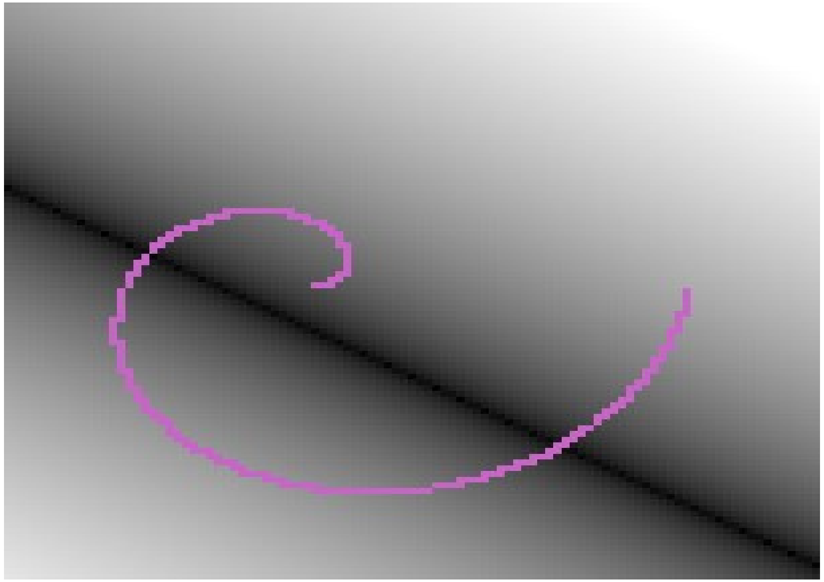
- **Contrastive: [they all are different ways to pick which points to push up]**
  - C1: push down of the energy of data points, push up everywhere else: Max likelihood (needs tractable partition function or variational approximation)
  - C2: push down of the energy of data points, push up on chosen locations: max likelihood with MC/MMC/HMC, Contrastive divergence, Metric learning, 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)
- **Architectural: [they all are different ways to limit the information capacity of the code]**
  - A1: build the machine so that the volume of low energy stuff is bounded: PCA, K-means, Gaussian Mixture Model, Square ICA…
  - A2: use a regularization term that measures the volume of space that has low energy: Sparse coding, sparse auto-encoder, LISTA, Variational auto-encoders
  - 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

Simple examples: PCA and K-means

- **Limit the capacity of z so that the volume of low energy stuff is bounded**
  - PCA, K-means, GMM, square ICA...

PCA: z is low dimensional

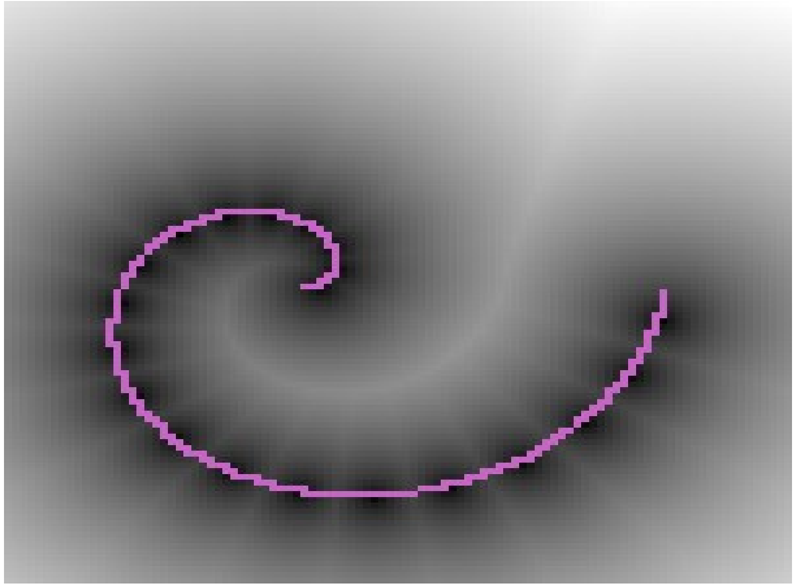
$$F(Y) = ||W^T W Y - Y||^2$$



K-Means,

Z constrained to 1-of-K code

$$F(Y) = min_z \sum_i ||Y - W_i Z_i||^2$$



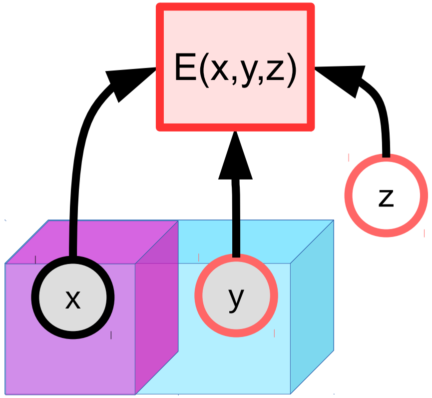
Latent-Variable EBM

- **Allowing multiple predictions through a latent variable**

- **Conditional:**

$$F(x,y)=min_z E(x,y,z)$$

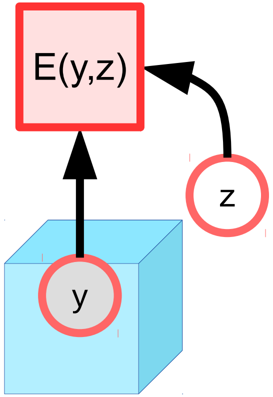
$$F(x,y)=-\frac{1}{\beta}\log\left[\int_z \exp(-\beta E(x,y,z))\right]$$



- **Unconditional**

$$F(y)=min_z E(y,z)$$

$$F(y)=-\frac{1}{\beta}\log\left[\int_z \exp(-\beta E(y,z))\right]$$



Latent-Variable EBM for multimodal prediction

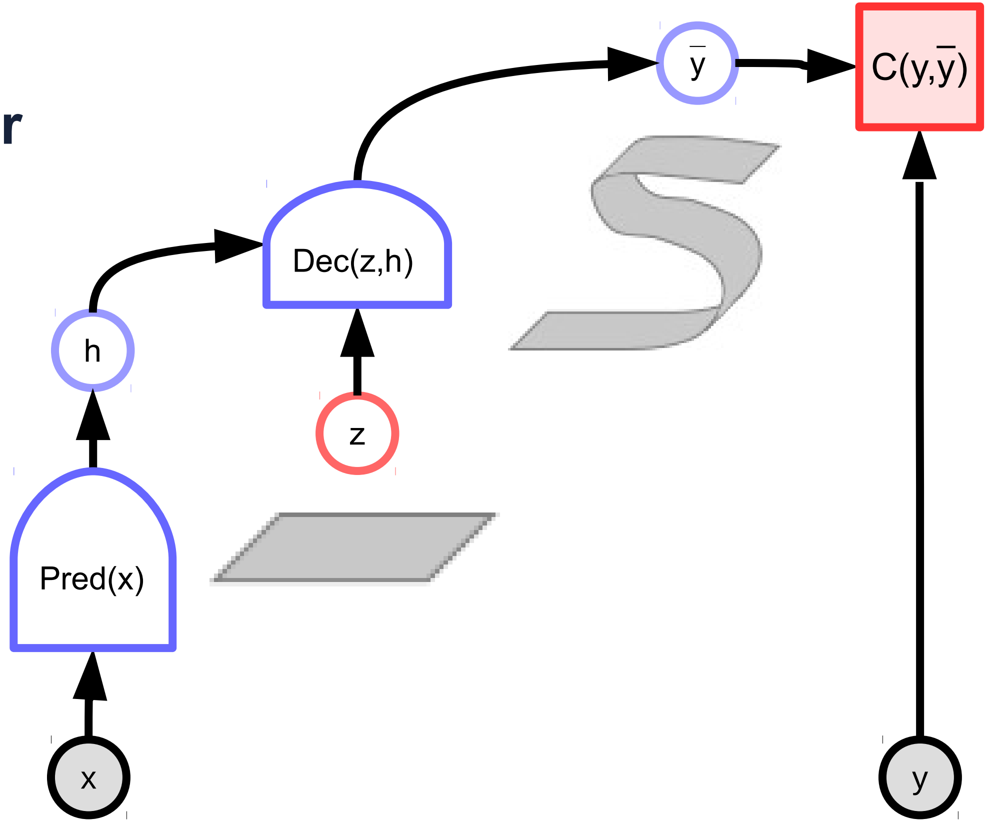
- **Allowing multiple predictions through a latent variable**

- **As z varies over a set, y varies over the manifold of possible predictions**

  $$F(x,y)=\min_z E(x,y,z)$$

- **Examples:**
  - K-means
  - Sparse modeling
  - GLO

    [Bojanowski arXiv:1707.05776]

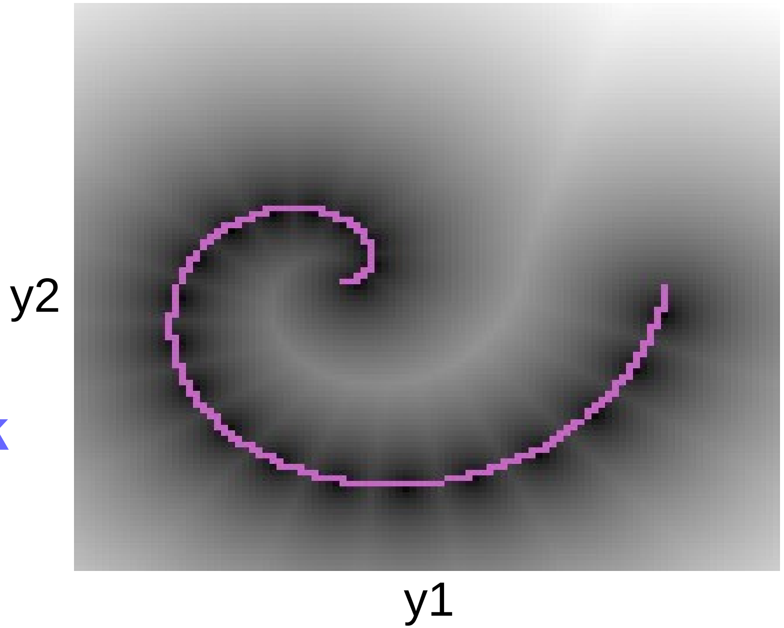


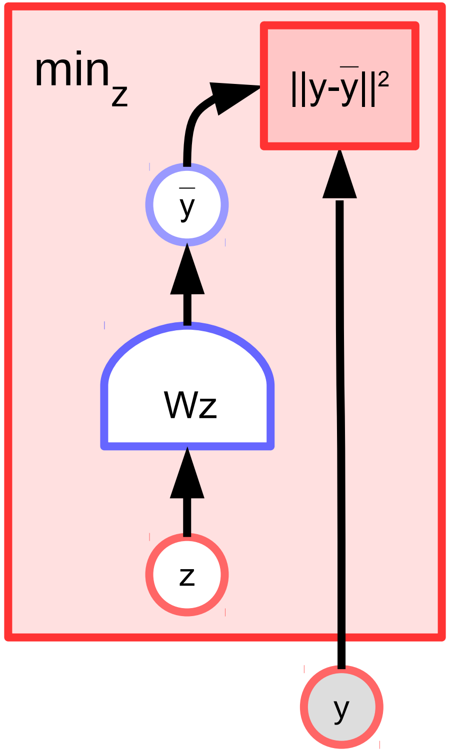
Latent-Variable EBM example: K-means

- **Decoder is linear, z is a 1-hot vector (discrete)**
- **Energy function:** $E(y,z) = ||y - Wz||^2 \quad z \in 1\,hot$
- **Inference by exhaustive search**

$$F(y) = min_z E(y,z)$$

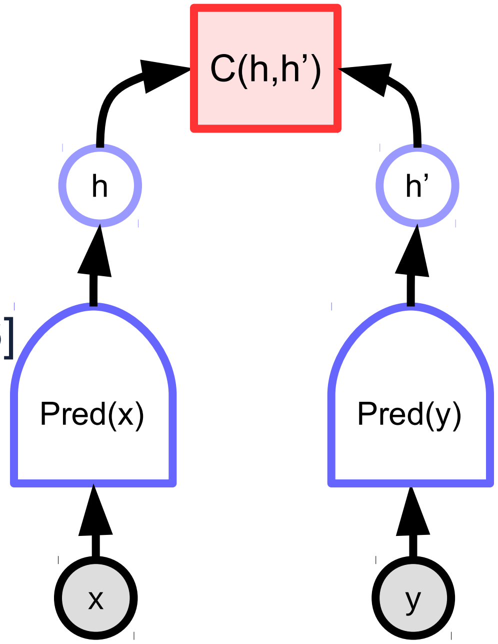
- **Volume of low-energy regions limited by number of prototypes k**





Contrastive Embedding

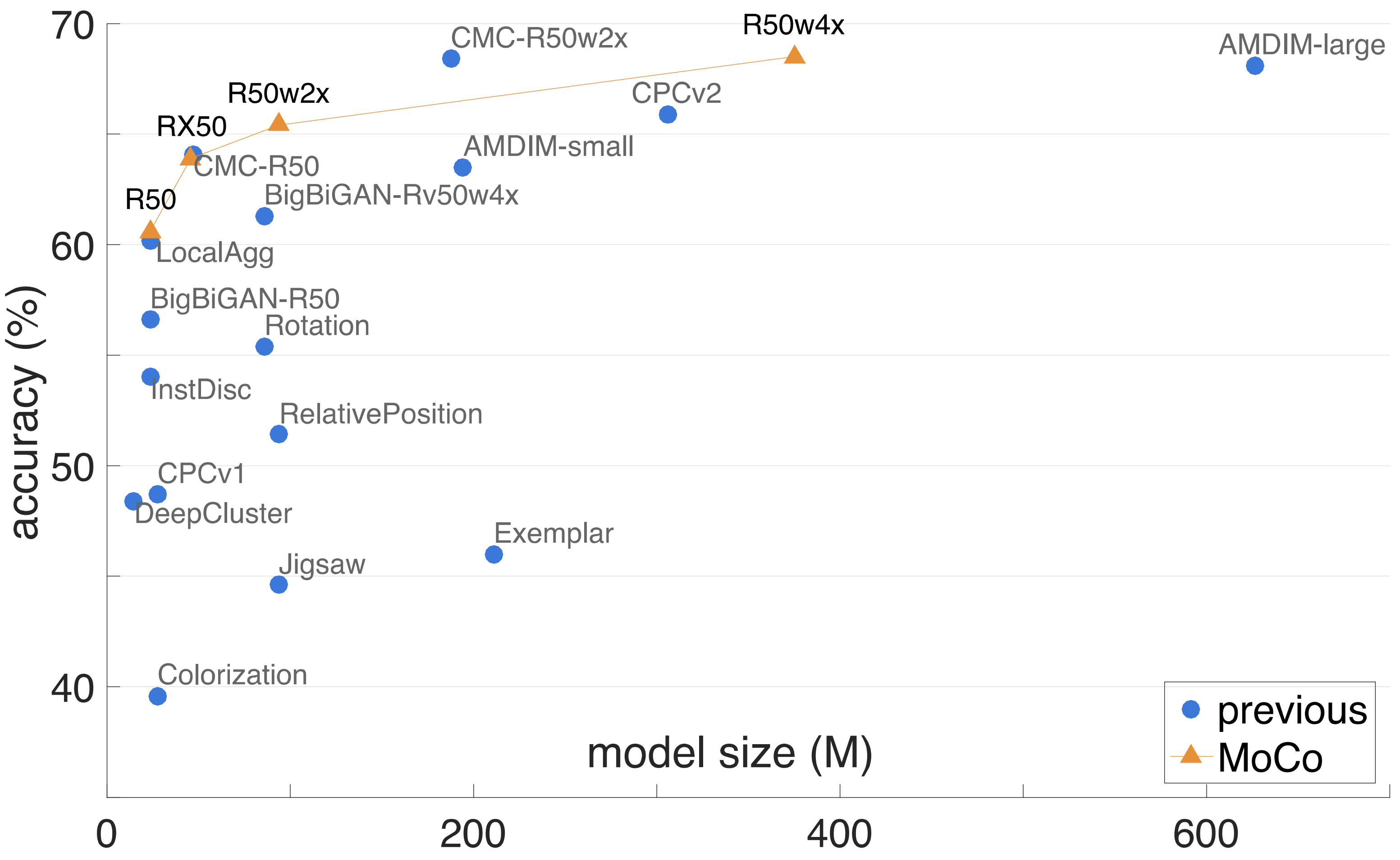
- **Distance measured in feature space**
- **Multiple "predictions" through feature invariance**
- **Siamese nets, metric learning** [YLC NIPS'93,CVPR'05,CVPR'06]
- **Advantage: no pixel-level reconstruction**
- **Difficulty: hard negative mining**
- **Successful examples for images:**
  - DeepFace [Taigman et al. CVPR'14]
  - PIRL [Misra et al. To appear]
  - MoCo [He et al. Arxiv:1911.05722]
- **Video / Audio**
  - Temporal proximity [Taylor CVPR'11]
  - Slow feature [Goroshin NIPS'15]



Positive pair:
Make F small

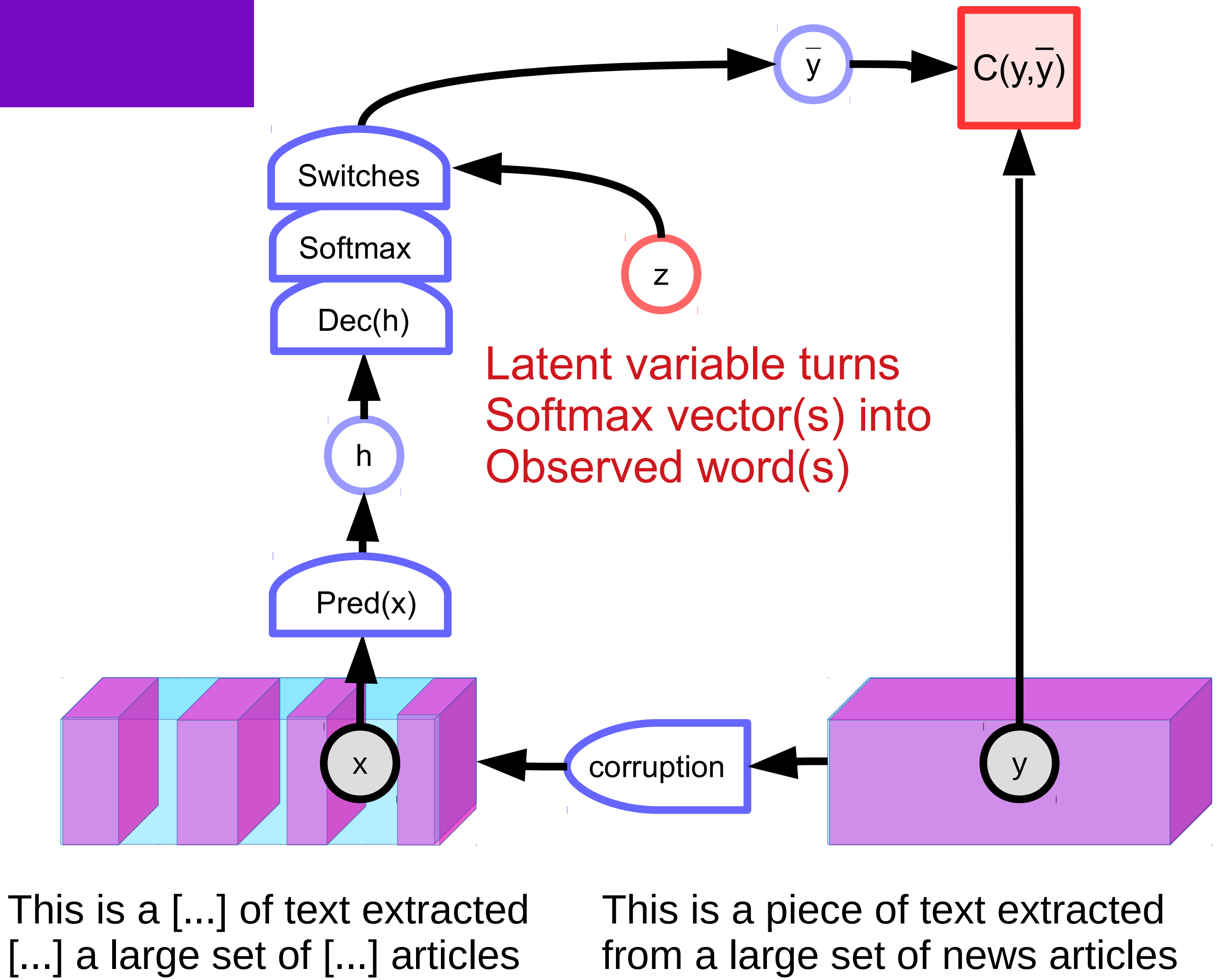
Negative pair:
Make F large

MoCo on ImageNet [He et al. Arxiv:1911.05722]



Denoising AE: discrete

- **[Vincent et al. JMLR 2008]**
- **Masked Auto-Encoder**
  - [BERT et al.]
- **Issues:**
  - latent variables are in output space
  - No abstract LV to control the output
  - How to cover the space of corruptions?

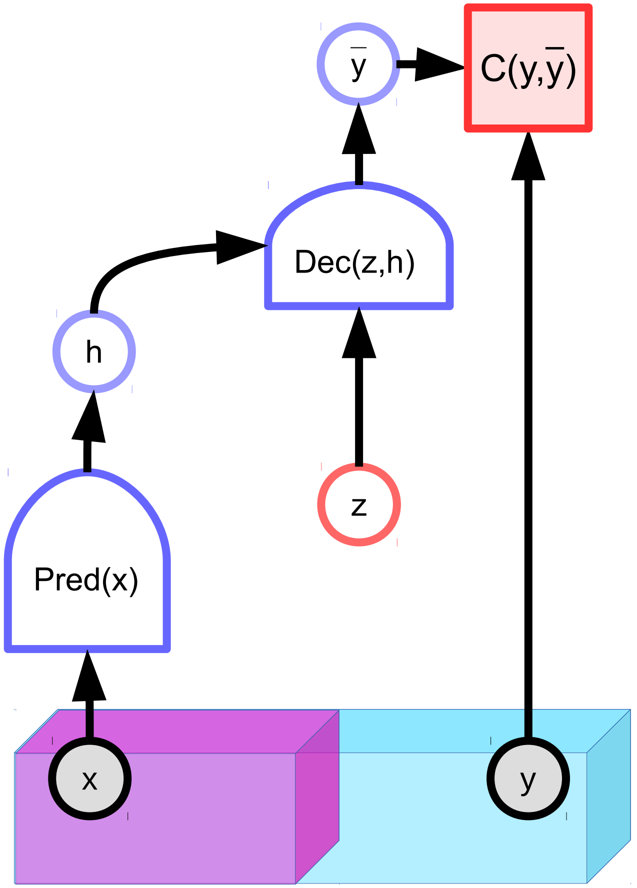


Prediction with Latent Variables

- **If the Latent has too much capacity...**
  - e.g. if it has the same dimension as y
- **… then the entire y space could be perfectly reconstructed**

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

- **For every y, there is always a z that will reconstruct it perfectly**
  - The energy function would be zero everywhere
  - This is no a good model….
- **Solution: limiting the information capacity of the latent variable z.**

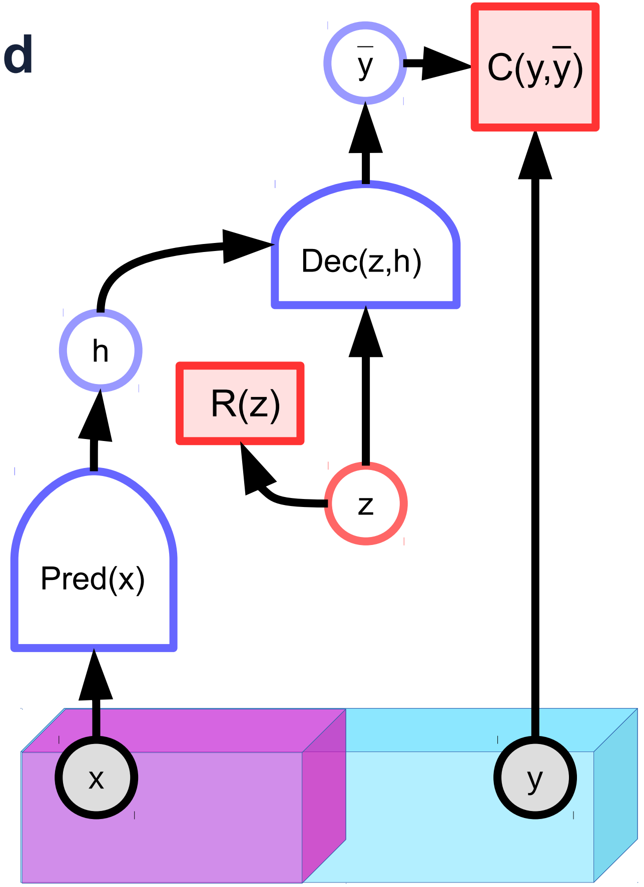


Regularized Latent Variable EBM

- **Regularizer R(z) limits the information capacity of z**
- **Without regularization, every y may be reconstructed exactly (flat energy surface)**

$$E(x,y,z)=C(y,Dec(Pred(x),z))+\lambda R(z)$$

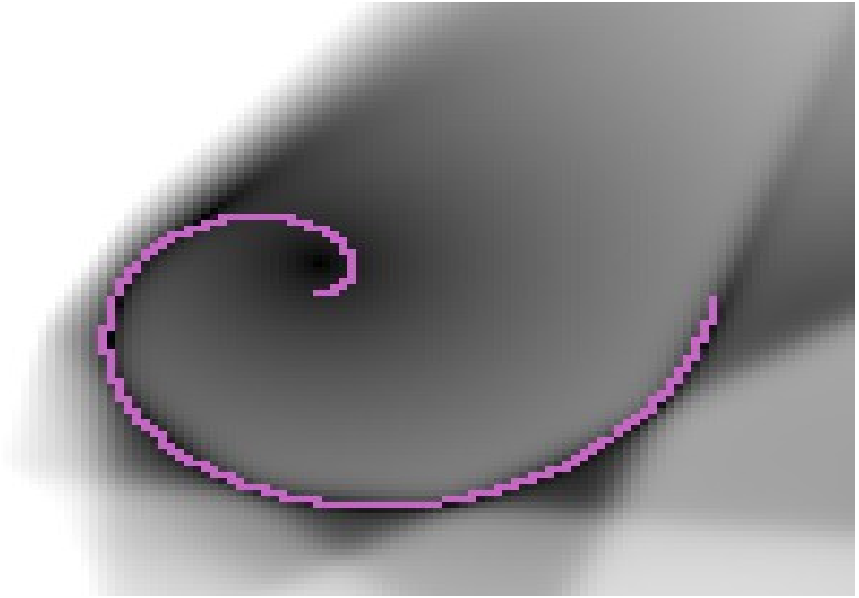
- **Examples of R(z):**
  - Effective dimension
  - Quantization / discretization
  - L0 norm (# of non-0 components)
  - L1 norm with decoder normalization
  - Maximize lateral inhibition / competition
  - Add noise to z while limiting its L2 norm (VAE)
  - <your_information_throttling_method_goes_here>

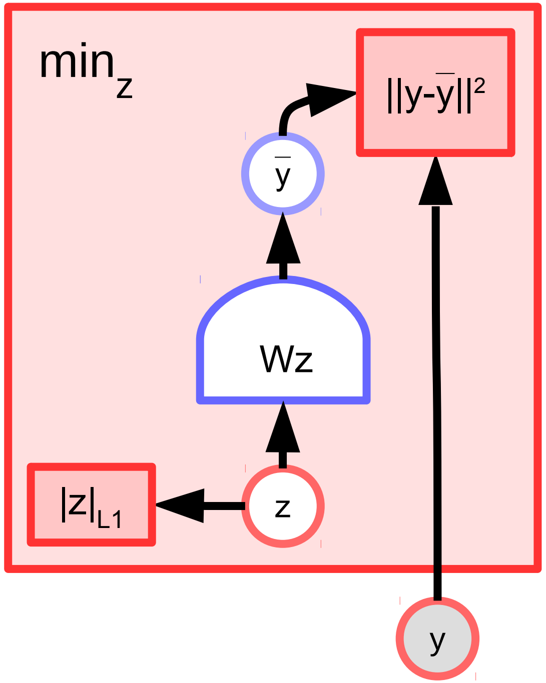


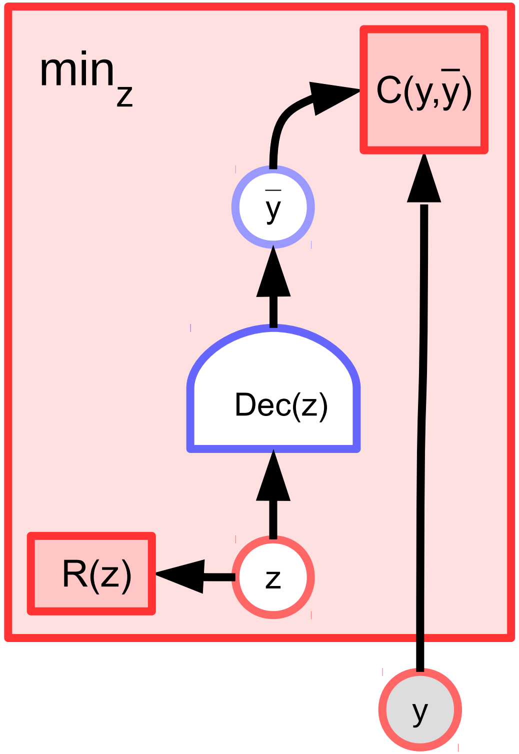
Unconditional Regularized Latent Variable EBM

- **Unconditional form. Reconstruction. No x, no predictor.**
- **Example: sparse modeling**
  - Linear decoder
  - L1 regularizer on Z

$$E(y,z)=\|y-Wz\|^2+\lambda|z|$$





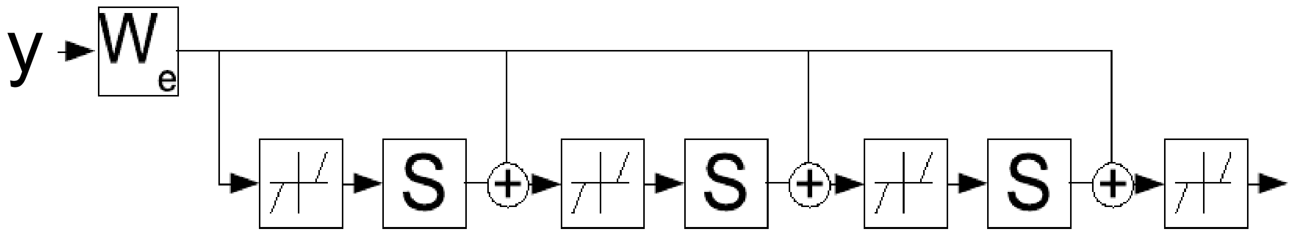


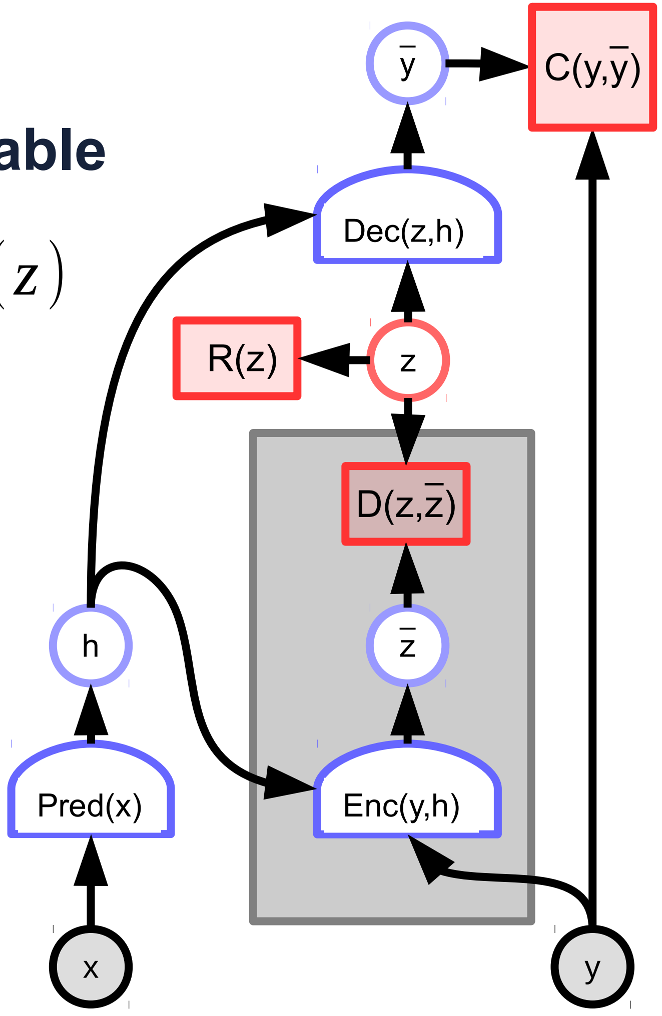
LatVar inference is expensive!

- **Let's train an encoder to predict the latent variable**

$$E(x,y,z)=C(y,Dec(z,h))+D(z,Enc(x,y))+\lambda R(z)$$

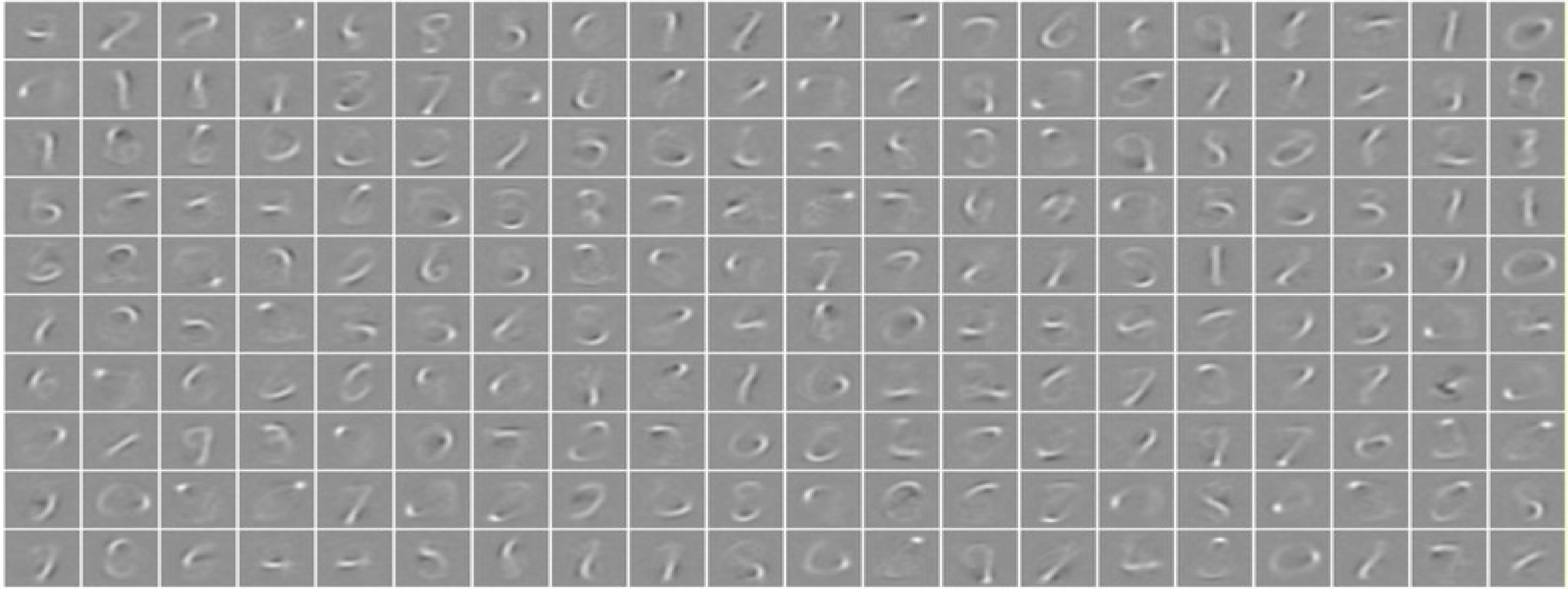
- **Predictive Sparse Modeling**
  - R(z) = L1 norm of z
  - Dec(z,h) gain must be bounded (clipped weights)
  - Sparse Auto-Encoder
  - LISTA [Gregor ICML 2010]





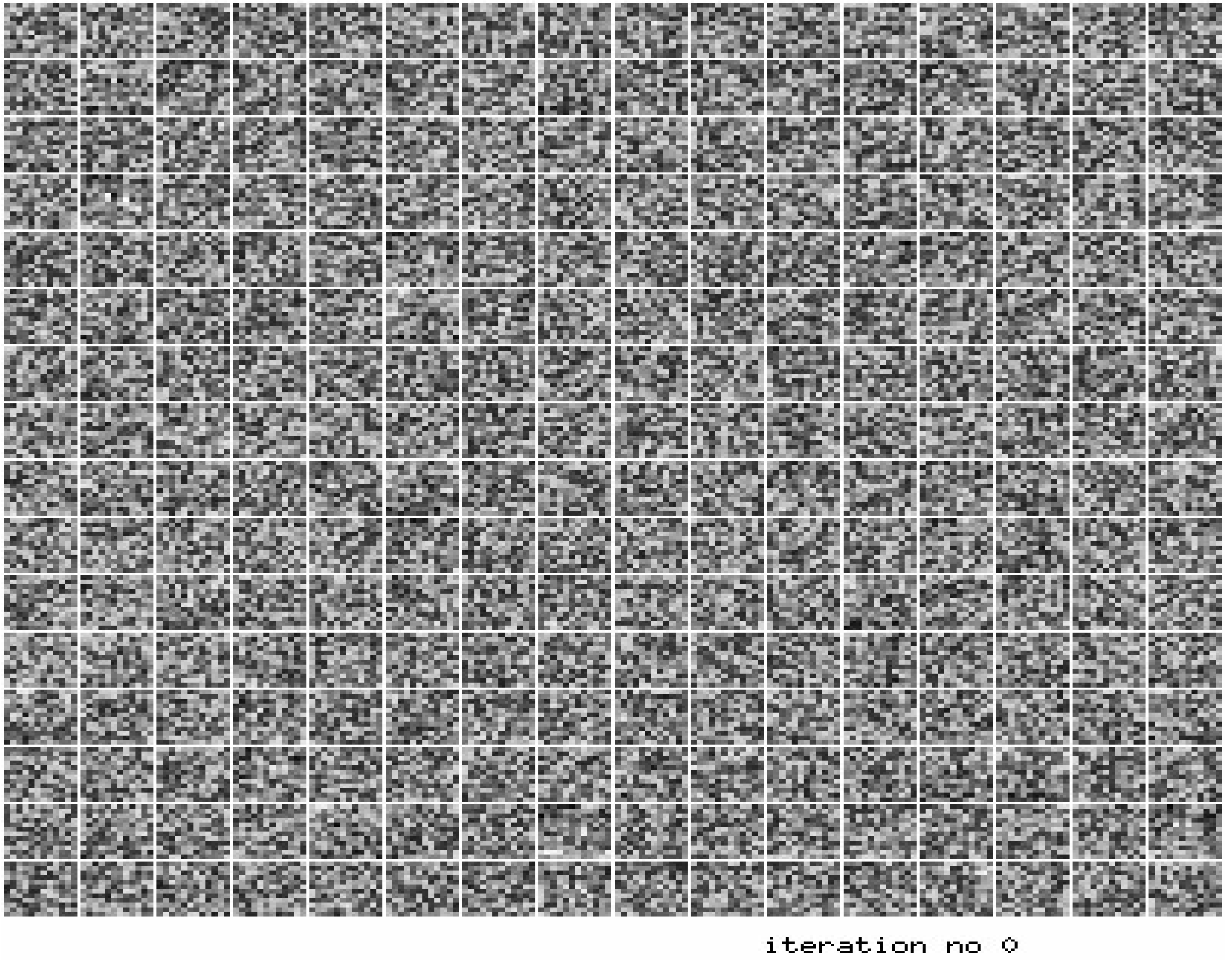
Sparse AE on handwritten digits (MNIST)

- 256 basis functionsBasis functions (columns of decoder matrix) are digit parts
- All digits are a linear combination of a small number of these



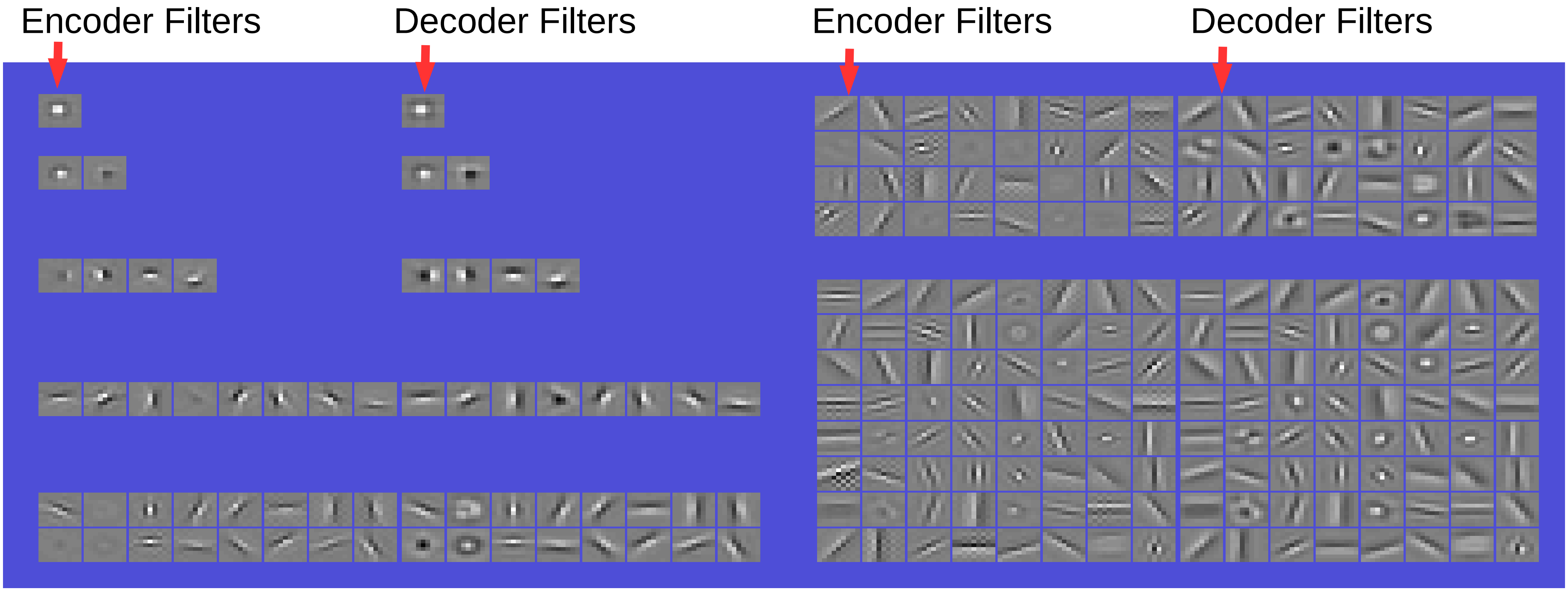
Predictive Sparse Decomposition (PSD): Training

- **Training on natural images patches.**
  - 12X12
  - 256 basis functions
  - [Ranzato 2007]



Convolutional Sparse Auto-Encoder on Natural Images

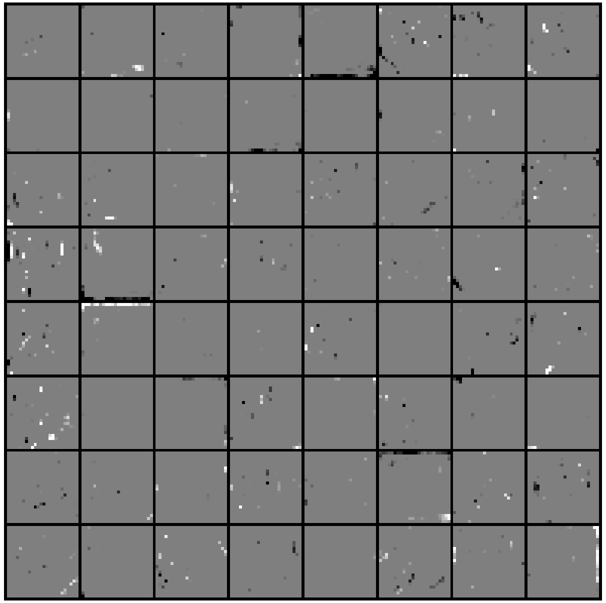
- **Filters and Basis Functions obtained. Linear decoder (conv)**
  - with 1, 2, 4, 8, 16, 32, and 64 filters [Kavukcuoglu NIPS 2010]



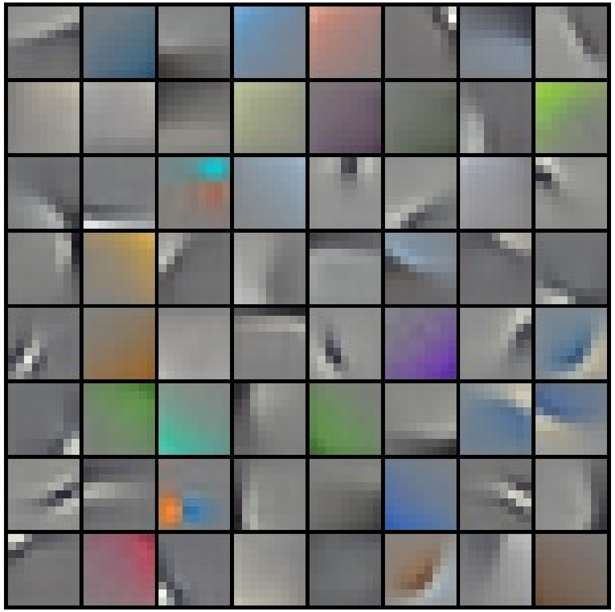
Convolutional Sparse Auto-Encoder on Natural Images

- Trained on CIFAR 10 (32x32 color images)
- Architecture: Linear decoder, LISTA recurrent encoder

sparse codes (z) from encoder



9x9 decoder kernels



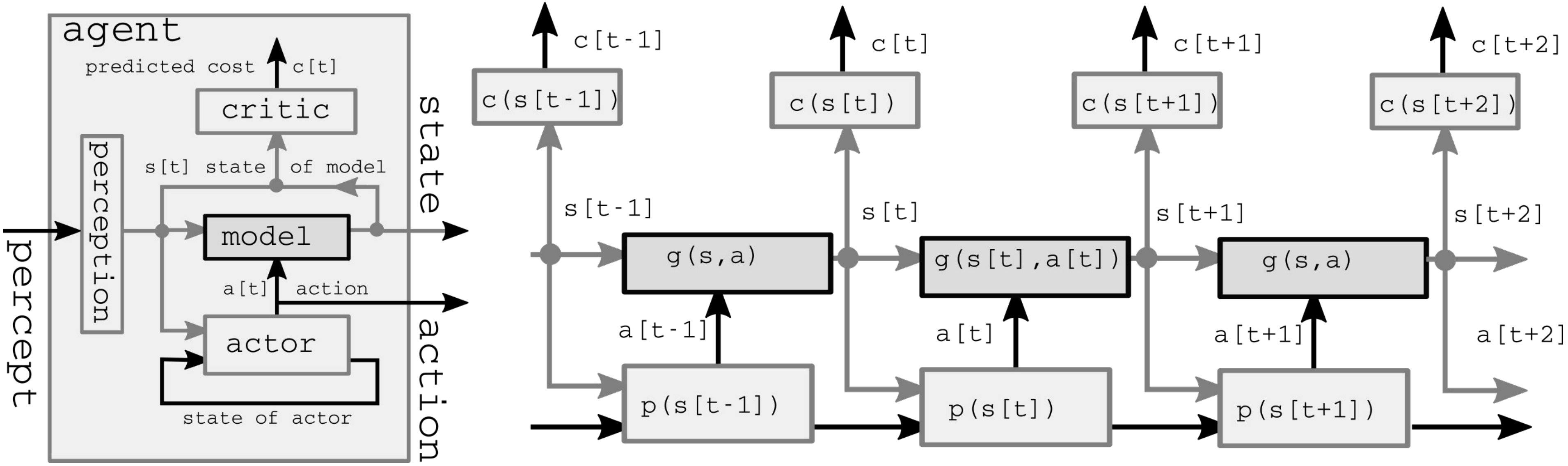
FACEBOOK AI

Learning a Forward Model for Autonomous Driving

Learning to predict what others around you will do

A Forward Model of the World

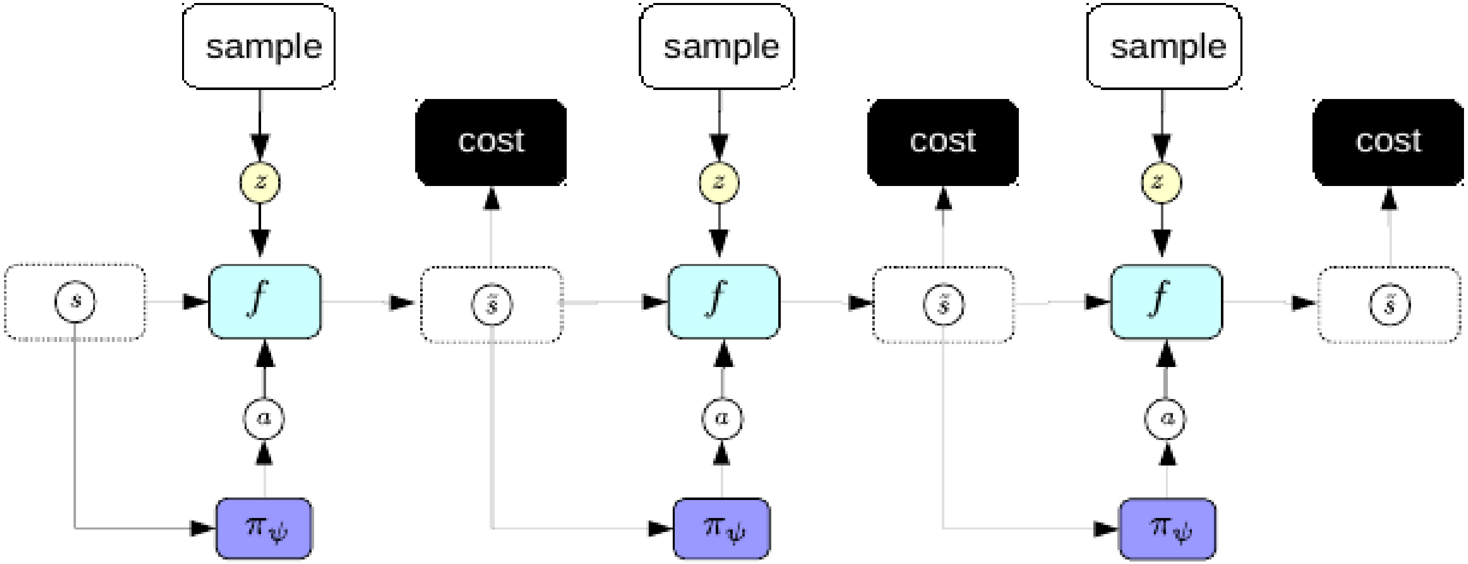
- **Learning forward models for control**
  - s[t+1] = g(s[t], a[t], z[t])
  - Classical optimal control: find a sequence of action that minimize the cost, according to the predictions of the forward model



Planning/learning using a self-supervised predictive world model

- **Feed initial state**
- **Run the forward model**
- **Backpropagate gradient of cost**
- **Act**
  - (model-predictive control)

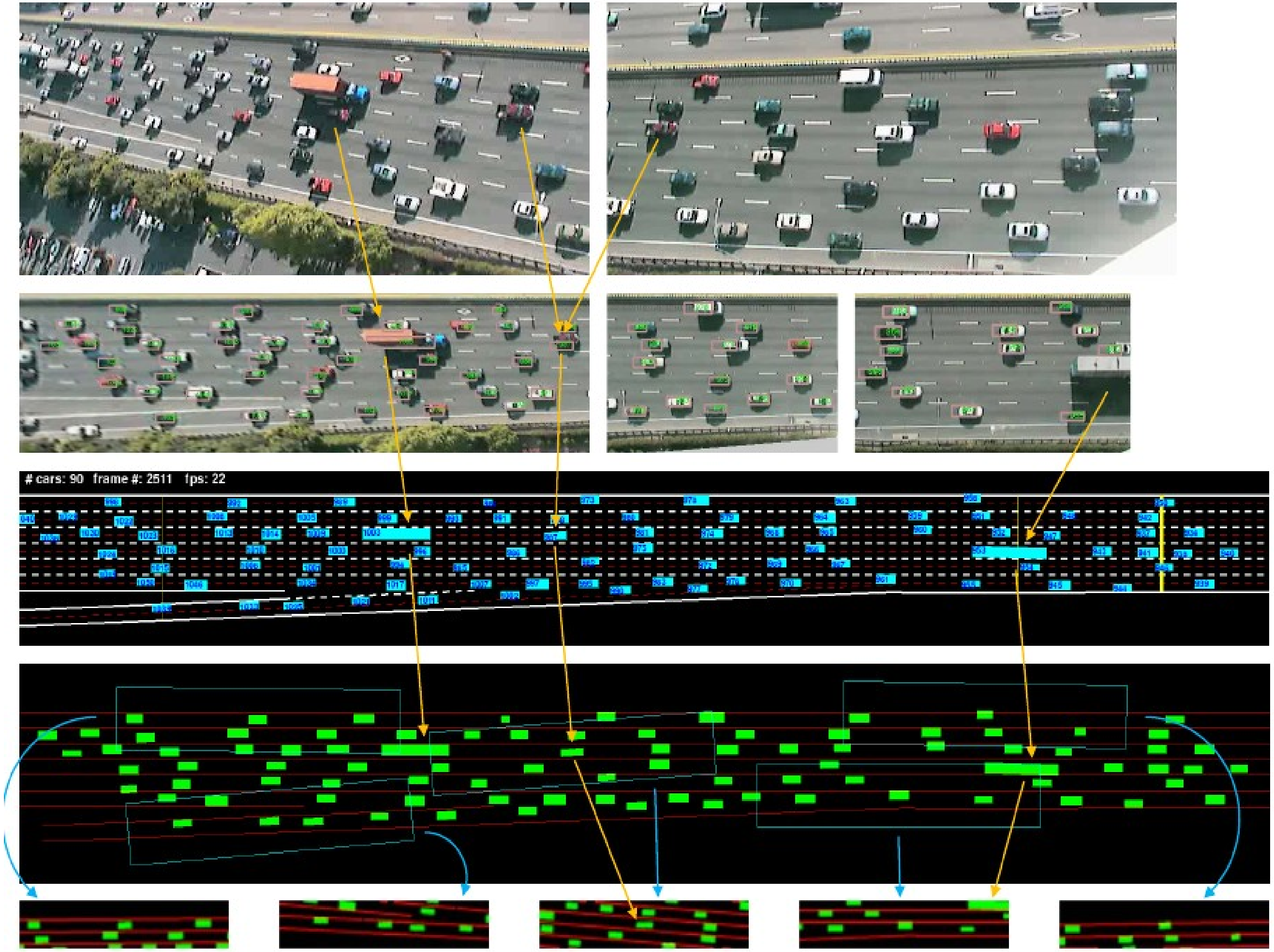
  or
- **Use the gradient t train a policy network.**
- **Iterate**



Stochastic policy network (optimized)

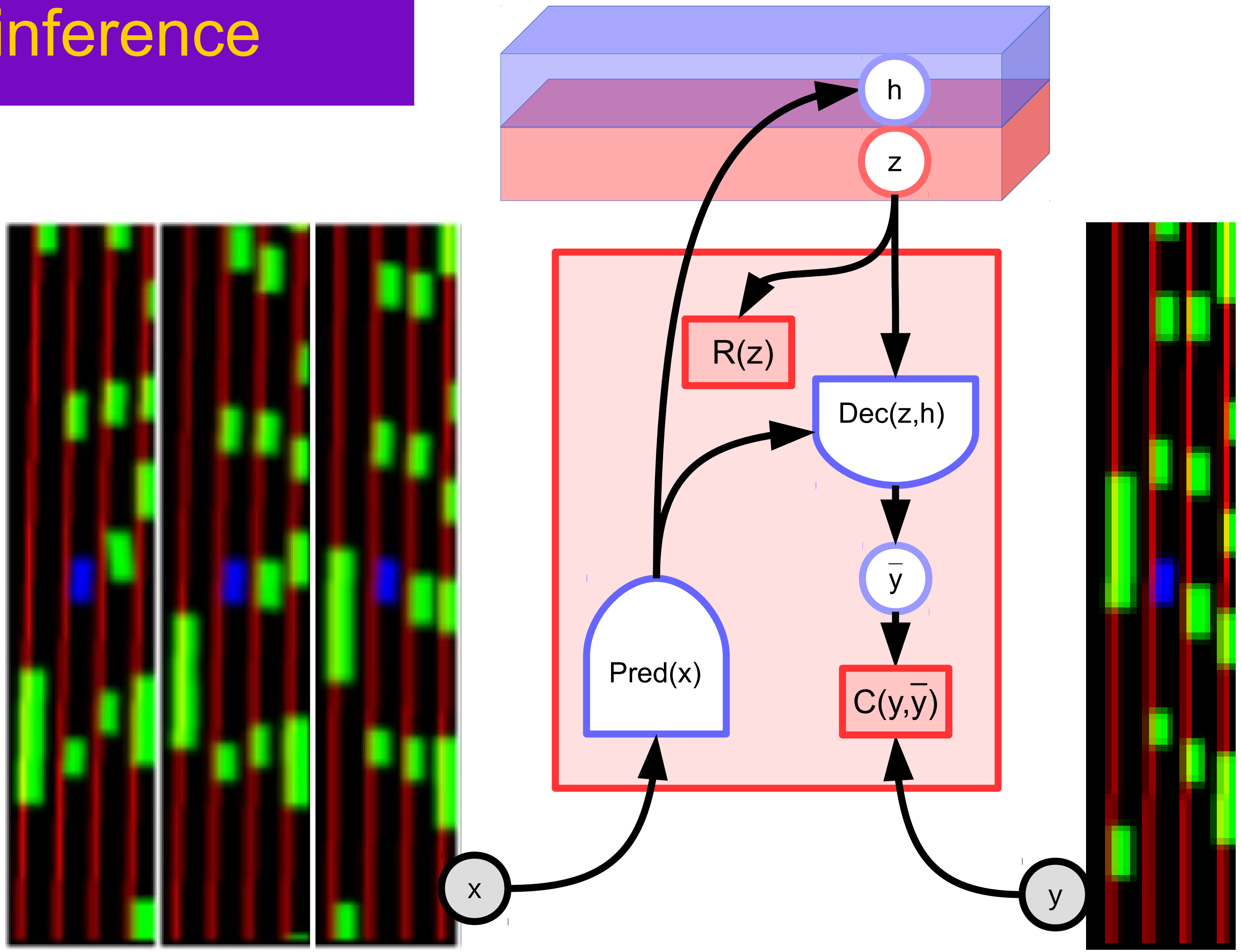
Using Forward Models to Plan (and to learn to drive)

- **Overhead camera on highway.**
  - Vehicles are tracked
- **A "state" is a pixel representation of a rectangular window centered around each car.**
- **Forward model is trained to predict how every car moves relative to the central car.**
  - steering and acceleration are computed



Video Prediction: inference

- **After training:**
  - Observe frames
  - Compute h
  - Sample z
  - Predict next frame

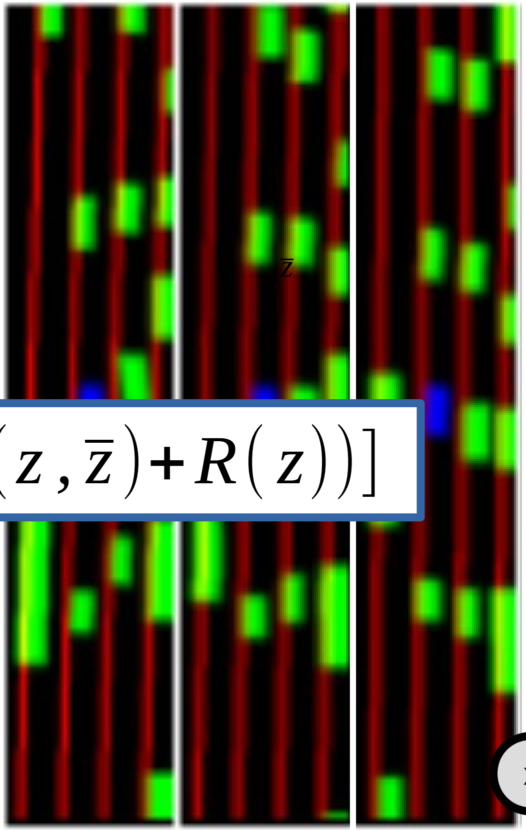


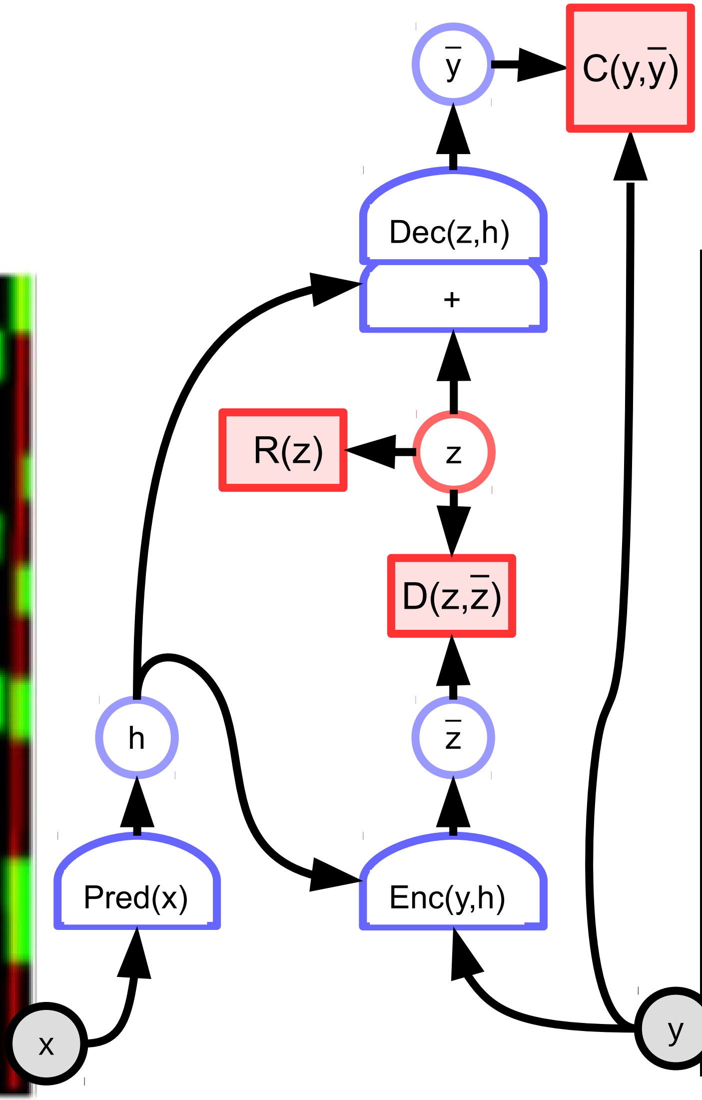
Video Prediction: training

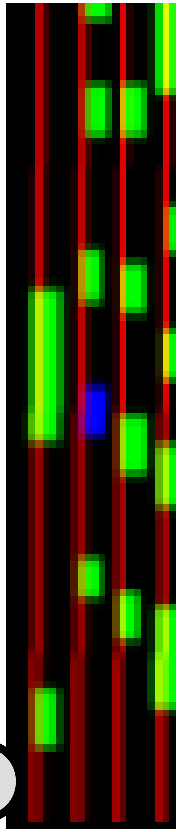
- **Training:**
  - Observe frames
  - Compute h
  - Predict $\bar{z}$ from encoder
  - Sample z, with:

$$P(z/\bar{z}) \propto \exp[-\beta(D(z,\bar{z})+R(z))]$$

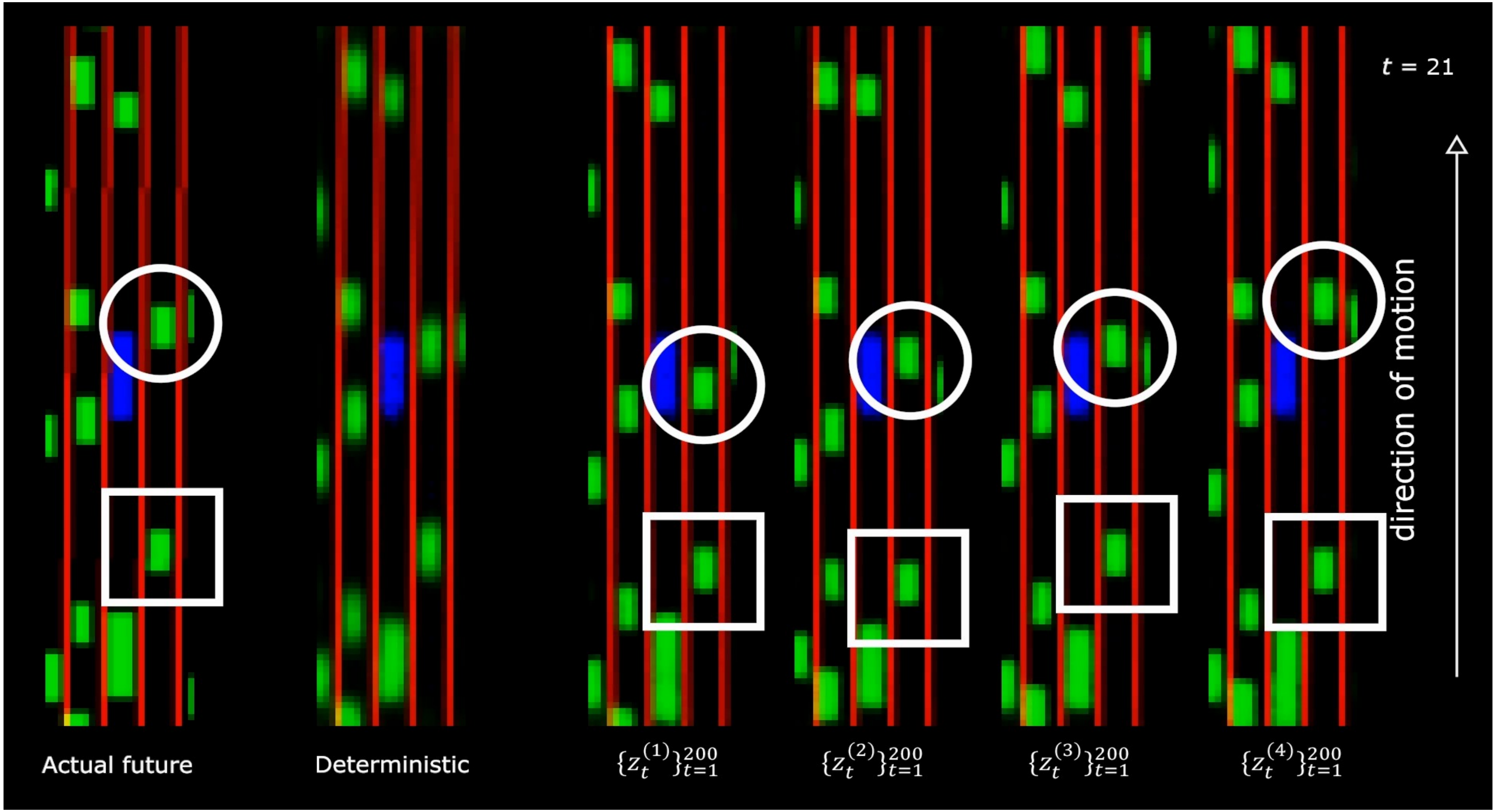
  - Predict next frame
  - backprop





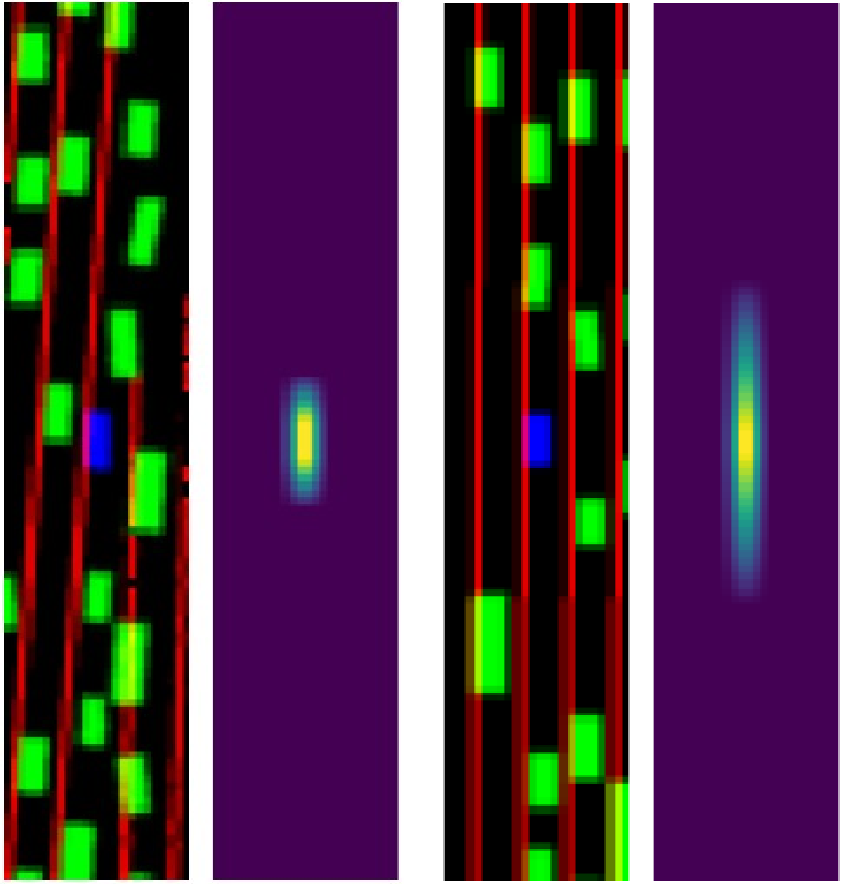


Actual, Deterministic, VAE+Dropout Predictor/encoder



Cost optimized for Planning & Policy Learning

- **Differentiable cost function**
  - Increases as car deviates from lane
  - Increases as car gets too close to other cars nearby in a speed-dependent way
- **Uncertainty cost:**
  - Increases when the costs from multiple predictions (obtained through sampling of drop-out) have high variance.
  - Prevents the system from exploring unknown/unpredictable configurations that may have low cost.

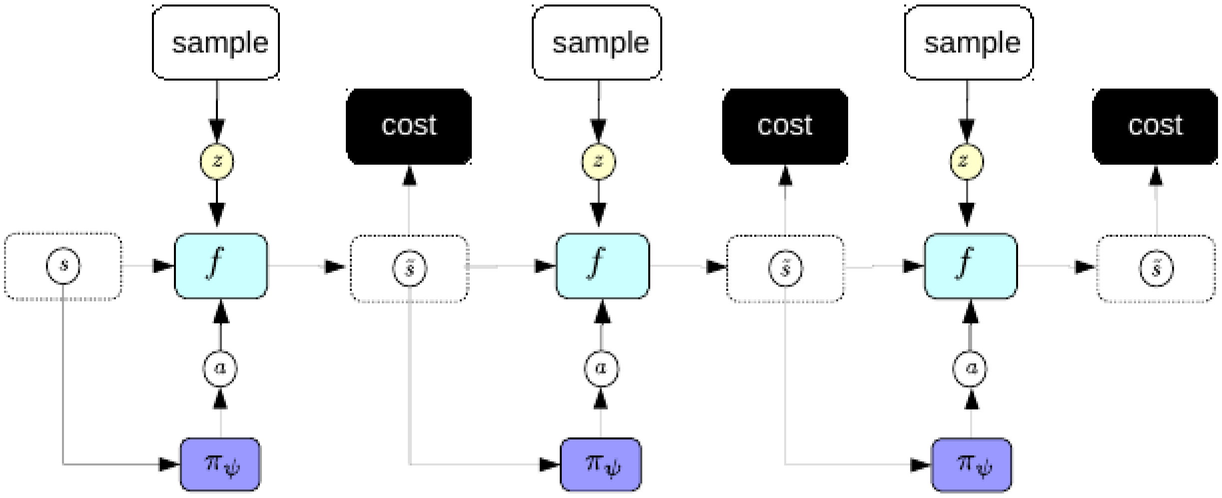


(a) 19.8 km/h (b) 50.3 km/h

Learning to Drive by Simulating it in your Head

- Feed initial state
- Sample latent variable sequences of length 20
- Run the forward model with these sequences
- Backpropagate gradient of cost to train a policy network.
- Iterate

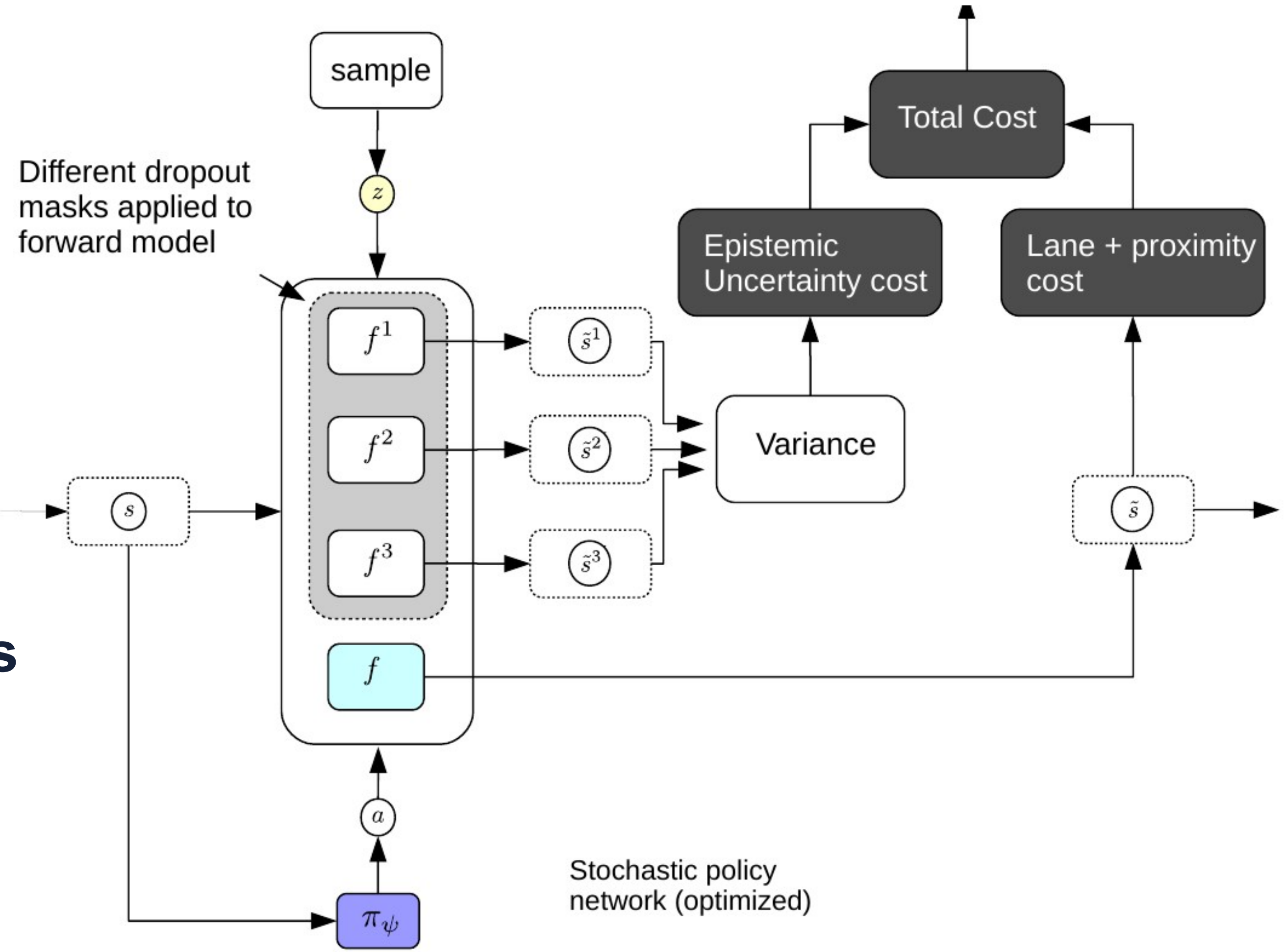
- No need for planning at run time.



Stochastic policy
network (optimized)

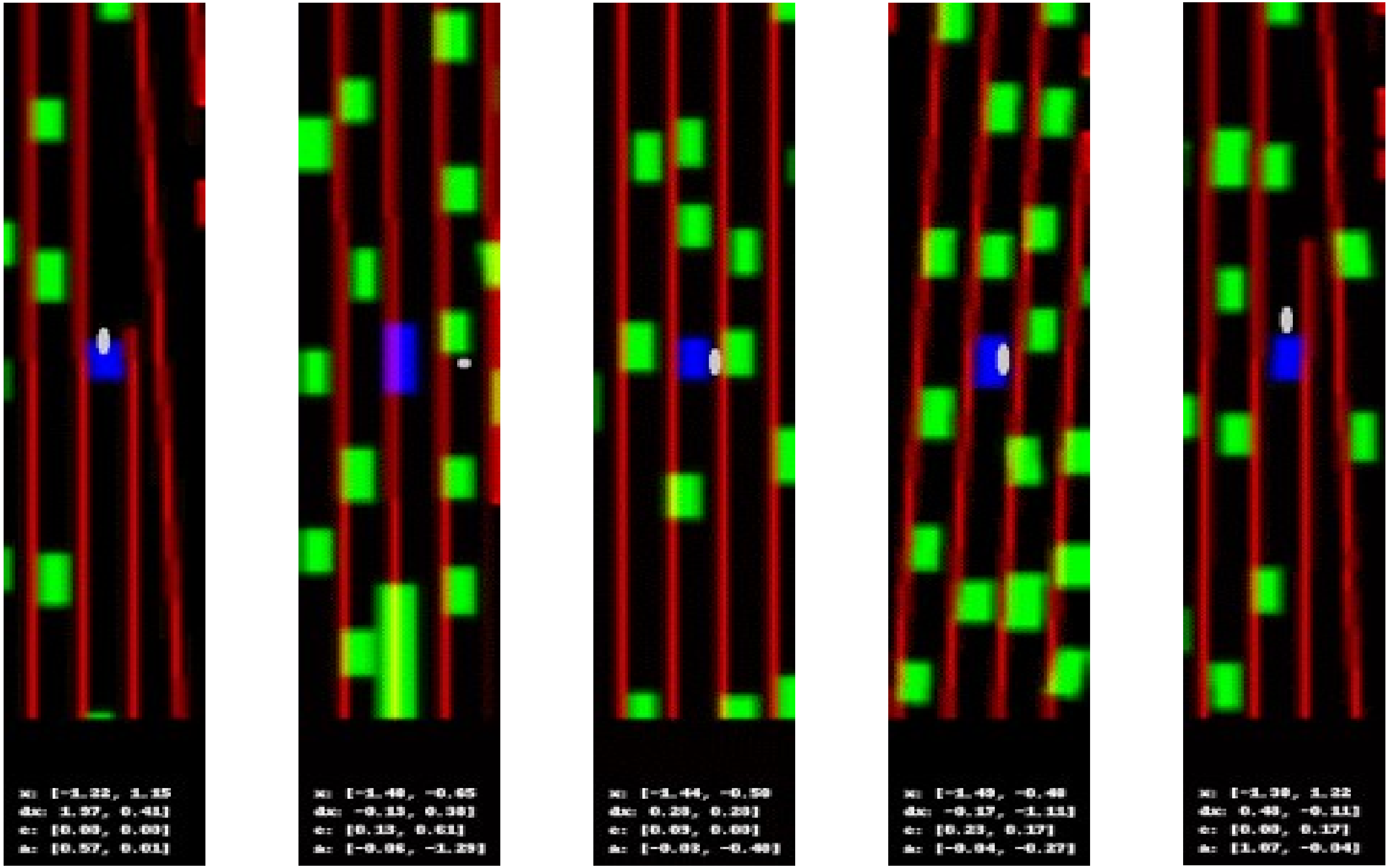
Adding an Uncertainty Cost (doesn't work without it)

- **Estimates epistemic uncertainty**
- **Samples multiple drop-puts in forward model**
- **Computes variance of predictions (differentiably)**
- **Train the policy network to minimize the lane&proximity cost plus the uncertainty cost.**
- **Avoids unpredictable outcomes**



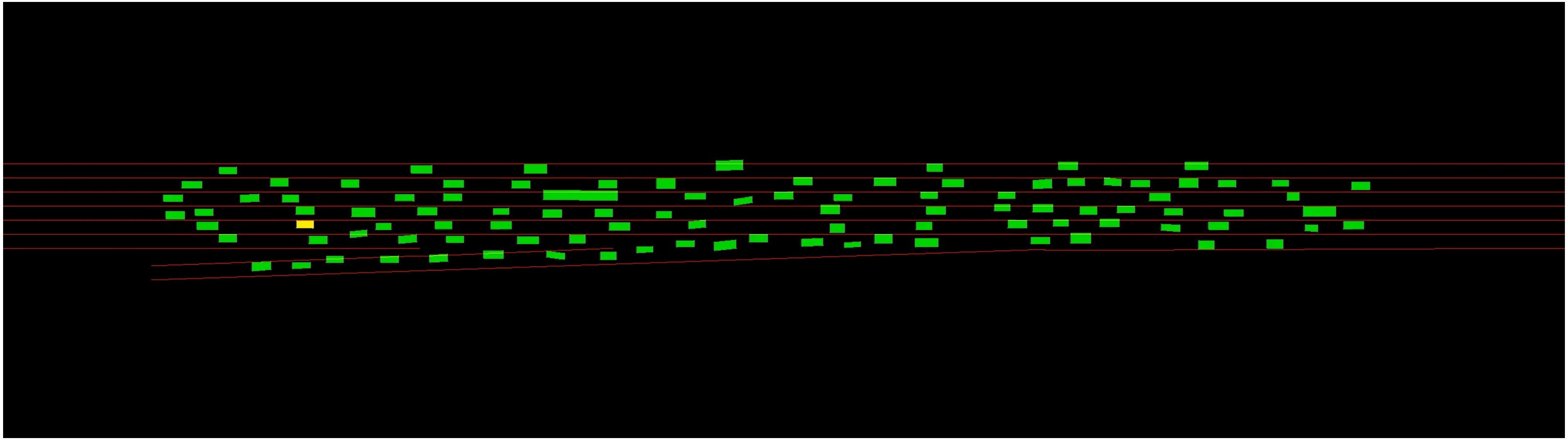
Y. LeCun

Driving an Invisible Car in “Real” Traffic



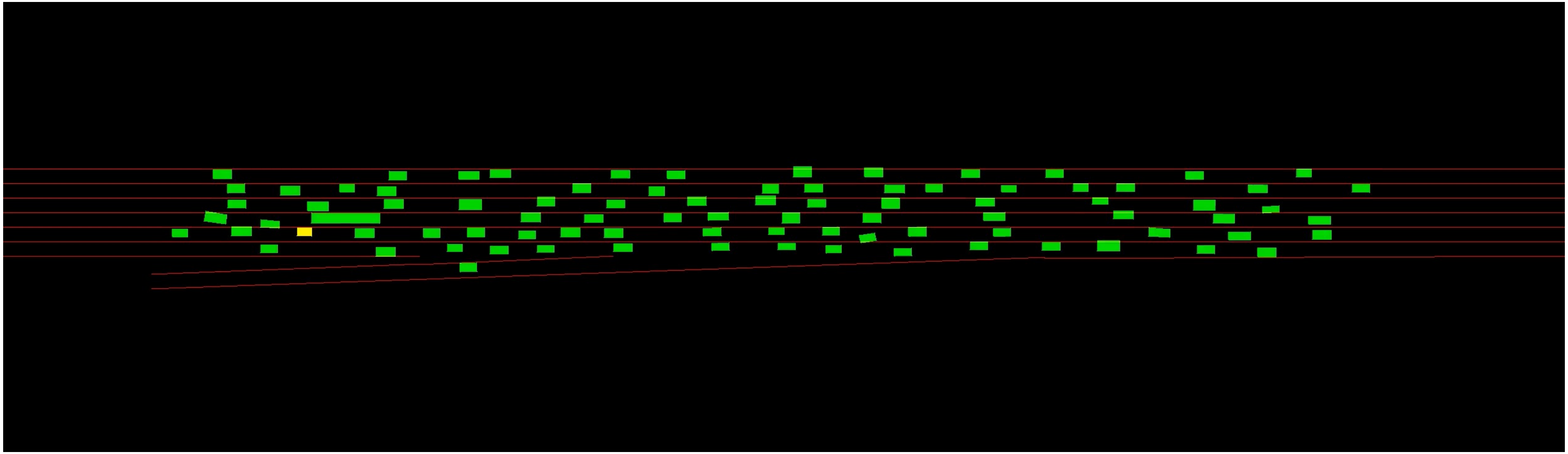
Driving!

- **Yellow: real car**
- **Blue: bot-driven car**



Driving!

- Yellow: real car
- Blue: bot-driven car



Take-Home Messages

- **SSL is the future**
  - Hierarchical feature learning for low-resource tasks
  - Hierarchical feature learning for **massive** networks
  - Learning Forward Models for Model-Based Control/RL
- **My money is on:**
  - Energy-Based Approaches
  - Latent-variable models to handle multimodality
  - Regularized Latent Variable models
  - Sparse Latent Variable Models
  - Latent Variable Prediction through a Trainable Encoder

Speculations

- ***Spiking Neural Nets, and neuromorphic architectures?***
  - *I'm skeptical…..*
  - *No spike-based NN comes close to state of the art on practical tasks*
  - *Why build chips for algorithms that don't work?*

- ***Exotic technologies?***
  - *Resistor/Memristor matrices, and other analog implementations?*
    - *Conversion to and from digital kills us.*
    - *No possibility of hardware multiplexing*
  - *Spintronics?*
  - *Optical implementations?*

Thank You!