Predictive Learning

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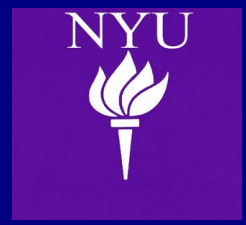

1st Connectionist Summer School, CMU July 1986

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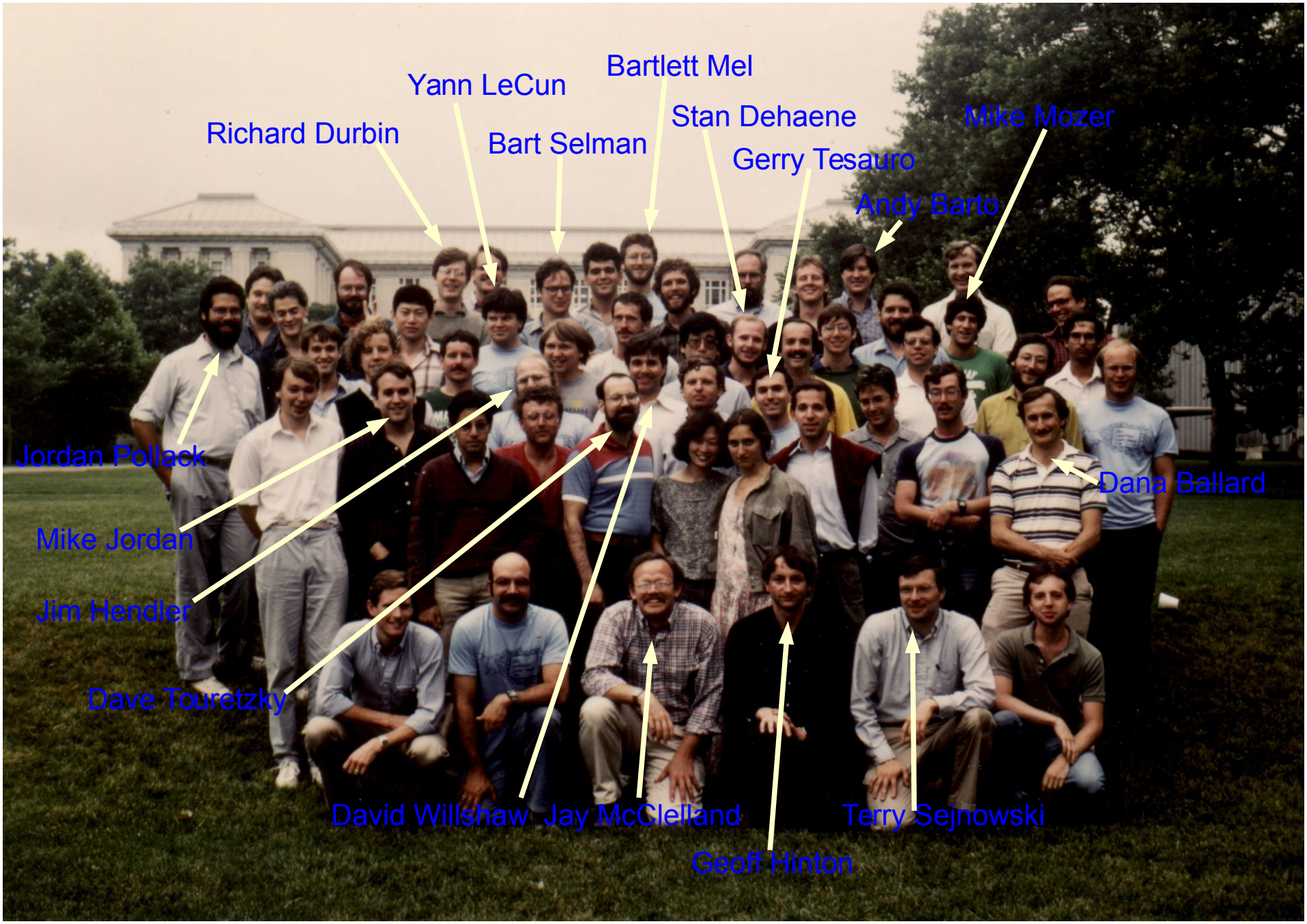
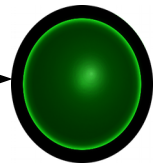
1st Connectionist Summer School, CMU July 1986

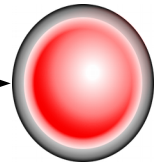


Supervised Learning

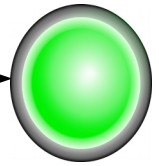
- We can train a machine on lots of examples of tables, chairs, dog, cars, and people
- But will it recognize table, chairs, dogs, cars, and people it has never seen before?



PLANE



CAR



CAR

Deep Learning = The Entire Machine is Trainable

Traditional Pattern Recognition: Fixed/Handcrafted Feature Extractor

Feature Extractor → Trainable Classifier

Mainstream Modern Pattern Recognition: Unsupervised mid-level features

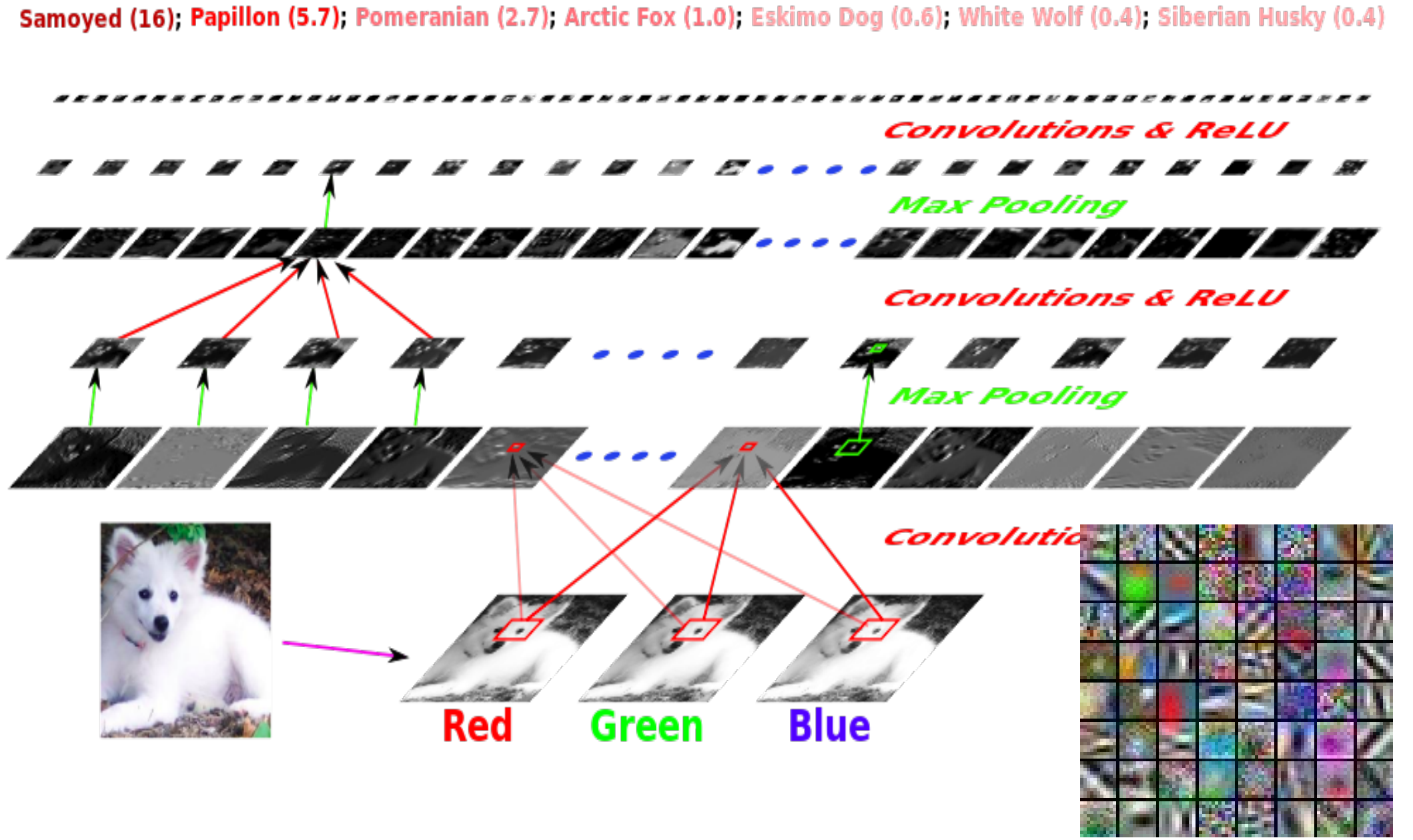
Feature Extractor → Mid-Level Features → Trainable Classifier

Deep Learning: Representations are hierarchical and trained

Low-Level Features → Mid-Level Features → High-Level Features → Trainable Classifier

Deep Convolutional Nets for Object Recognition

- 1 to 10 billion connections, 10 million to 1 billion parameters, 8 to 20 layers.



Deep Learning = Learning Hierarchical Representations

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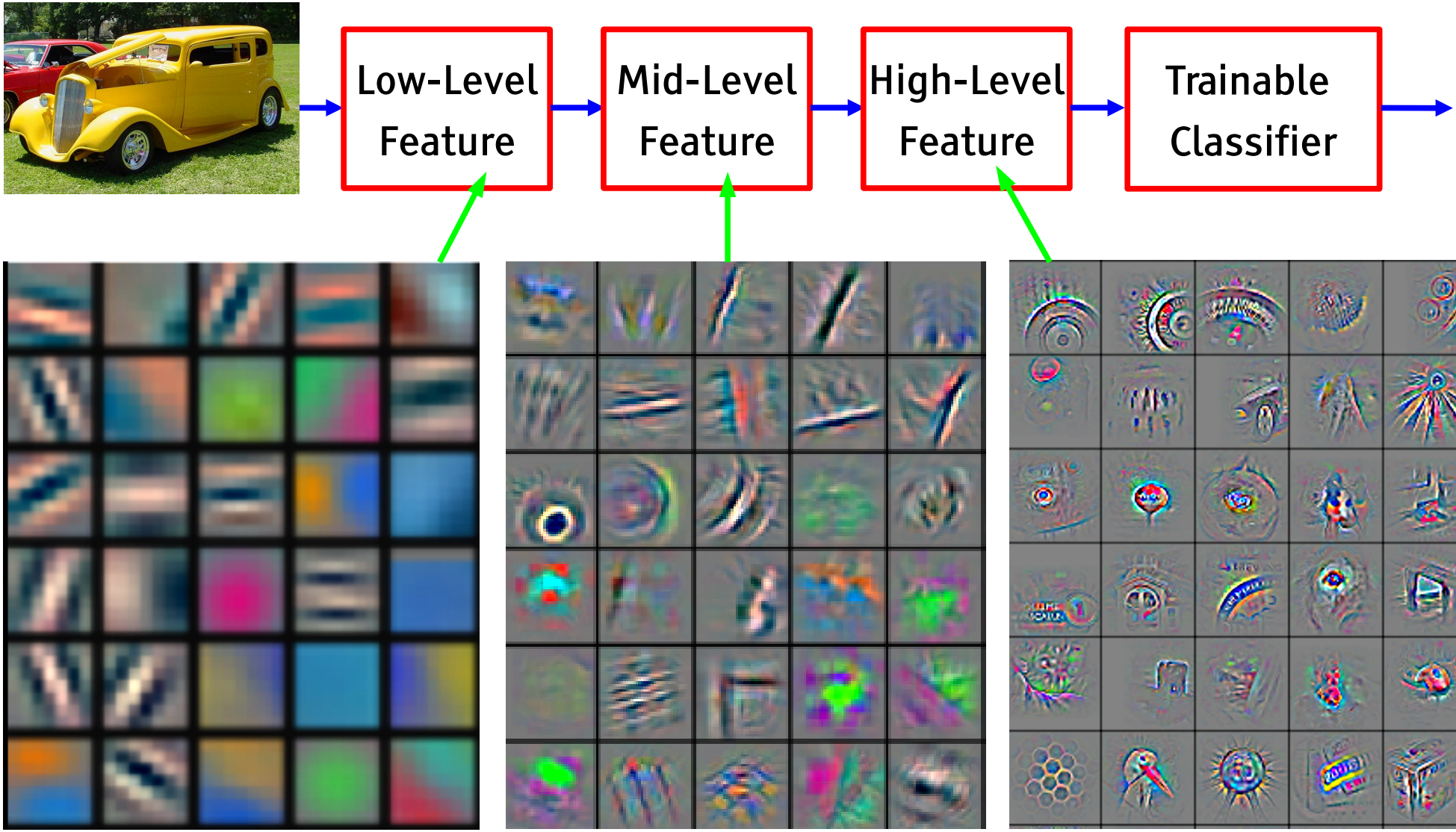
- It's deep if it has more than one stage of non-linear feature transformation



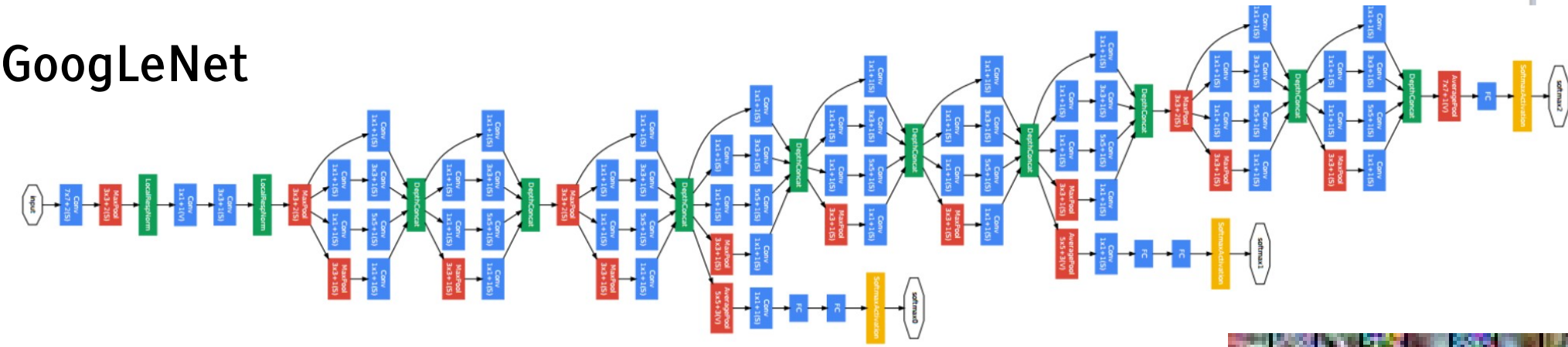
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Very Deep ConvNet Architectures

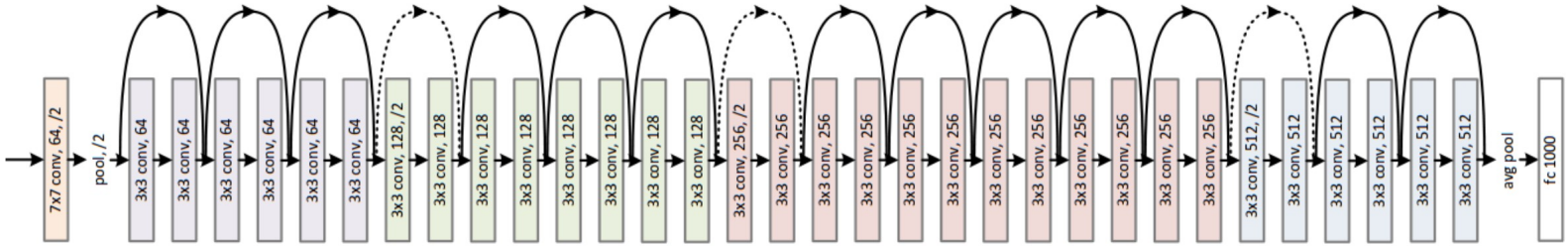
- Small kernels, not much subsampling (fractional subsampling).

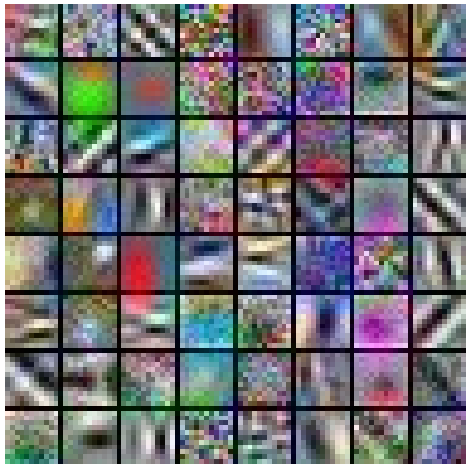
VGG

GoogLeNet



ResNet





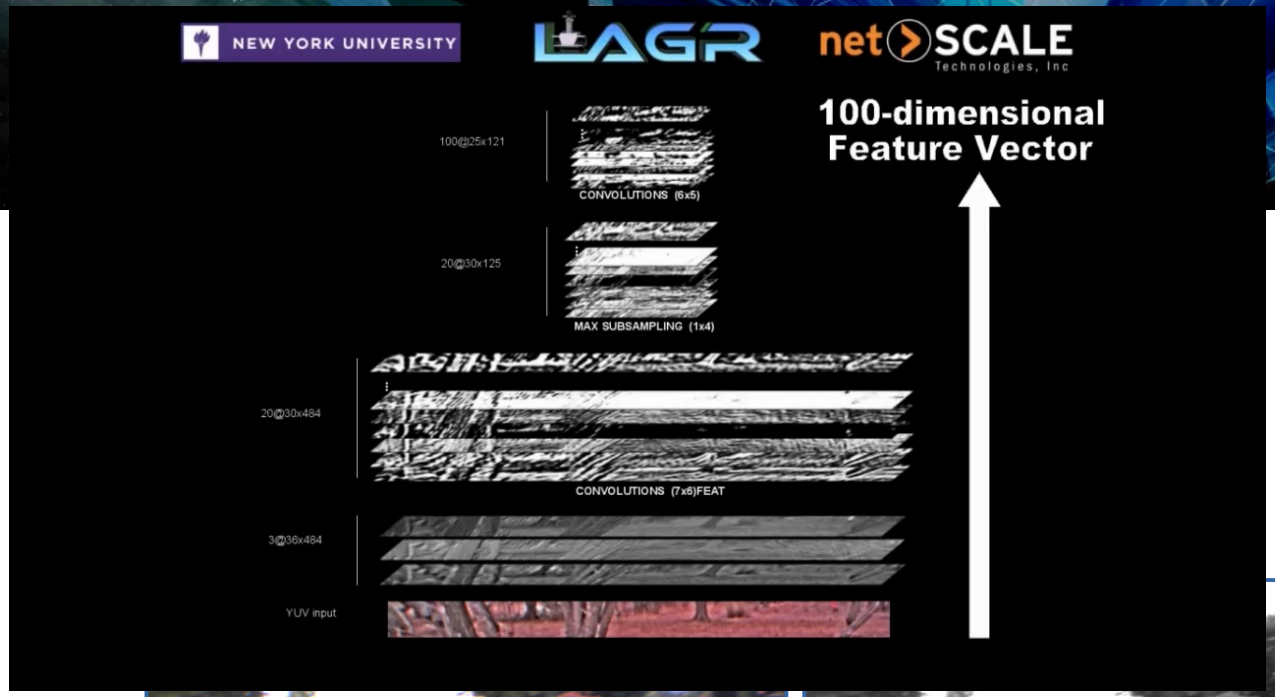
ConvNet for Driving

Y LeCun

NEW YORK UNIVERSITY

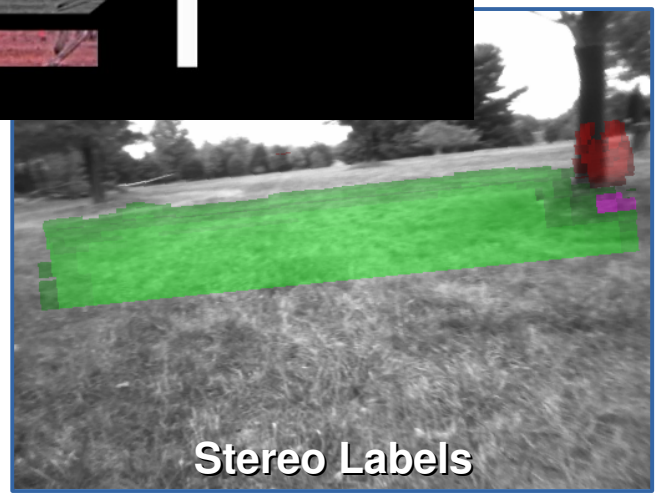
LAGR

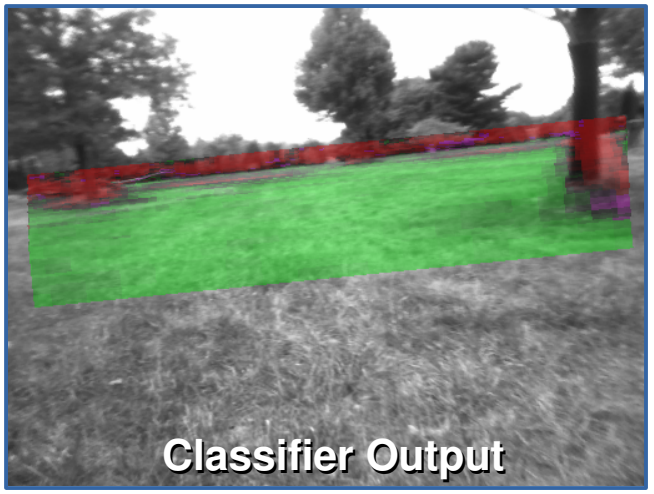
net SCALE Technologies, Inc

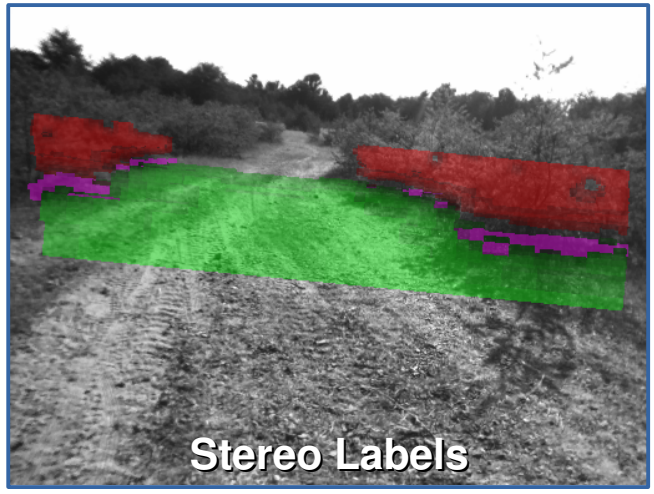


(DARPA LAGR program 2005-2008)

[Hadsell et al., J. of Field Robotics 2009]







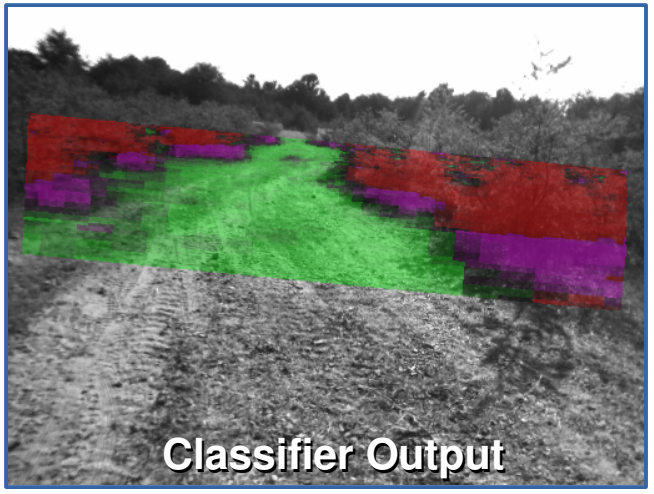


Image captioning, Semantic Segmentation with ConvNets

Y LeCun

[Farabet et al. ICML 2011]

[Farabet et al. PAMI 2013]

A man riding skis on a snow covered ski slope.

NP: a man, skis, the snow, a person, a woman, a snow covered slope, a slope, a snowboard, a skier, man.
VP: wearing, riding, holding, standing on, skiing down.
PP: on, in, of, with, down.

A man wearing skis on the snow.

A man is doing skateboard tricks on a ramp.

NP: a skateboard, a man, a trick, his skateboard, the air, a skateboarder, a ramp, a skate board, a person, a woman.
VP: doing, riding, is doing, performing, flying through.
PP: on, of, in, at, with.

A man riding a skateboard on a ramp.

The girl with blue hair stands under the umbrella.

NP: a woman, an umbrella, a man, a person, a girl, umbrellas, that, a little girl, a cell phone.
VP: holding, wearing, is holding, holds, carrying.
PP: with, on, of, in, under.

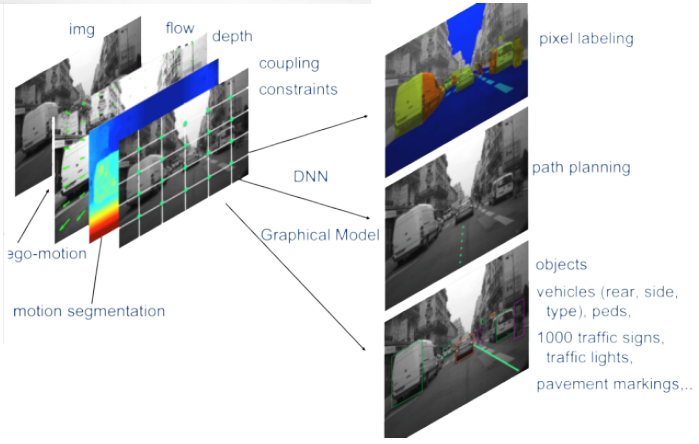
A woman is holding an umbrella.

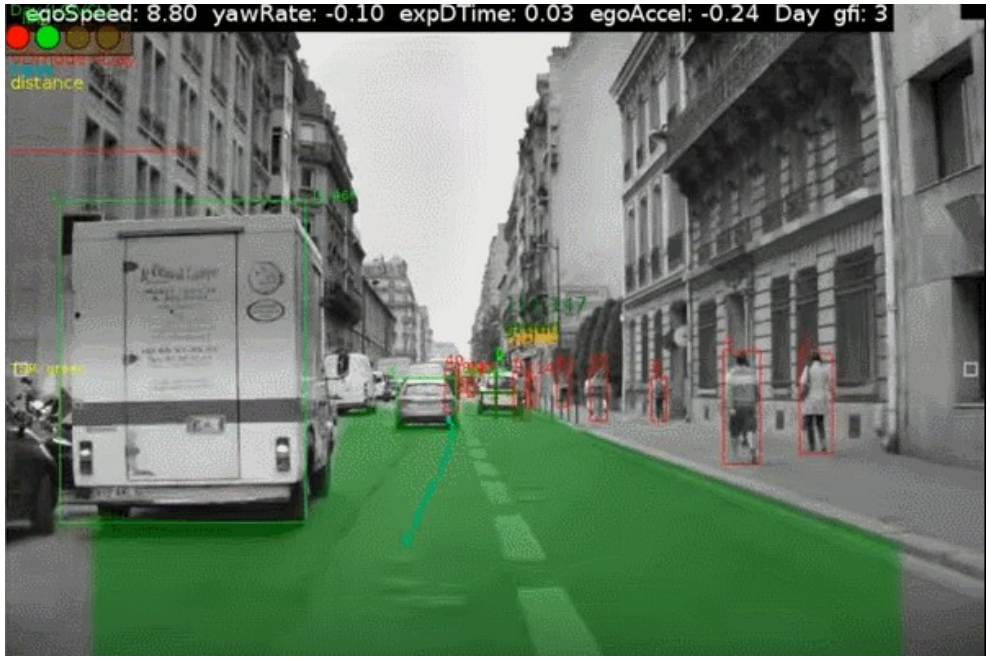
[Lebret, Pinheiro, Collobert 2015] [Kulkarni 11] [Mitchell 12] [Vinyals 14] [Mao 14] [Karpathy 14] [Donahue 14]...

Driving Cars with Convolutional Nets

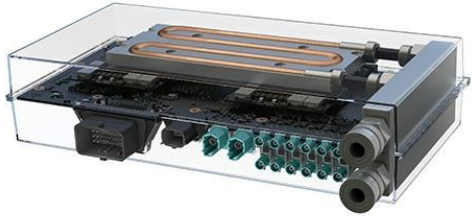
Y LeCun

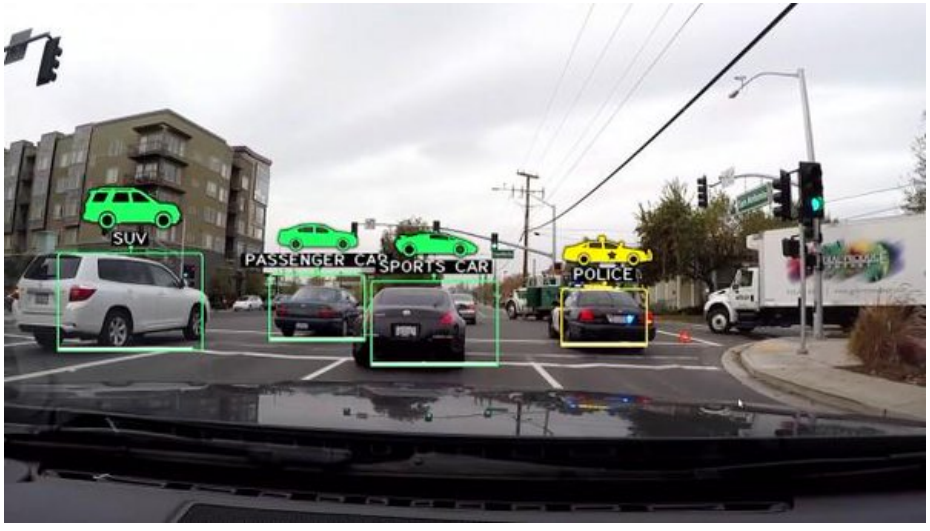
MobilEye





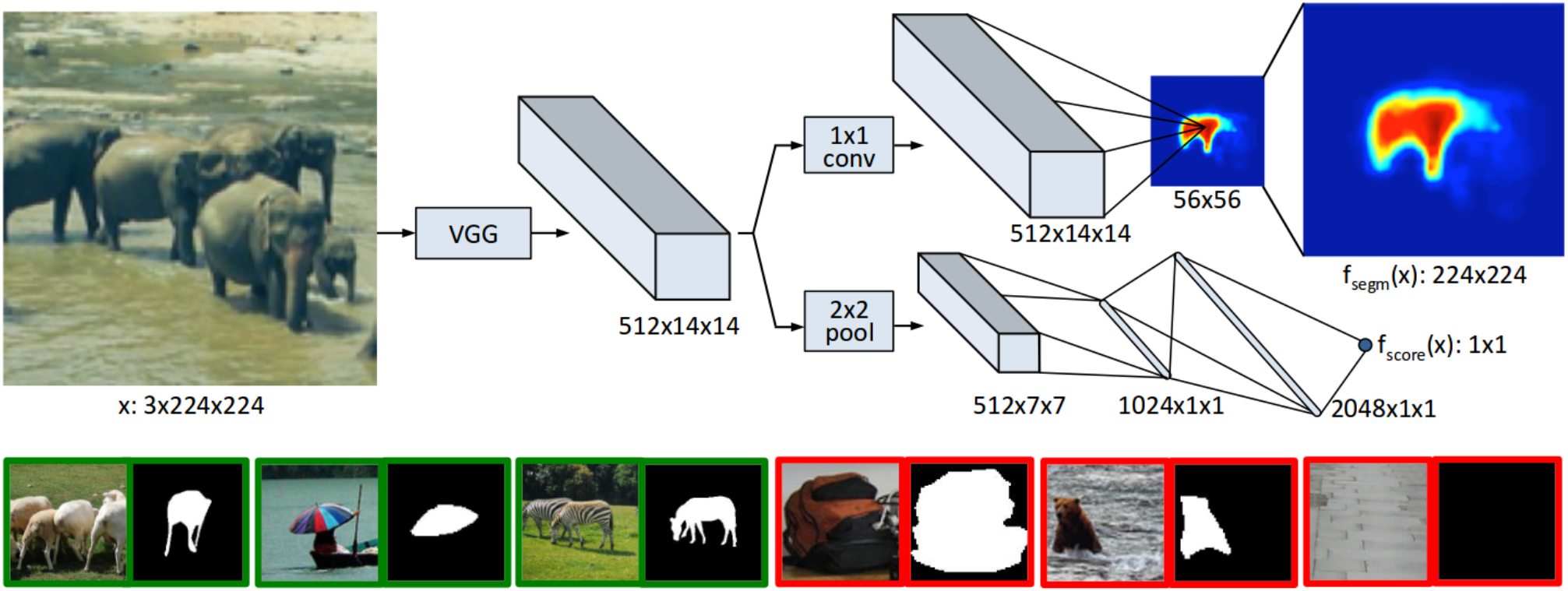
NVIDIA





DeepMask: ConvNet Locates and Recognizes Objects

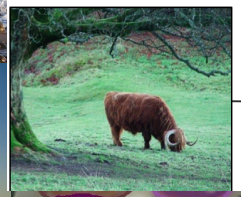
- [Pinheiro, Collobert, Dollar ICCV 2015]
  - ConvNet produces object masks and categories

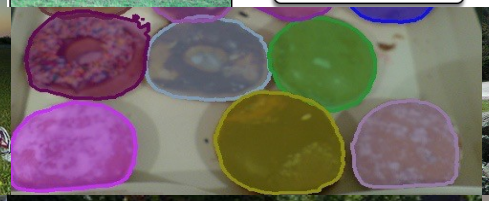


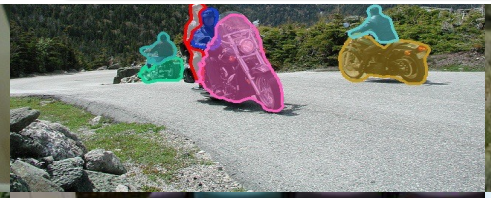
SharpMask++: Recognition Pipeline & Object Proposals

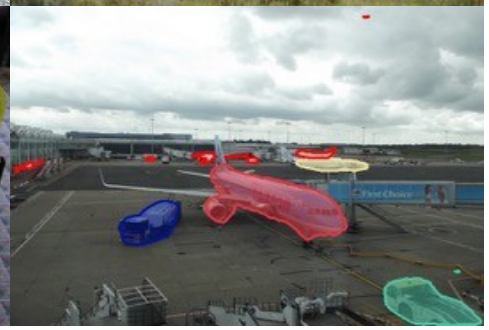
Y LeCun

- https://arxiv.org/abs/1604.02135
- Zagoruyko, Lerer, Lin, Pinheiro, Gross, Chintala, Dollár
- https://github.com/facebookresearch/deepmask









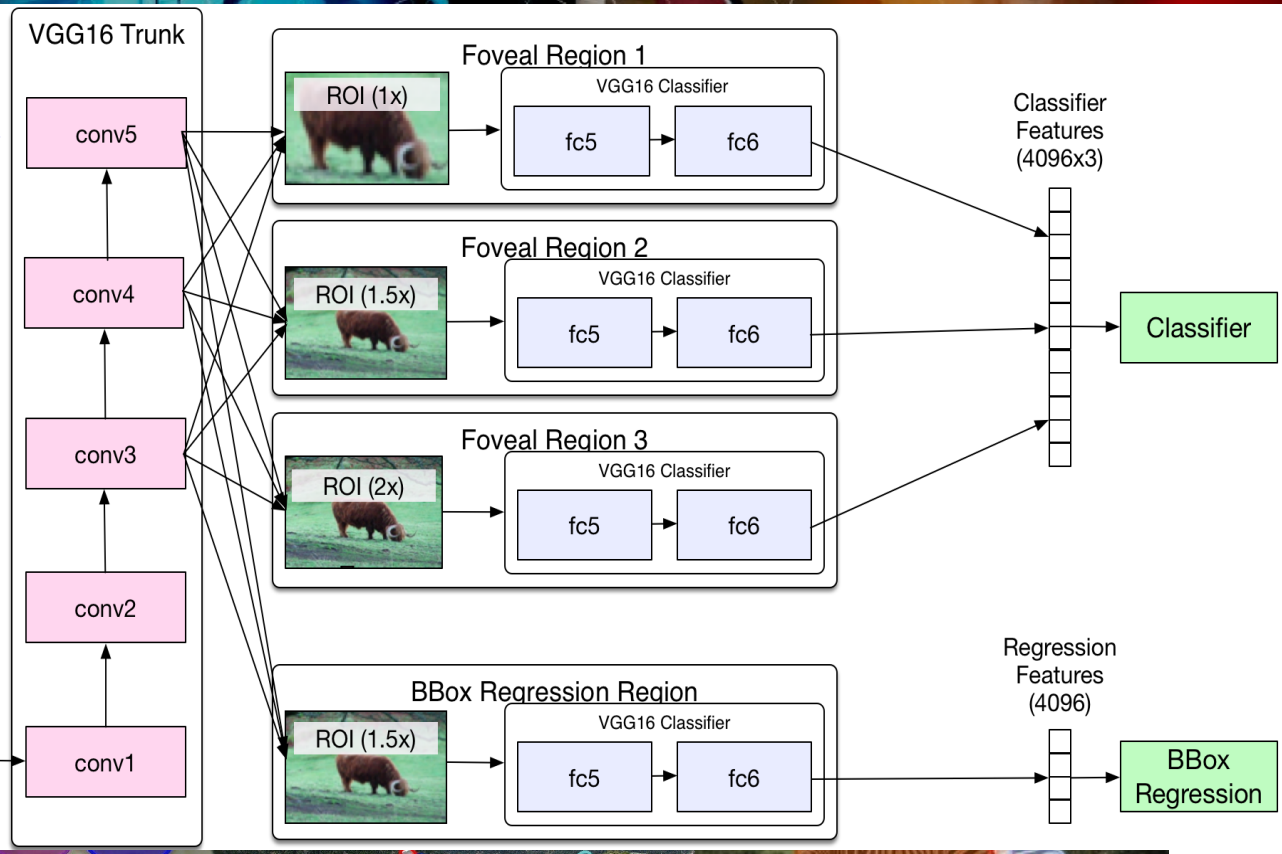


Image Recognition

Image Recognition

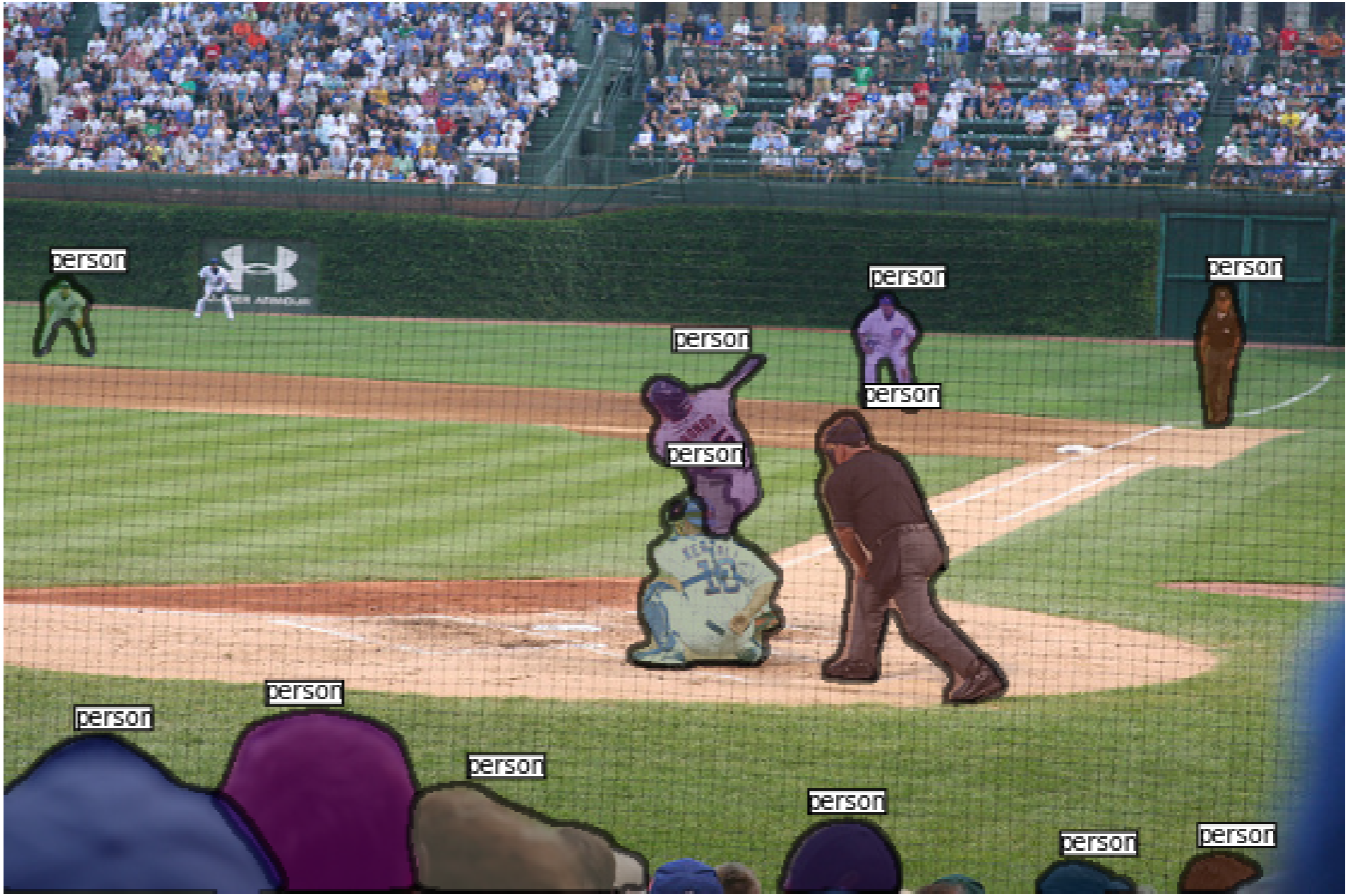


Image Recognition

Image Recognition

Image Recognition

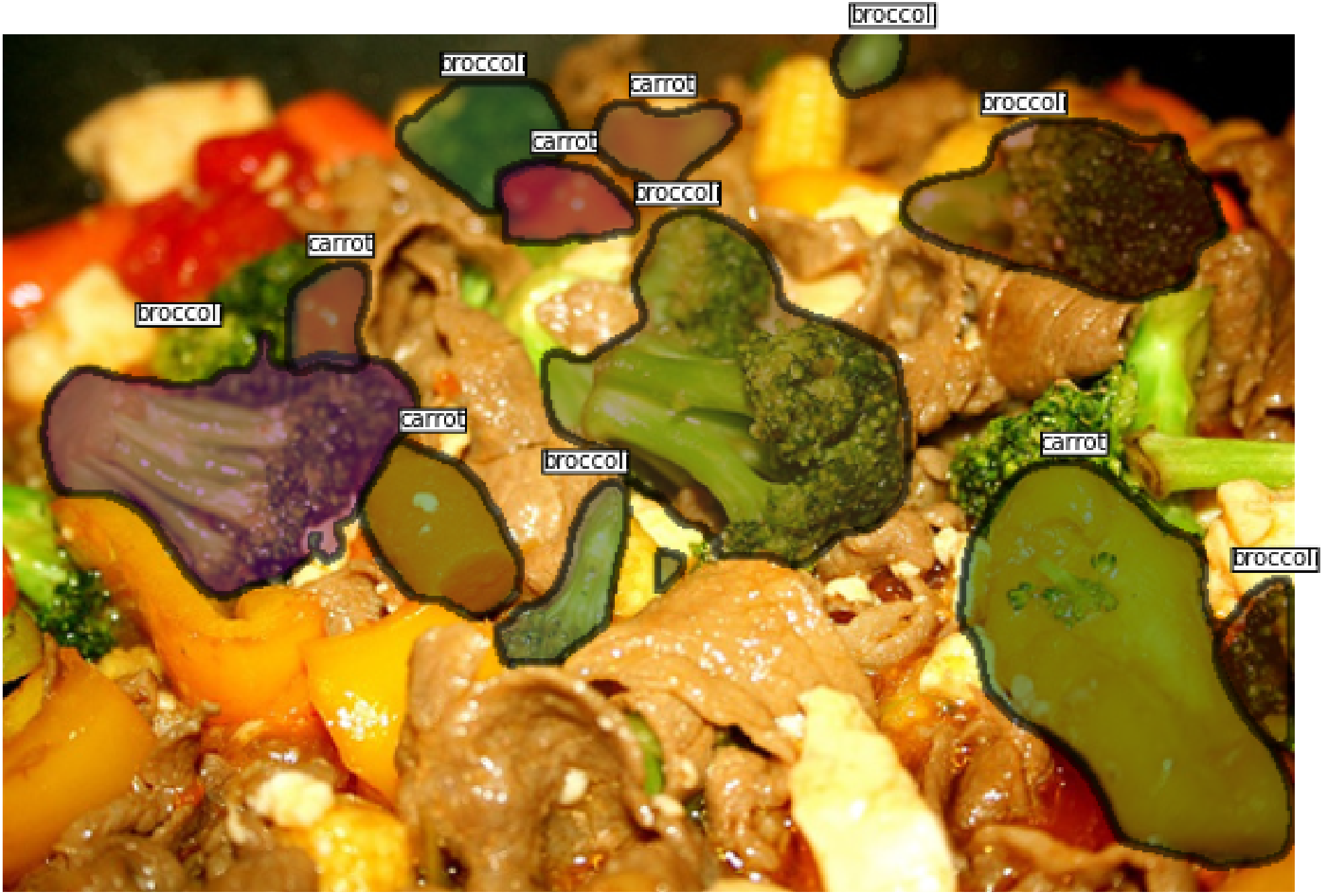


Image Recognition

Results


sheep
sheep
sheep
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sheep
sheep


Obstacles to AI

Obstacles to Progress in AI

- **Machines need to learn/understand how the world works**
  - Physical world, digital world, people,….
  - They need to acquire some level of common sense
- **They need to learn a very large amount of background knowledge**
  - Through observation and action
- **Machines need to perceive the state of the world**
  - So as to make accurate predictions and planning
- **Machines need to update and remember estimates of the state of the world**
  - Paying attention to important events. Remember relevant events
- **Machines neet to reason and plan**
  - Predict which sequence of actions will lead to a desired state of the world

- **Intelligence & Common Sense =**

  Perception + Predictive Model + Memory + Reasoning & Planning

What is Common Sense?

- "The trophy doesn't fit in the suitcase because it's too large/small"
  - (winograd schema)

- "Tom picked up his bag and left the room"

- We have common sense because we know how the world works

- How do we get machines to learn that?

Common Sense is the ability to fill in the blanks

Y LeCun

- Infer the state of the world from partial information
- Infer the future from the past and present
- Infer past events from the present state

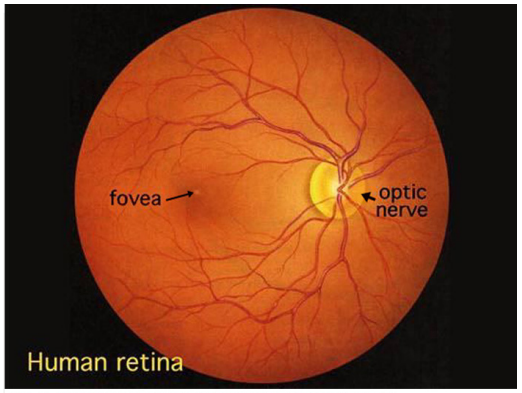


Fig. 1. Human retina as seen through an opthalmoscope.

- Filling in the visual field at the retinal blind spot
- Filling in occluded images
- Fillling in missing segments in text, missing words in speech.
- Predicting the consequences of our actions
- Predicting the sequence of actions leading to a result

- Predicting any part of the past, present or future percepts from whatever information is available.

- That's what predictive learning is
- But really, that's what many people mean by unsupervised learning

The Necessity of Unsupervised Learning / Predictive Learning

Y LeCun

- The number of samples required to train a large learning machine (for any task) depends on the amount of information that we ask it to predict.
  - The more you ask of the machine, the larger it can be.

- "The brain has about 10^14 synapses and we only live for about 10^9 seconds. So we have a lot more parameters than data. This motivates the idea that we must do a lot of unsupervised learning since the perceptual input (including proprioception) is the only place we can get 10^5 dimensions of constraint per second."
  - Geoffrey Hinton (in his 2014 AMA on Reddit)
  - (but he has been saying that since the late 1970s)

- Predicting human-provided labels is not enough

- Predicting a value function is not enough

How Much Information Does the Machine Need to Predict?

Y LeCun

- "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**
- Unsupervised/Predictive Learning (cake)
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

VizDoom Champion: Actor-Critic RL system from FAIR

Won the VizDoom 2016 competition.

[Wu & Tian, submitted to ICLR 2017]

"StarCraft: Brood War" RL-based system for battle tactics

Plug: TorchCraft: interface between Torch and StarCraft (on github)

[Usunier, Synnaeve, Lin, Chintala, submitted to ICLR 2017]

Sutton's Dyna Architecture: "try things in your head before acting"

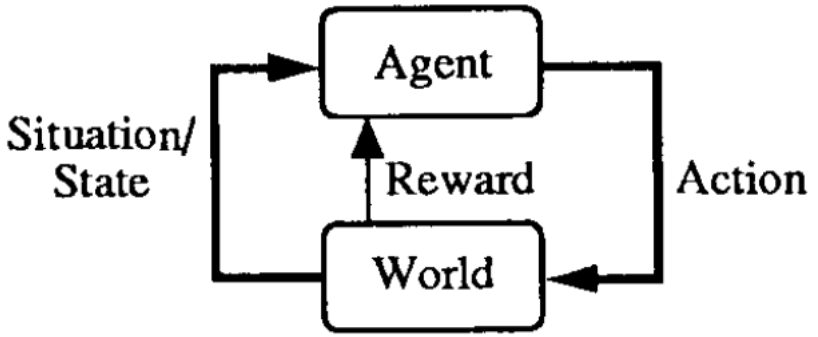
Dyna: an Integrated Architecture for Learning, Planning and Reacting

- [Rich Sutton, ACM SIGART 1991]

The main idea of Dyna is the old, commonsense idea that planning is 'trying things in your head,' using an internal model of the world (Craik, 1943; Dennett, 1978; Sutton & Barto, 1981). This suggests the existence of a more primitive process for trying things *not* in your head, but through direct interaction with the world. *Reinforcement learning* is the name we use for this more primitive, direct kind of trying, and Dyna is the extension of reinforcement learning to include a learned world model.

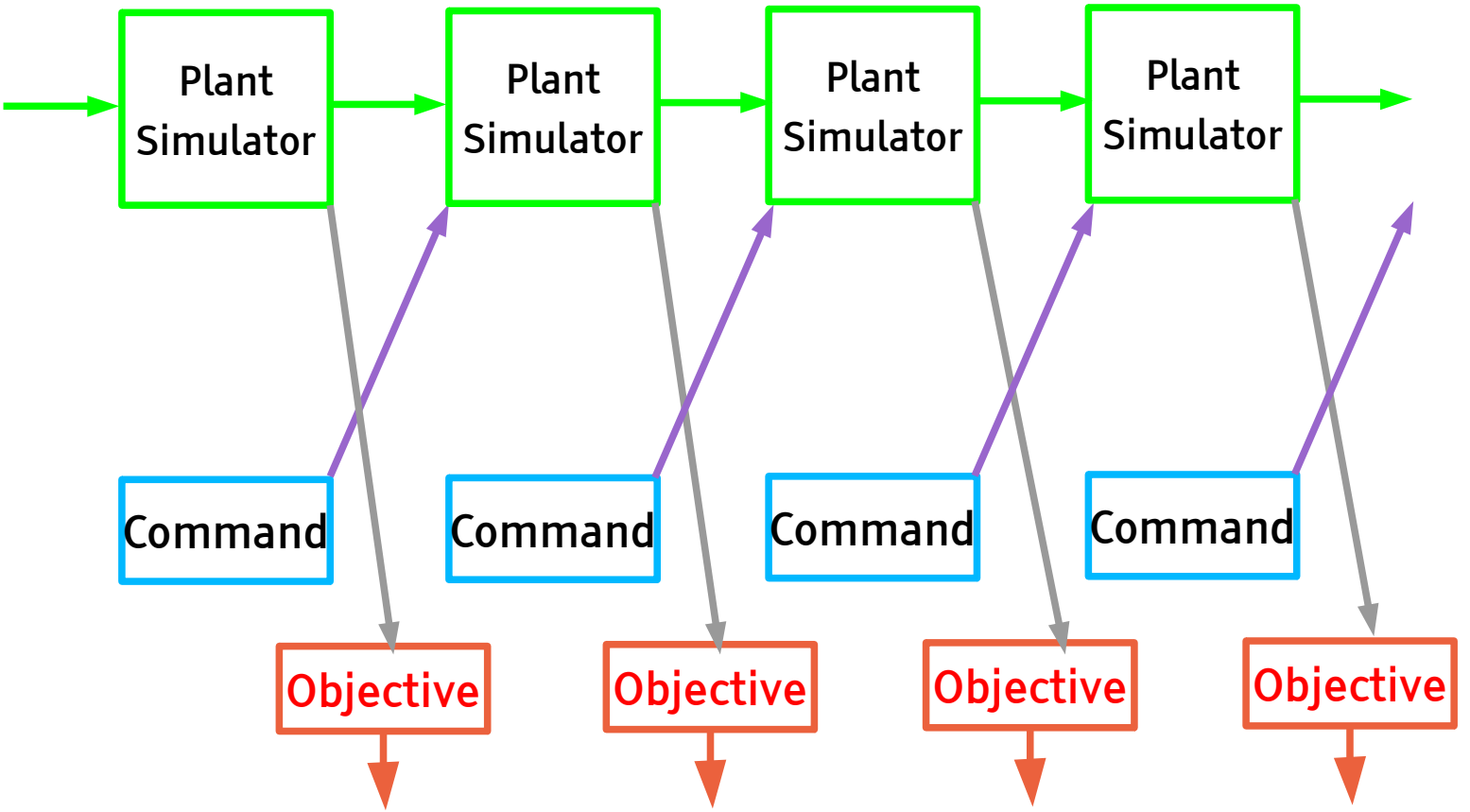
REPEAT FOREVER:

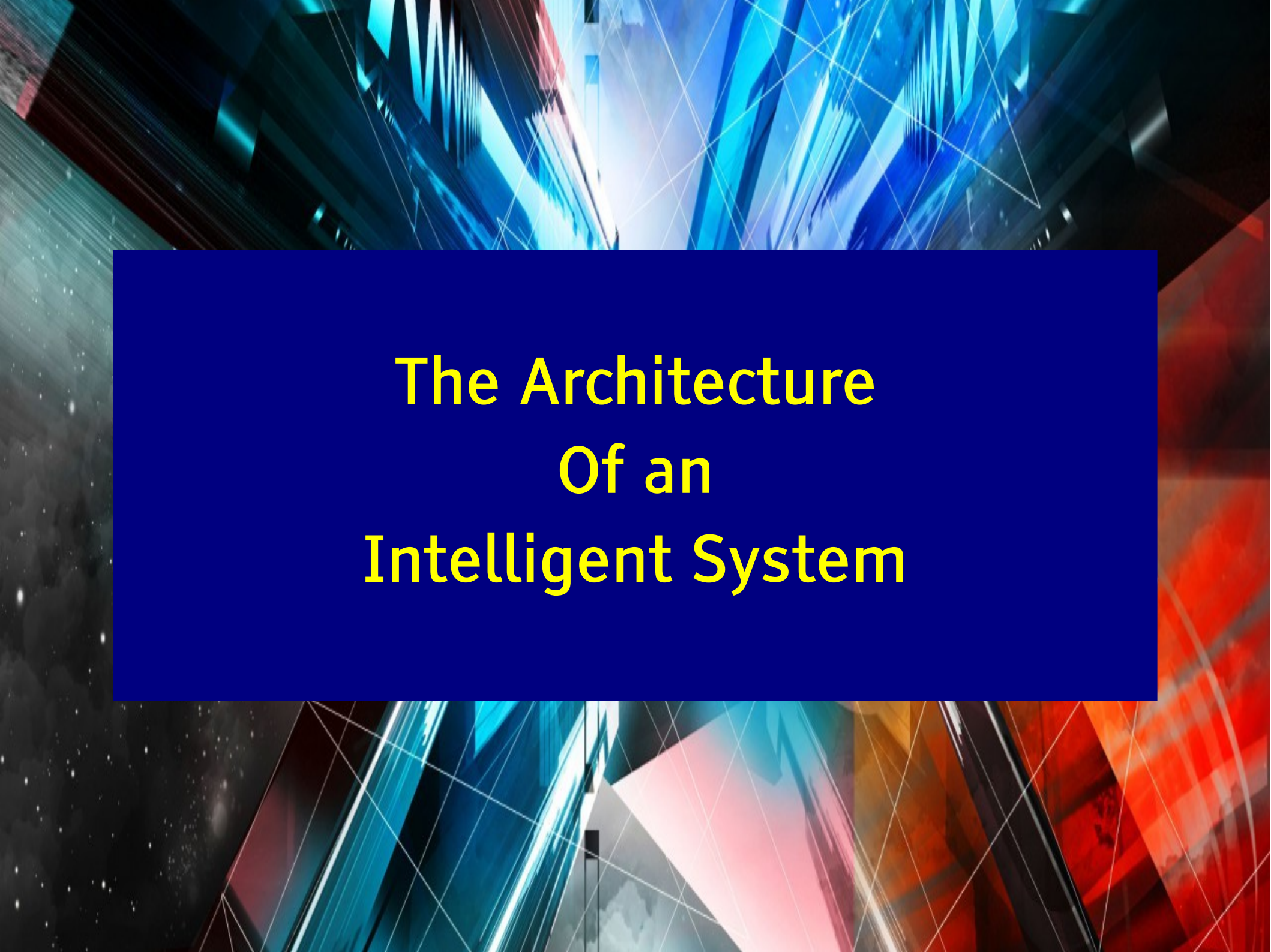
1. Observe the world's state and reactively choose an action based on it;
2. Observe resultant reward and new state;
3. Apply reinforcement learning to this experience;
4. Update action model based on this experience;
5. Repeat K times:
   - 5.1 Choose a hypothetical world state and action;
   - 5.2 Predict resultant reward and new state using action model;
   - 5.3 Apply reinforcement learning to this hypothetical experience.



Classical model-based optimal control

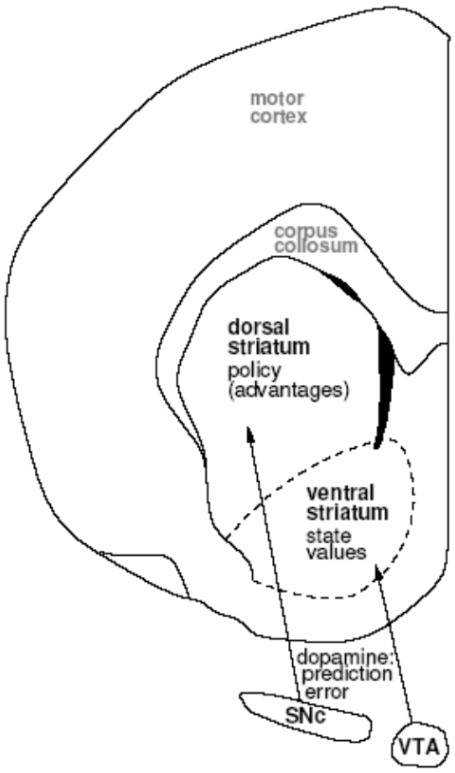
- **Simulate the world (the plant) with an initial control sequence**
- **Adjust the control sequence to optimize the objective through gradient descent**
- **Backprop through time was invented by control theorists in the late 1950s**
  - it's sometimes called the adjoint state method
  - [Athans & Falb 1966, Bryson & Ho 1969]

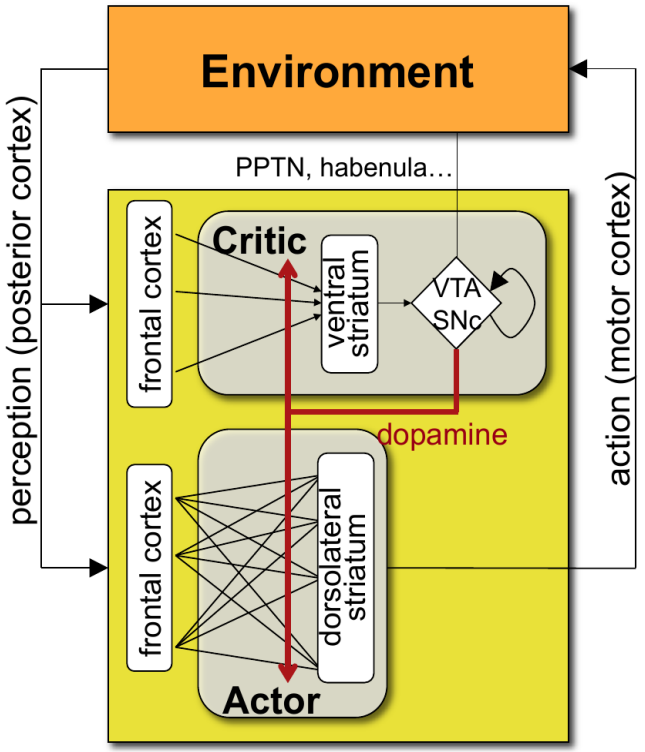


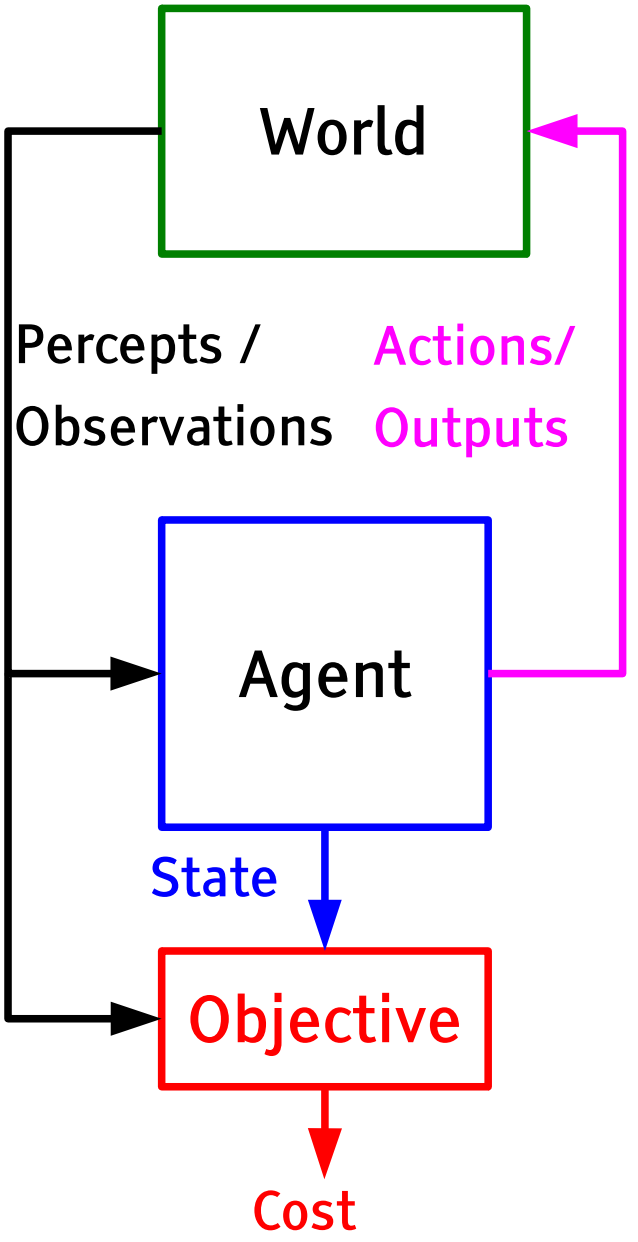

The Architecture
Of an
Intelligent System

AI System: Learning Agent + Immutable Objective

- The agent gets percepts from the world
- The agent acts on the world
- The agents tries to minimize the long-term expected cost.

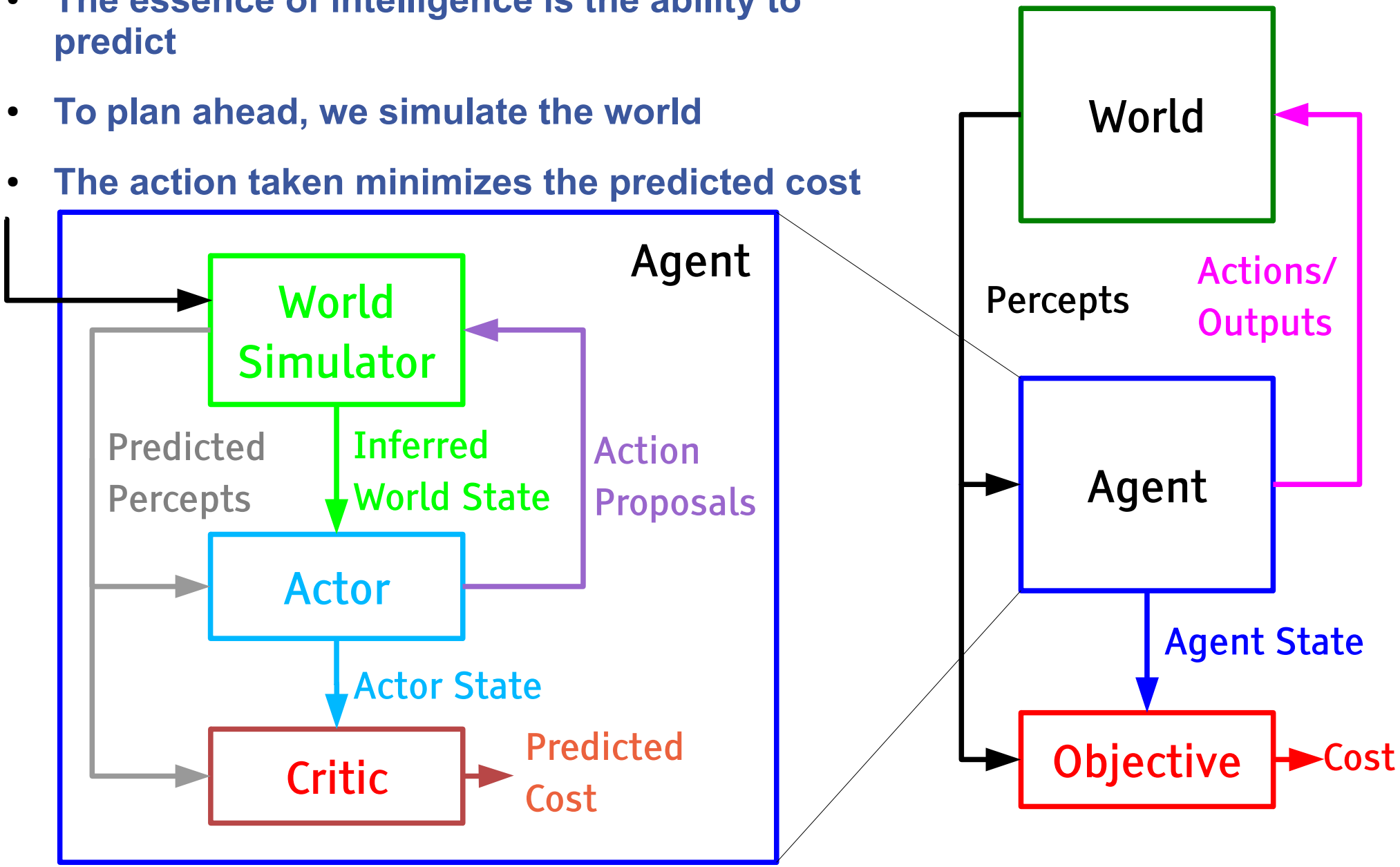






AI System: Predicting + Planning = Reasoning

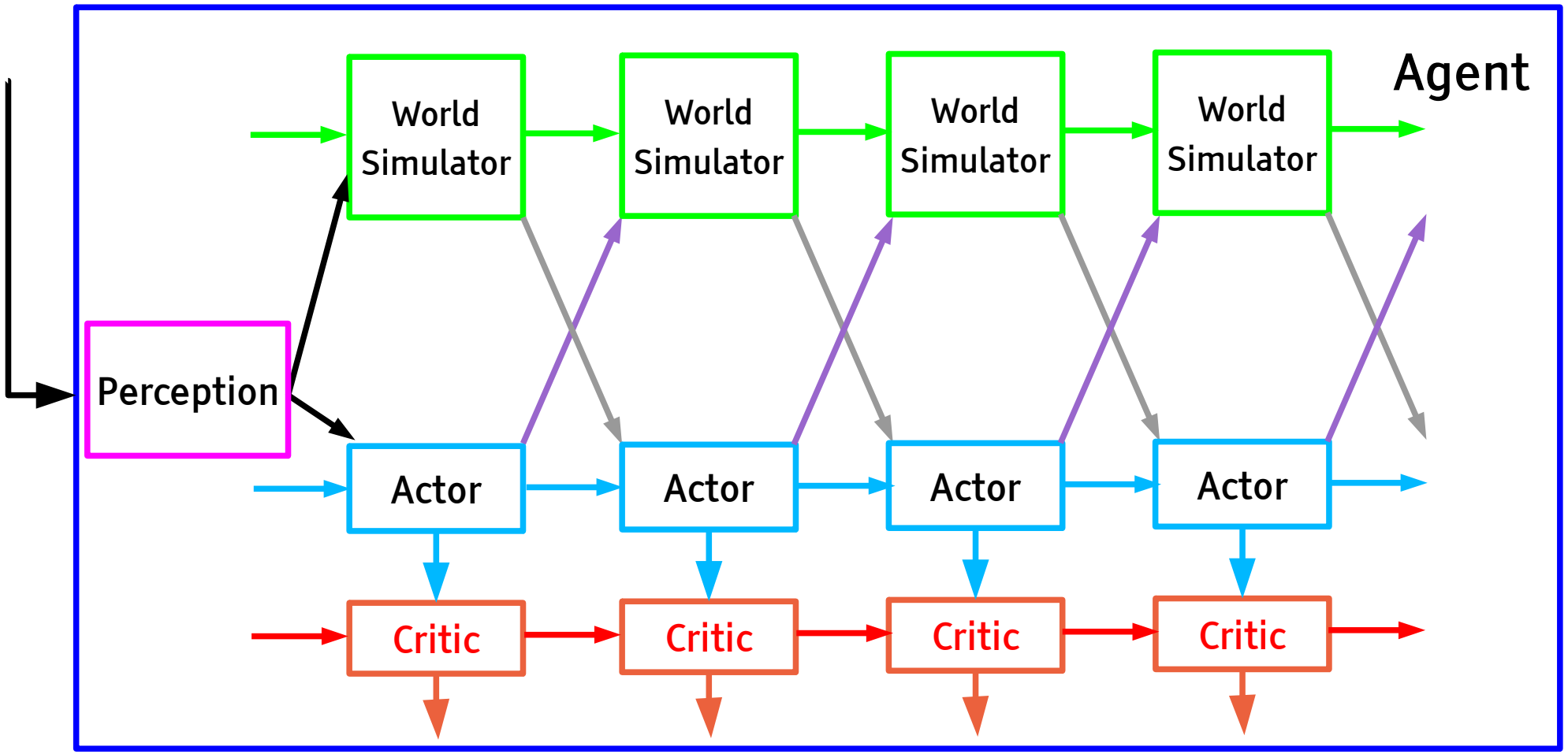
- The essence of intelligence is the ability to predict
- To plan ahead, we simulate the world
- The action taken minimizes the predicted cost

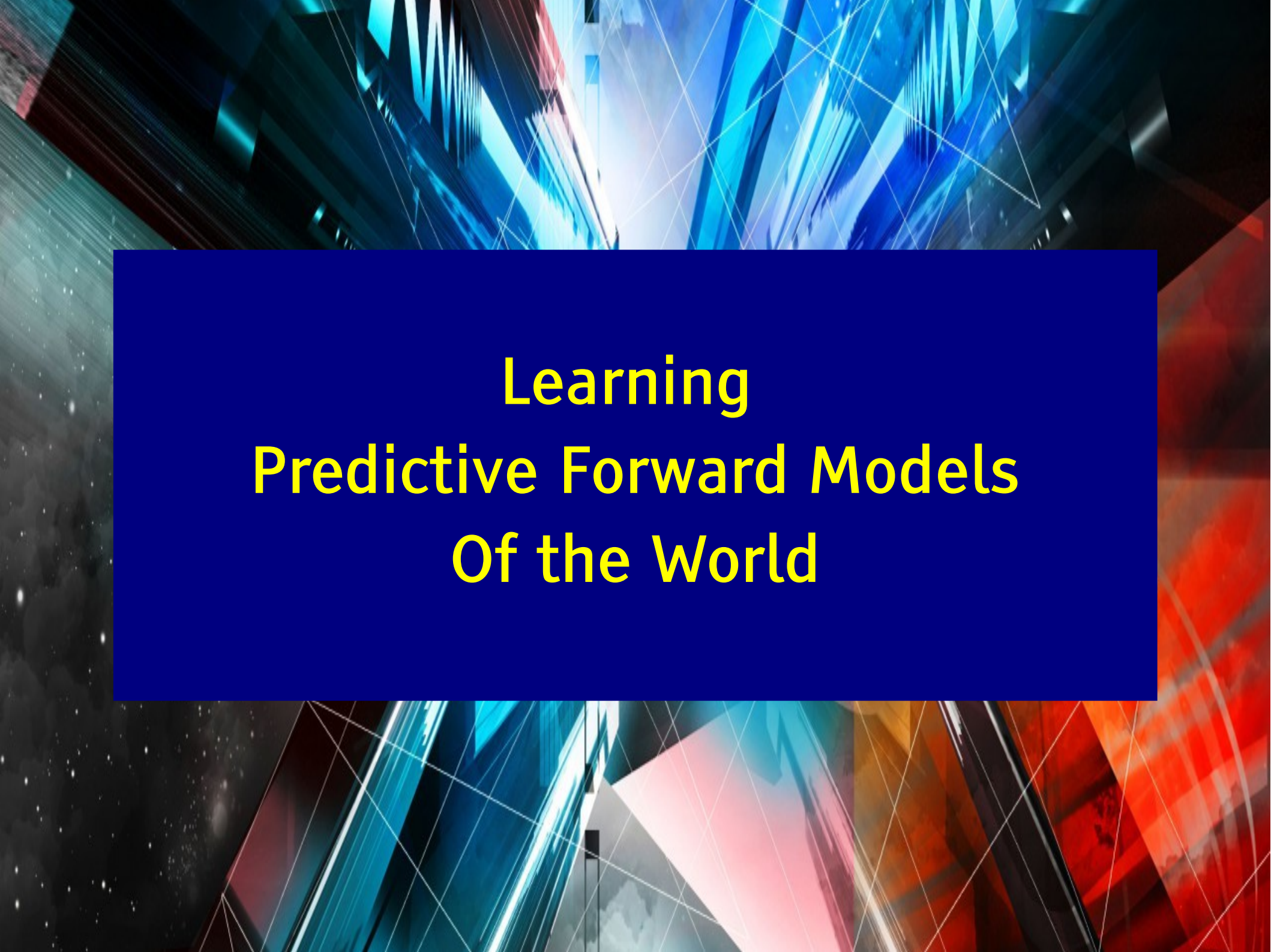


What we need is Model-Based Reinforcement Learning

Y LeCun

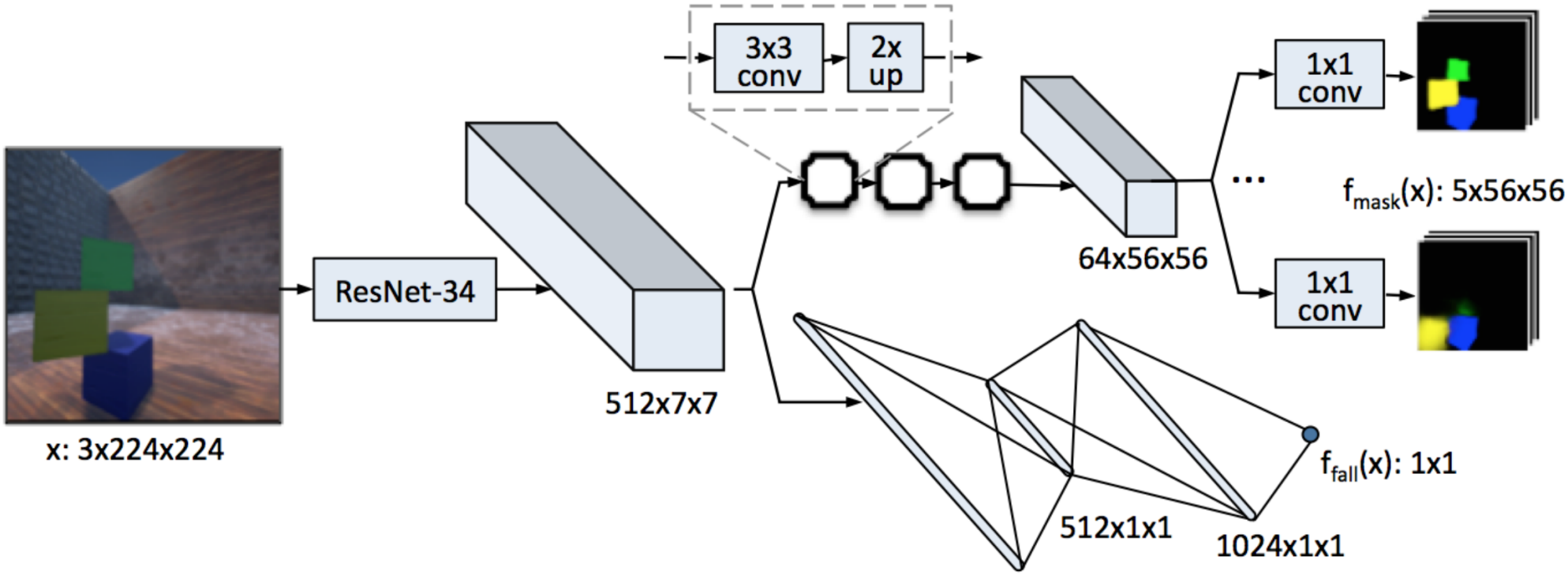
- The essence of intelligence is the ability to predict
- To plan ahead, we must simulate the world, so as to minimizes the predicted value of some objective function.




Learning
Predictive Forward Models
Of the World

Learning Physics (PhysNet)

- [Lerer, Gross, Fergus arxiv:1603.01312]
  - ConvNet produces object masks that predict the trajectories of falling blocks
  - Uses the Unreal game engine.



Learning Physics (PhysNet)

- [Lerer, Gross, Fergus arxiv:1603.01312]
  - ConvNet produces object masks that predict the trajectories of falling blocks
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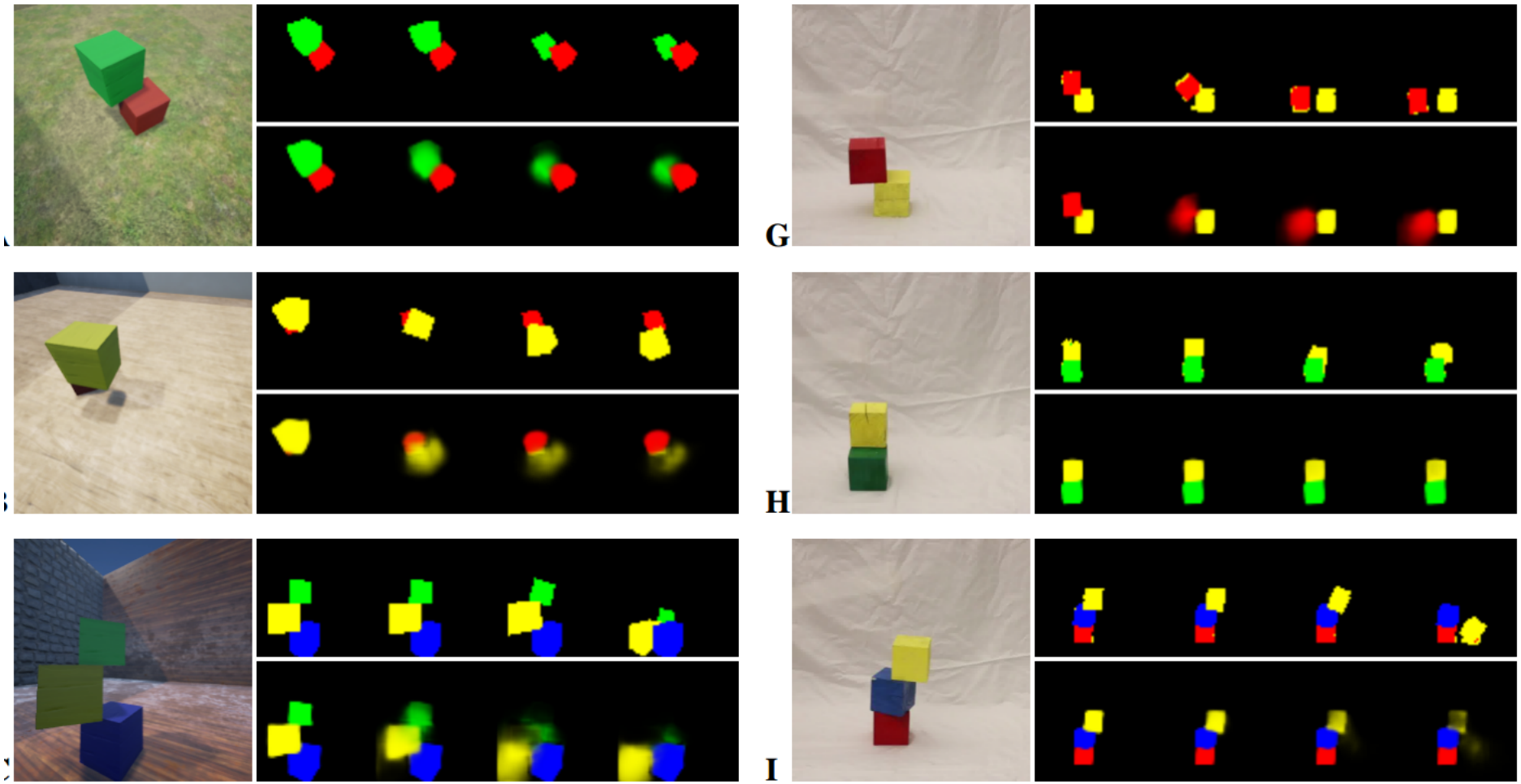

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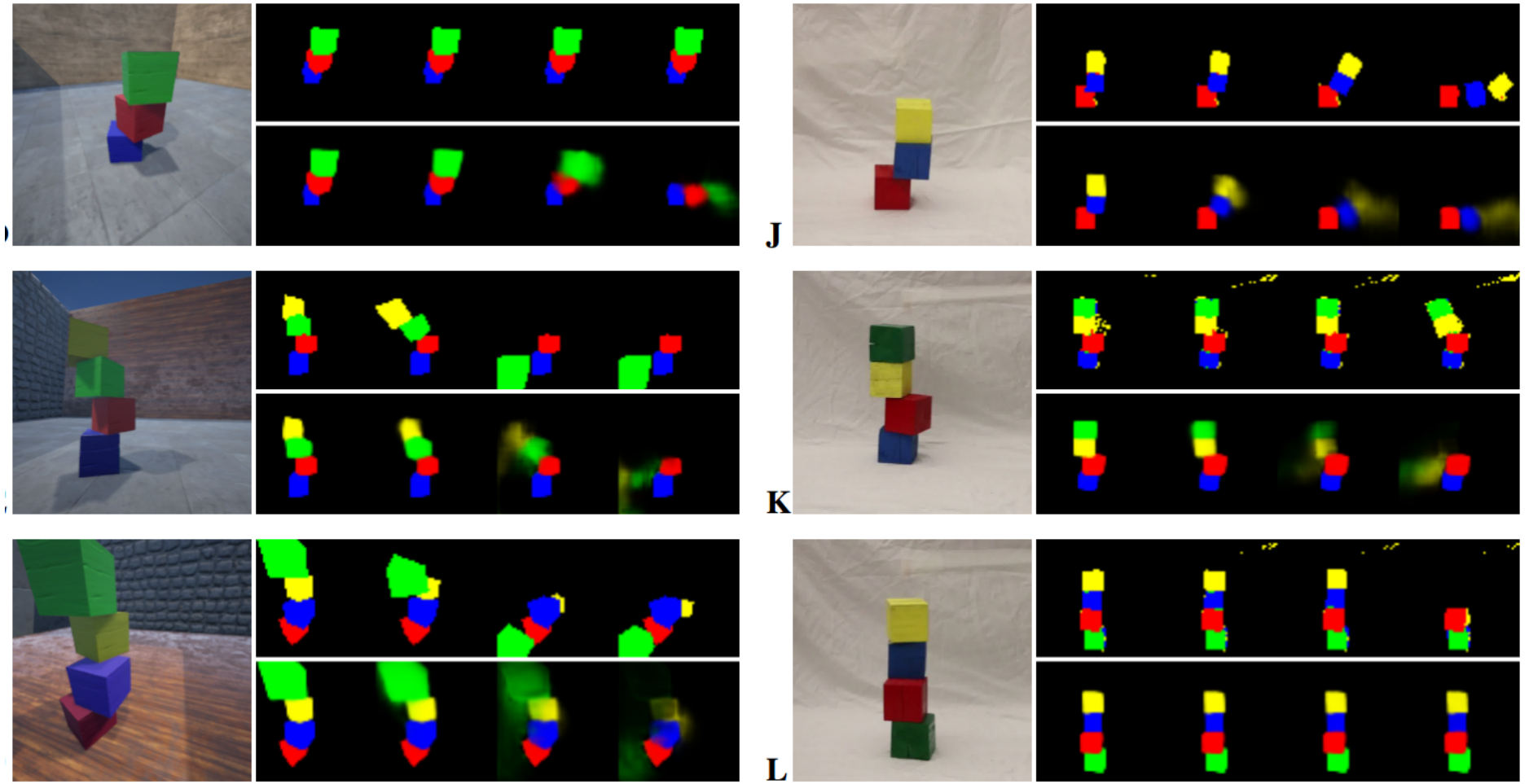
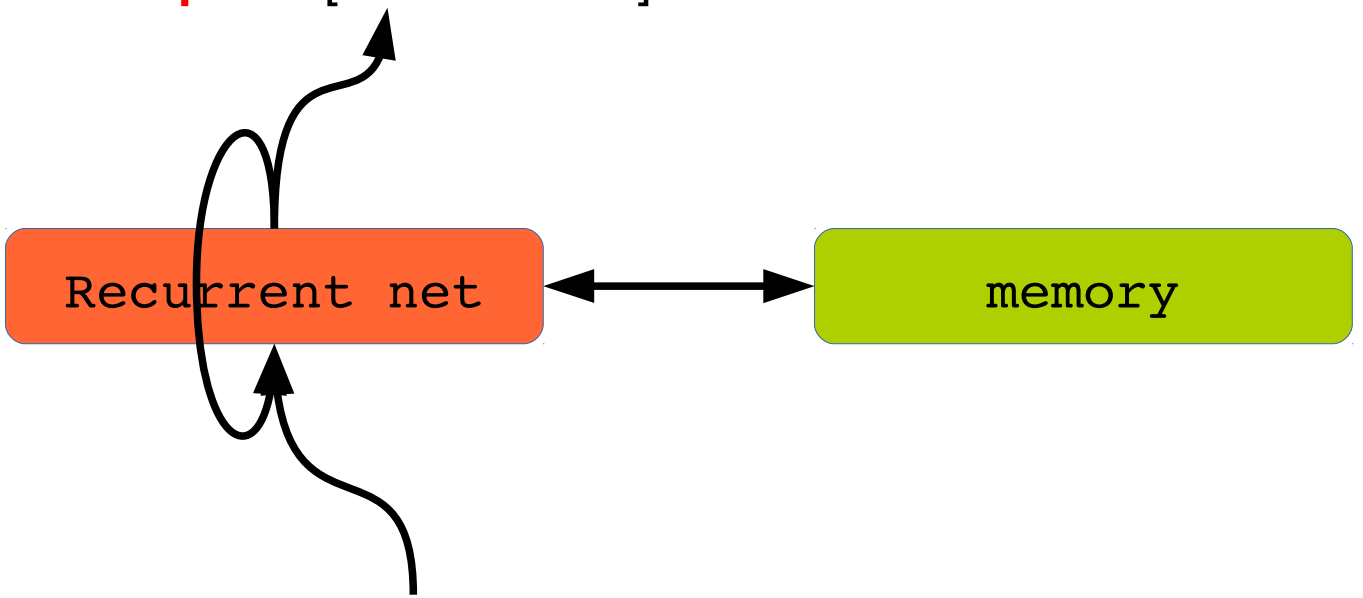



Inferring the
State of the World from Text:
Entity RNN

Augmenting Neural Nets with a Memory Module

- **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]

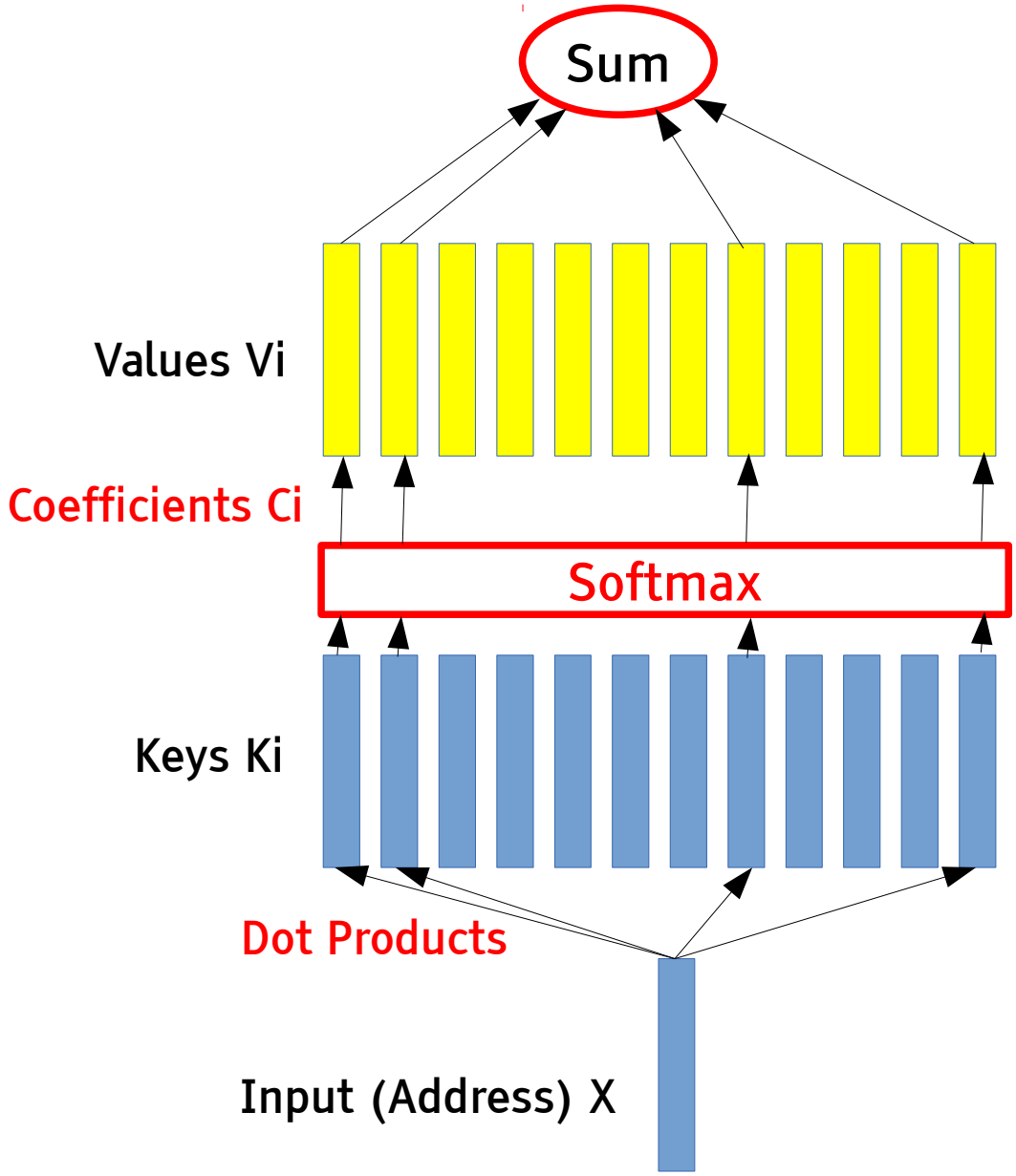


Differentiable Memory

- Like a "soft" RAM circuit
- Or a "soft" hash table
- Stores Key-Value pairs (Ki,Vi)

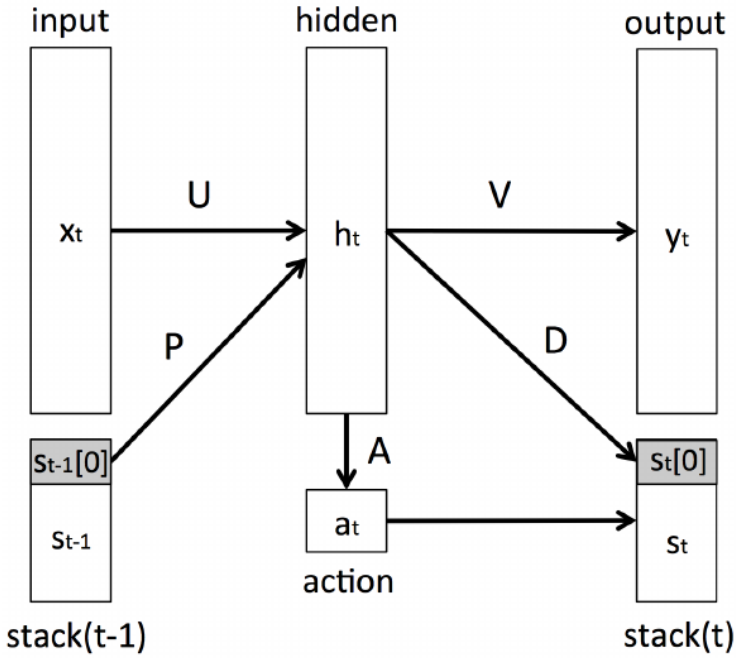
$$C_i = \frac{e^{K_i^T X}}{\sum_j e^{K_j^T X}}$$

$$Y = \sum_i C_i V_i$$

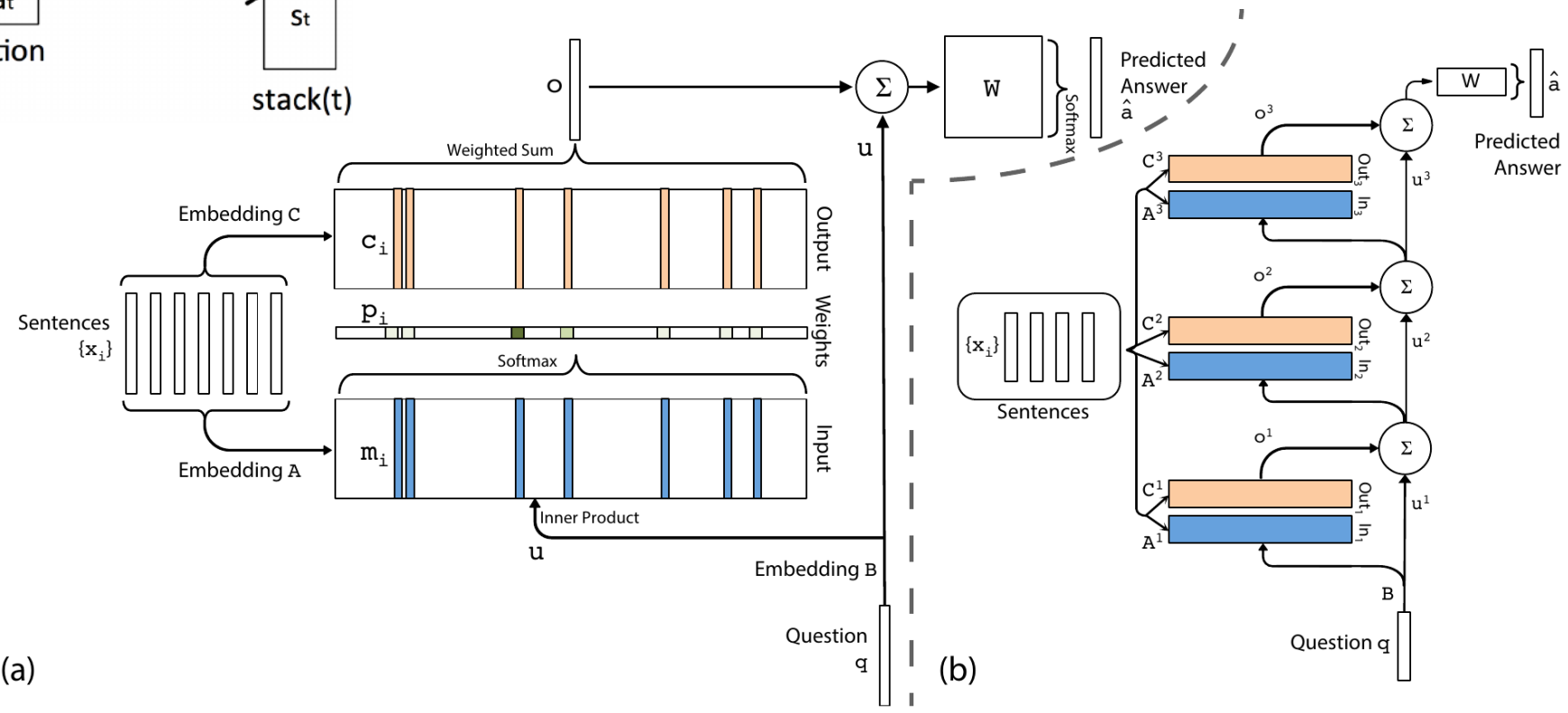


Memory/Stack-Augmented Recurrent Nets

Y LeCun



- [Joulin & Mikolov, ArXiv:1503.01007]
  - Stack-augmented RNN
- [Sukhbataar, Szlam, Weston, Fergus NIPS 2015]
  - ArXiv:1503.08895]
- Weakly-supervised MemNN:
  - discovers which memory location to use.



Memory Network [Weston, Chopra, Bordes 2014]

Add a short-term memory to a network

http://arxiv.org/abs/1410.3916

I: (input feature map) – converts the incoming input to the internal feature representation.
G: (generalization) – updates old memories given the new input.
O: (output feature map) – produces a new output (in the feature representation space), given the new input and the current memory.
R: (response) – converts the output into the response format desired. For example, a textual response or an action.

Method	F1
(Fader et al., 2013) [4]	0.54
(Bordes et al., 2014) [3]	0.73
MemNN	0.71
MemNN (with BoW features)	0.79

Results on Question Answering Task

Bilbo travelled to the cave.
Gollum dropped the ring there.
Bilbo took the ring.
Bilbo went back to the Shire.
Bilbo left the ring there.
Frodo got the ring.
Frodo journeyed to Mount-Doom.
Frodo dropped the ring there.
Sauron died.
Frodo went back to the Shire.
Bilbo travelled to the Grey-havens.
The End.
Where is the ring? A: Mount-Doom
Where is Bilbo now? A: Grey-havens
Where is Frodo now? A: Shire

Fig. 2. An example story with questions correctly answered by a MemNN. The MemNN was trained on the simulation described in Section 4.2 and had never seen many of these words before, e.g. Bilbo, Frodo and Gollum.

End-to-End Memory Network on bAbI tasks [Weston 2015]

Y LeCun

```
Sam walks into the kitchen.
Sam picks up an apple.
Sam walks into the bedroom.
Sam drops the apple.
Q: Where is the apple?
A. Bedroom
```

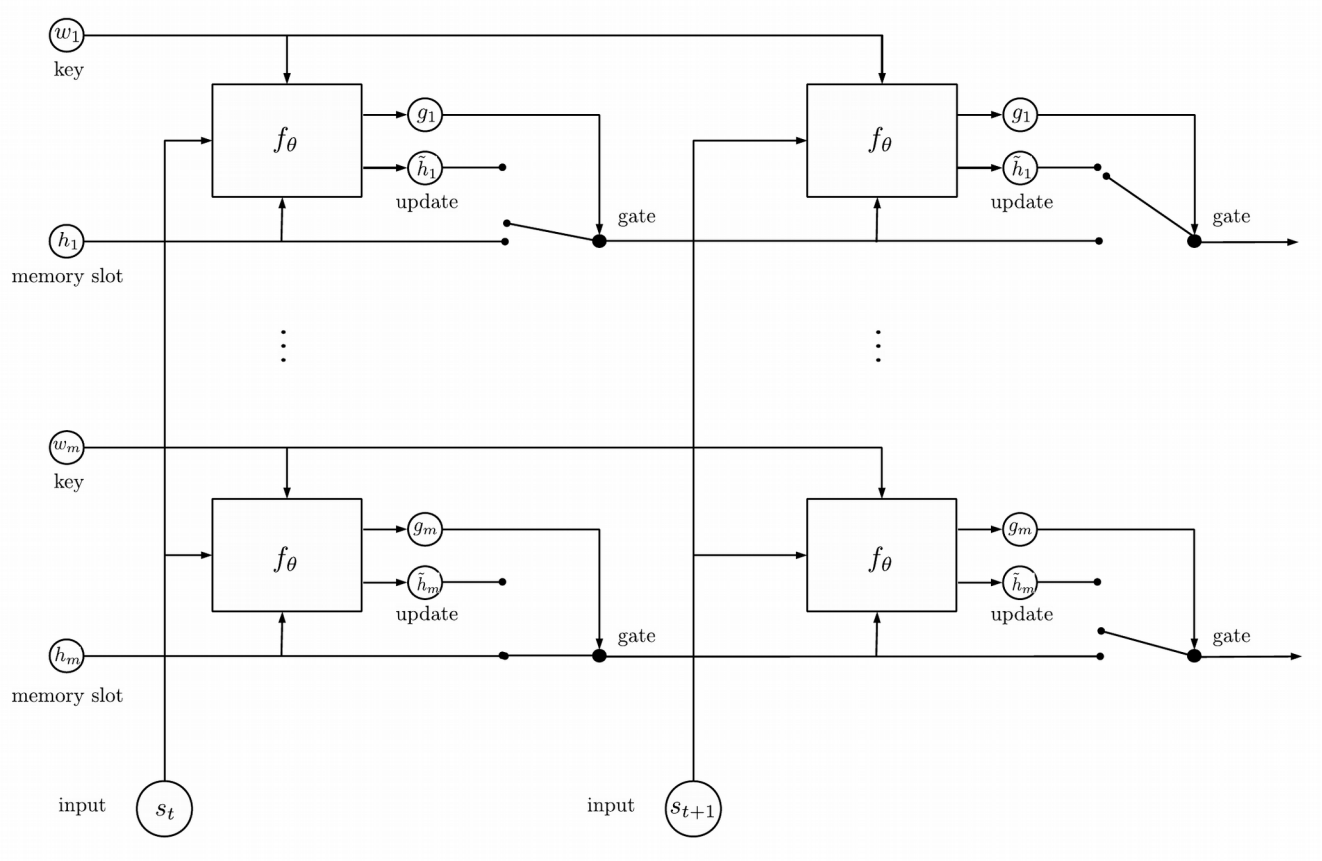
```
Brian is a lion.
Julius is a lion.
Julius is white.
Bernhard is green.
Q: What color is Brian?
A. White
```

```
Mary journeyed to the den.
Mary went back to the kitchen.
John journeyed to the bedroom.
Mary discarded the milk.
Q: Where was the milk before the den?
A. Hallway
```

	Baseline			MemN2N								
Task	Strongly Supervised MemNN [21]	LSTM [21]	MemNN WSH	BoW	PE	PE LS	PE LS RN	1 hop PE LS joint	2 hops PE LS joint	3 hops PE LS joint	PE LS RN joint	PE LS LW joint
1: 1 supporting fact	0.0	50.0	0.1	0.6	0.1	0.2	0.0	0.8	0.0	0.1	0.0	0.1
2: 2 supporting facts	0.0	80.0	42.8	17.6	21.6	12.8	8.3	62.0	15.6	14.0	11.4	18.8
3: 3 supporting facts	0.0	80.0	76.4	71.0	64.2	58.8	40.3	76.9	31.6	33.1	21.9	31.7
4: 2 argument relations	0.0	39.0	40.3	32.0	3.8	11.6	2.8	22.8	2.2	5.7	13.4	17.5
5: 3 argument relations	2.0	30.0	16.3	18.3	14.1	15.7	13.1	11.0	13.4	14.8	14.4	12.9
6: yes/no questions	0.0	52.0	51.0	8.7	7.9	8.7	7.6	7.2	2.3	3.3	2.8	2.0
7: counting	15.0	51.0	36.1	23.5	21.6	20.3	17.3	15.9	25.4	17.9	18.3	10.1
8: lists/sets	9.0	55.0	37.8	11.4	12.6	12.7	10.0	13.2	11.7	10.1	9.3	6.1
9: simple negation	0.0	36.0	35.9	21.1	23.3	17.0	13.2	5.1	2.0	3.1	1.9	1.5
10: indefinite knowledge	2.0	56.0	68.7	22.8	17.4	18.6	15.1	10.6	5.0	6.6	6.5	2.6
11: basic coreference	0.0	38.0	30.0	4.1	4.3	0.0	0.9	8.4	1.2	0.9	0.3	3.3
12: conjunction	0.0	26.0	10.1	0.3	0.3	0.1	0.2	0.4	0.0	0.3	0.1	0.0
13: compound coreference	0.0	6.0	19.7	10.5	9.9	0.3	0.4	6.3	0.2	1.4	0.2	0.5
14: time reasoning	1.0	73.0	18.3	1.3	1.8	2.0	1.7	36.9	8.1	8.2	6.9	2.0
15: basic deduction	0.0	79.0	64.8	24.3	0.0	0.0	0.0	46.4	0.5	0.0	0.0	1.8
16: basic induction	0.0	77.0	50.5	52.0	52.1	1.6	1.3	47.4	51.3	3.5	2.7	51.0
17: positional reasoning	35.0	49.0	50.9	45.4	50.1	49.0	51.0	44.4	41.2	44.5	40.4	42.6
18: size reasoning	5.0	48.0	51.3	48.1	13.6	10.1	11.1	9.6	10.3	9.2	9.4	9.2
19: path finding	64.0	92.0	100.0	89.7	87.4	85.6	82.8	90.7	89.9	90.2	88.0	90.6
20: agent's motivation	0.0	9.0	3.6	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.2
Mean error (%)	6.7	51.3	40.2	25.1	20.3	16.3	13.9	25.8	15.6	13.3	12.4	15.2
Failed tasks (err. $>$ 5%)	4	20	18	15	13	12	11	17	11	11	11	10
On 10k training data												
Mean error (%)	3.2	36.4	39.2	15.4	9.4	7.2	6.6	24.5	10.9	7.9	7.5	11.0
Failed tasks (err. $>$ 5%)	2	16	17	9	6	4	4	16	7	6	6	6

Entity Recurrent Neural Net

- Maintains a current estimate of the state of the world.
- Each module is a recurrent net with a "memory"
- Each input event causes some of the memory cells to get updated
- "Tracking the World State with Recurrent Entity Networks", Henaff, Weston, Szlam, Bordes, LeCun (submitted to ICLR2017 on OpenReview.net)



EntNet is the first model to solve all 20 bAbI tasks

Y LeCun

Task	D-NTM	MemN2N	DNC	DMN+	EntNet
1: 1 supporting fact	4.4	0	0	0	0
2: 2 supporting facts	27.5	0.3	0.4	0.3	0.1
3: 3 supporting facts	71.3	2.1	1.8	1.1	4.1
4: 2 argument relations	0	0	0	0	0
5: 3 argument relations	1.7	0.8	0.8	0.5	0.3
6: yes/no questions	1.5	0.1	0	0	0.2
7: counting	6.0	2.0	0.6	2.4	0
8: lists/sets	1.7	0.9	0.3	0.0	0.5
9: simple negation	0.6	0.3	0.2	0.0	0.1
10: indefinite knowledge	19.8	0	0.2	0	0.6
11: basic coreference	0	0.0	0	0.0	0.3
12: conjunction	6.2	0	0	0.2	0
13: compound coreference	7.5	0	0	0	1.3
14: time reasoning	17.5	0.2	0.4	0.2	0
15: basic deduction	0	0	0	0	0
16: basic induction	49.6	51.8	55.1	45.3	0.2
17: positional reasoning	1.2	18.6	12.0	4.2	0.5
18: size reasoning	0.2	5.3	0.8	2.1	0.3
19: path finding	39.5	2.3	3.9	0.0	2.3
20: agent's motivation	0	0	0	0	0
Failed Tasks ($> 5\%$ error):	9	3	2	1	**0**
Mean Error:	12.8	4.2	3.8	2.8	**0.5**

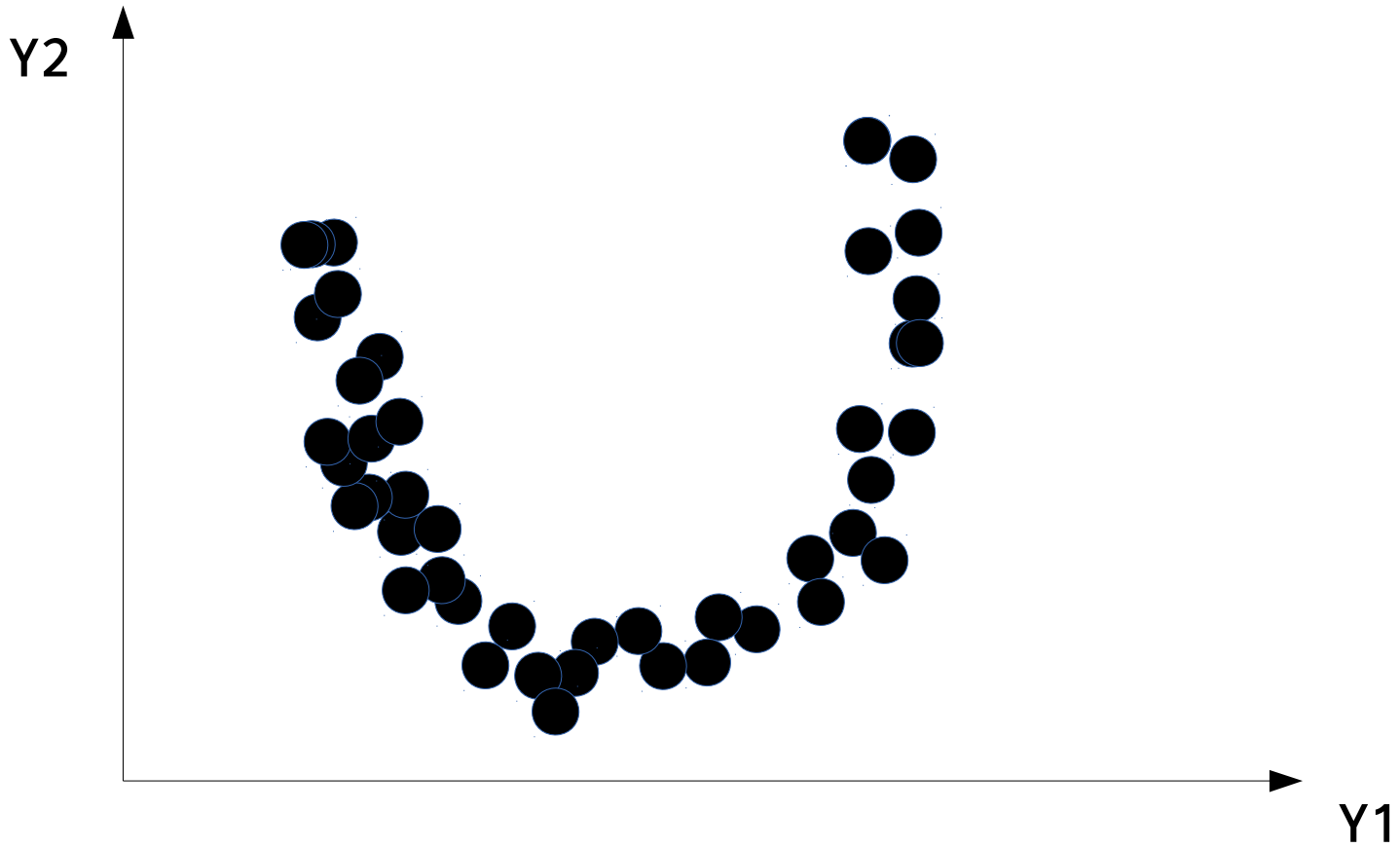
EntNet is the first model to solve all 20 bAbI tasks

Story	Key	1-NN	2-NN
mary got the milk there	football	hallway (0.135)	dropped (0.056)
john moved to the bedroom	milk	garden (0.111)	took (0.011)
sandra went back to the kitchen	john	kitchen (0.501)	dropped (0.027)
mary travelled to the hallway	mary	garden (0.442)	took (0.034)
john got the football there	sandra	hallway (0.394)	kitchen (0.121)
john went to the hallway	daniel	hallway (0.689)	to (0.076)
john put down the football	bedroom	hallway (0.367)	dropped (0.075)
mary went to the garden	kitchen	kitchen (0.483)	daniel (0.029)
john went to the kitchen	garden	garden (0.281)	where (0.026)
sandra travelled to the hallway	hallway	hallway (0.475)	left (0.060)
daniel went to the hallway			
mary discarded the milk			
where is the milk ?			
answer: garden			


Unsupervised Learning

Energy-Based Unsupervised Learning

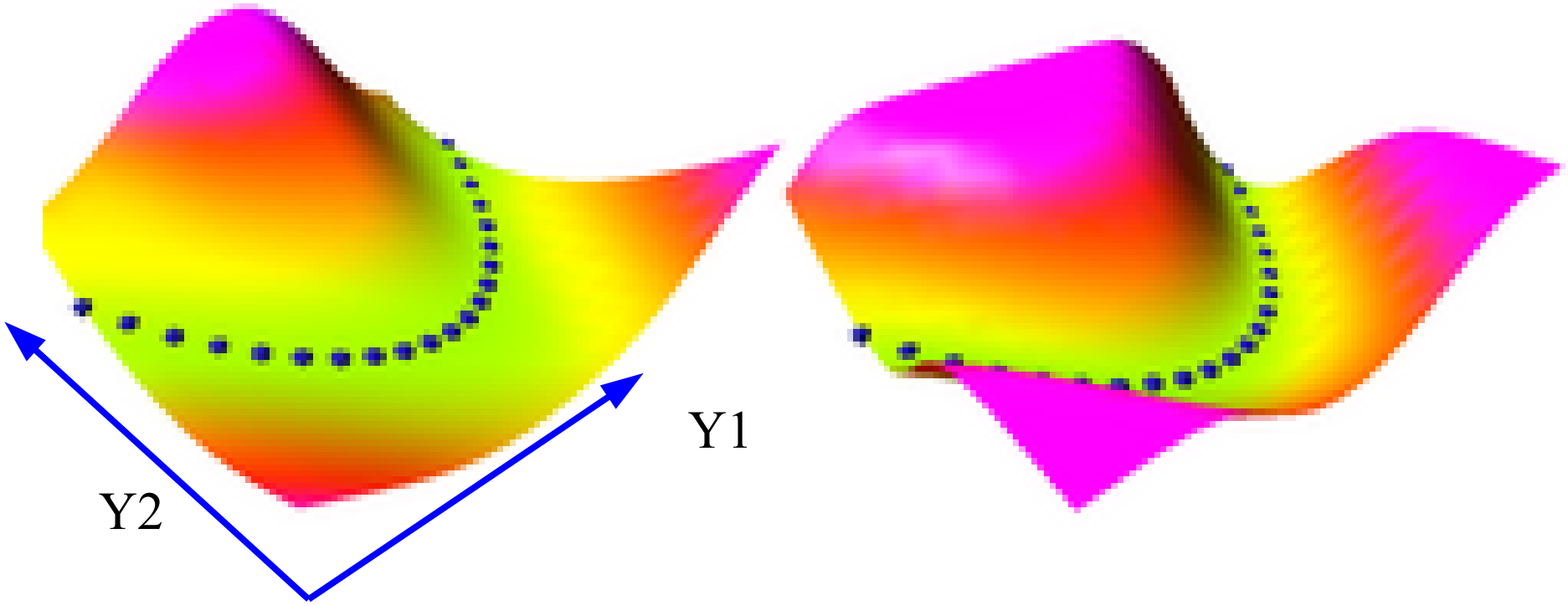
- Learning an energy function (or contrast function) that takes
  - Low values on the data manifold
  - Higher values everywhere else



Capturing Dependencies Between Variables with an Energy Function

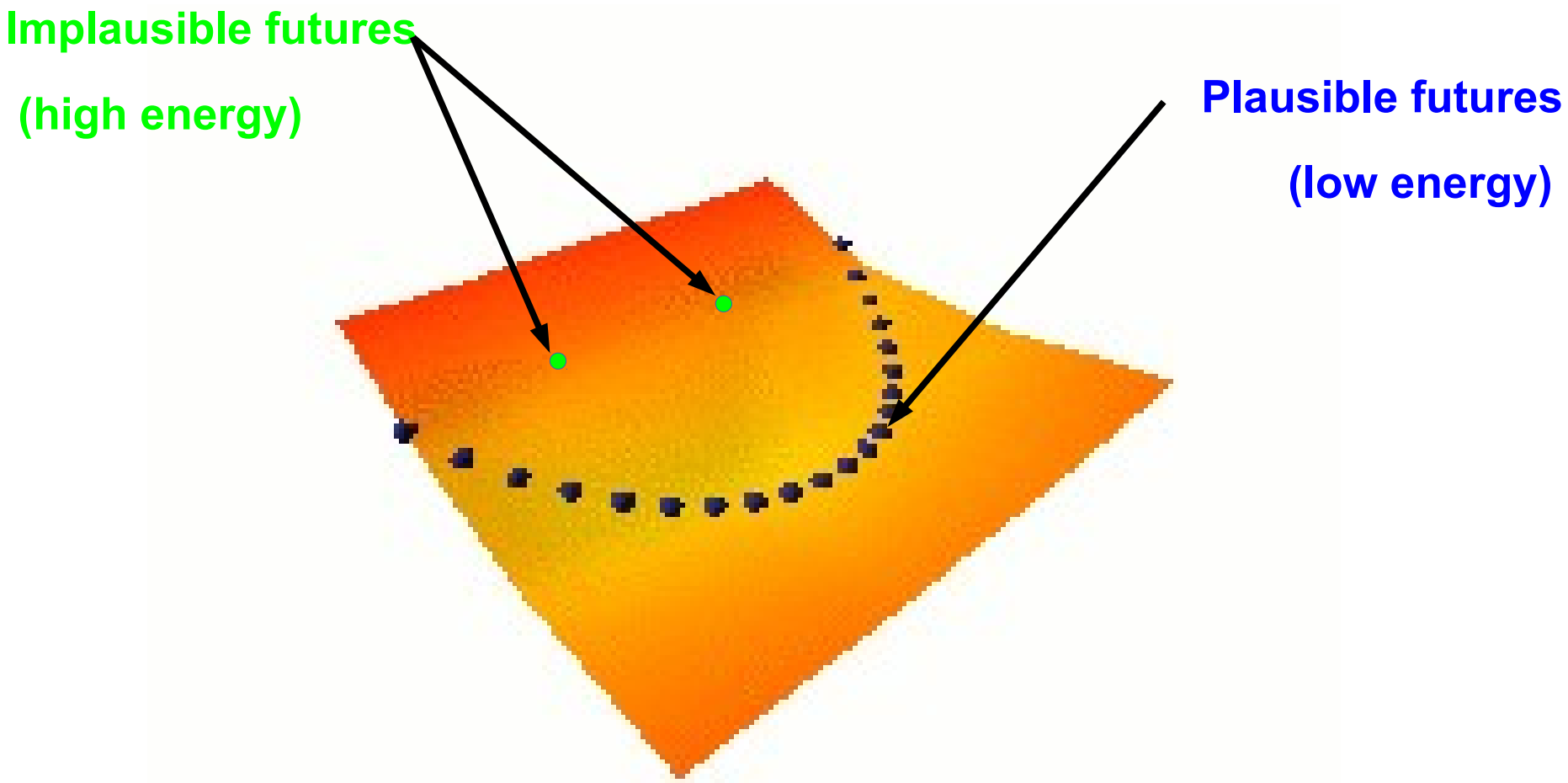
- The energy surface is a "contrast function" that takes low values on the data manifold, and higher values everywhere else
  - Special case: energy = negative log density
  - Example: the samples live in the manifold

$$Y_2 = (Y_1)^2$$



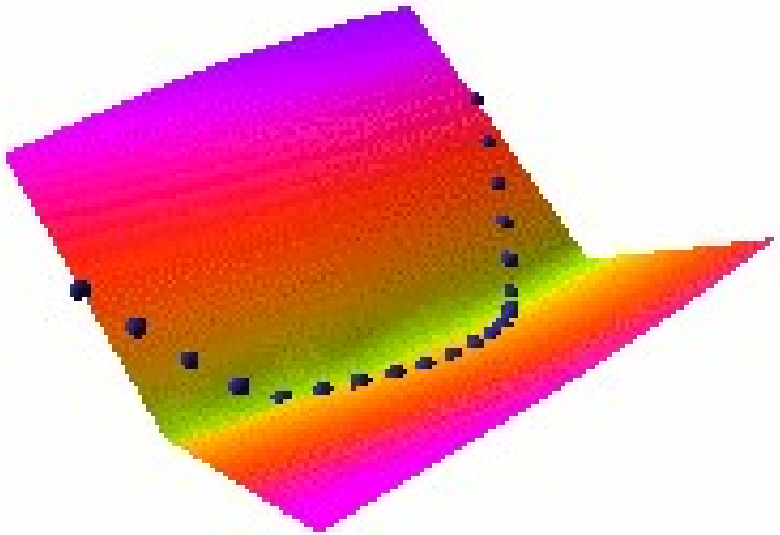
Energy-Based Unsupervised Learning

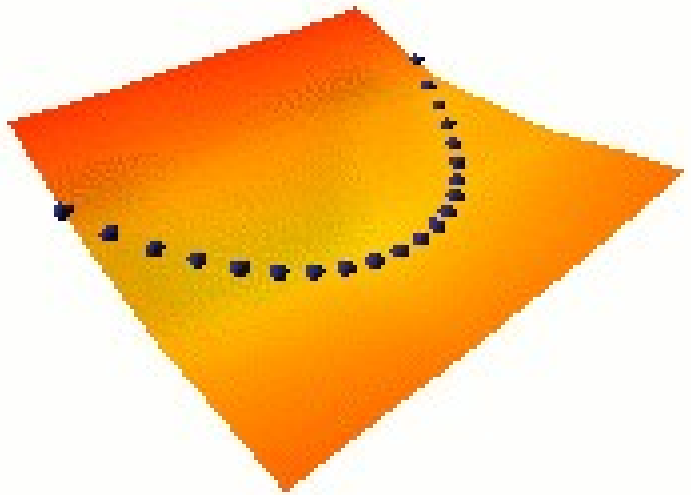
- **Energy Function:** Takes low value on data manifold, higher values everywhere else
- Push down on the energy of desired outputs. Push up on everything else.
- But how do we choose where to push up?



Learning the Energy Function

- parameterized energy function E(Y,W)
  - Make the energy low on the samples
  - Make the energy higher everywhere else
  - Making the energy low on the samples is easy
  - But how do we make it higher everywhere else?





Seven Strategies to Shape the Energy Function

- 1. build the machine so that the volume of low energy stuff is constant
  - PCA, K-means, GMM, square ICA
- 2. push down of the energy of data points, push up everywhere else
  - Max likelihood (needs tractable partition function)
- 3. push down of the energy of data points, push up on chosen locations
  - contrastive divergence, Ratio Matching, Noise Contrastive Estimation, Minimum Probability Flow
- 4. minimize the gradient and maximize the curvature around data points
  - score matching
- 5. train a dynamical system so that the dynamics goes to the manifold
  - denoising auto-encoder
- 6. use a regularizer that limits the volume of space that has low energy
  - Sparse coding, sparse auto-encoder, PSD
- 7. if E(Y) = ||Y - G(Y)||^2, make G(Y) as "constant" as possible.
  - Contracting auto-encoder, saturating auto-encoder

#1: constant volume of low energy
Energy surface for PCA and K-means

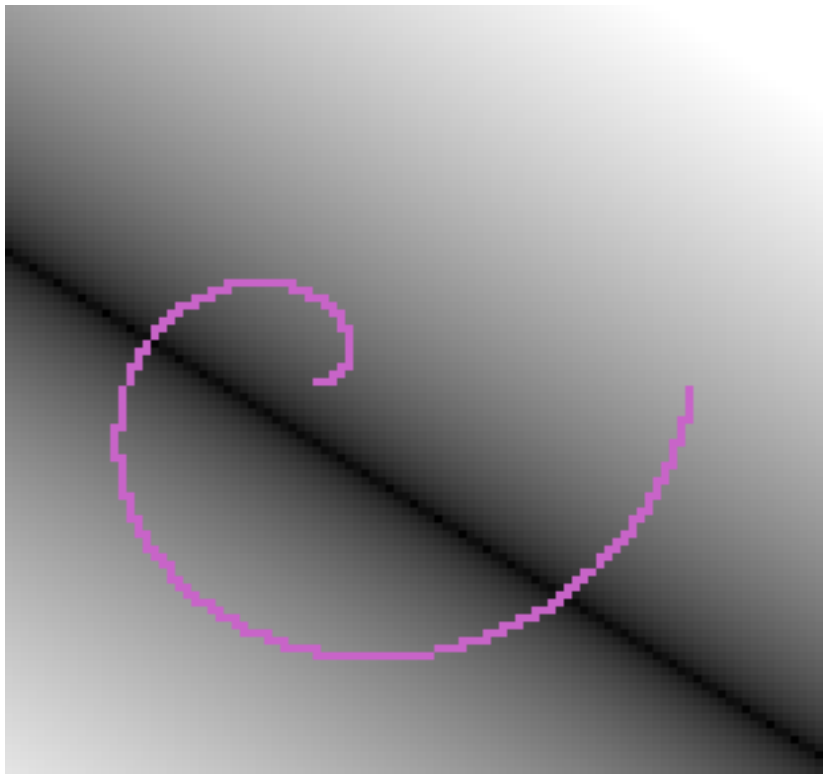
- 1. build the machine so that the volume of low energy stuff is constant
  - PCA, K-means, GMM, square ICA...

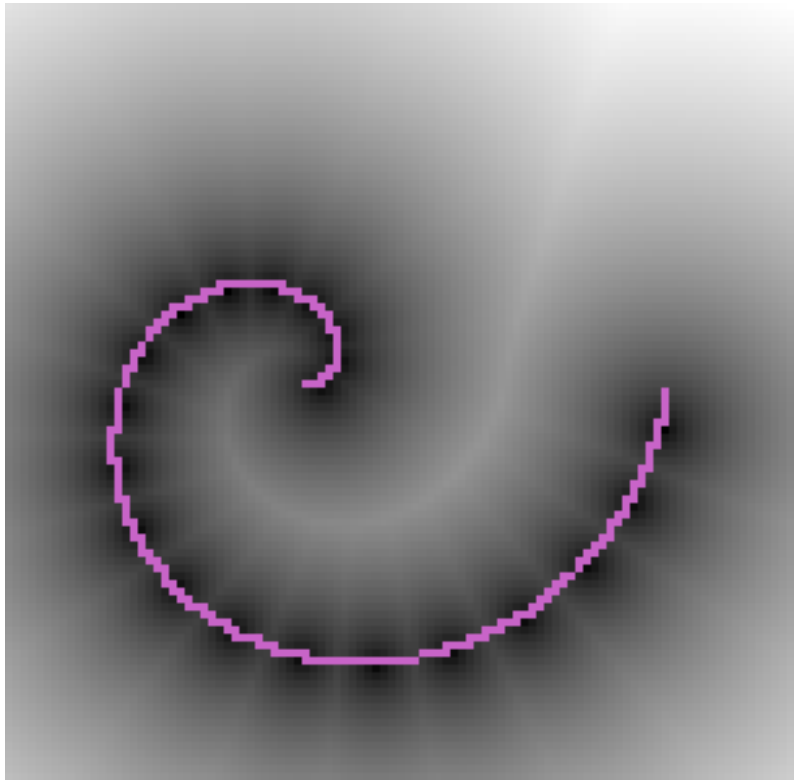
PCA

$$E(Y) = \|W^T WY - Y\|^2$$

K-Means,
Z constrained to 1-of-K code

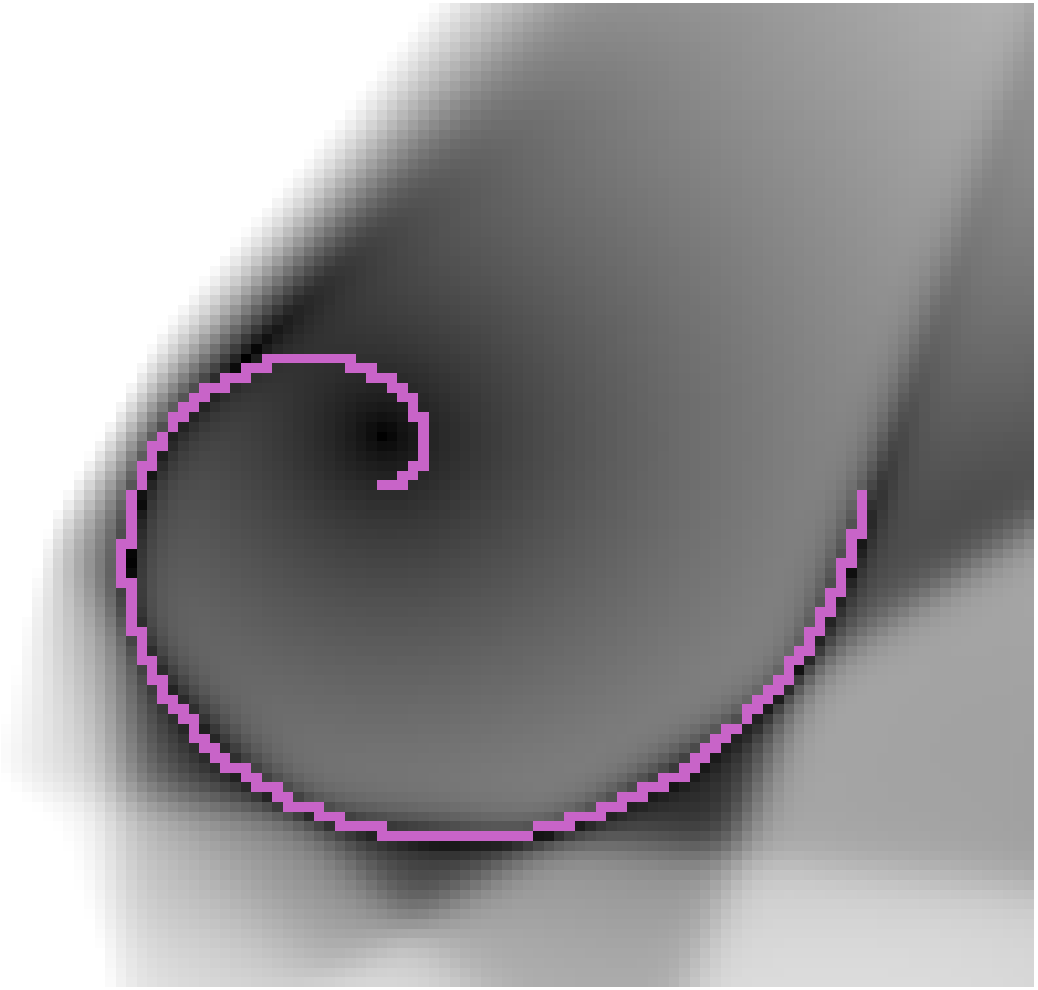
$$E(Y) = min_z \sum_i \|Y - W_i Z_i\|^2$$





#6. use a regularizer that limits the volume of space that has low energy

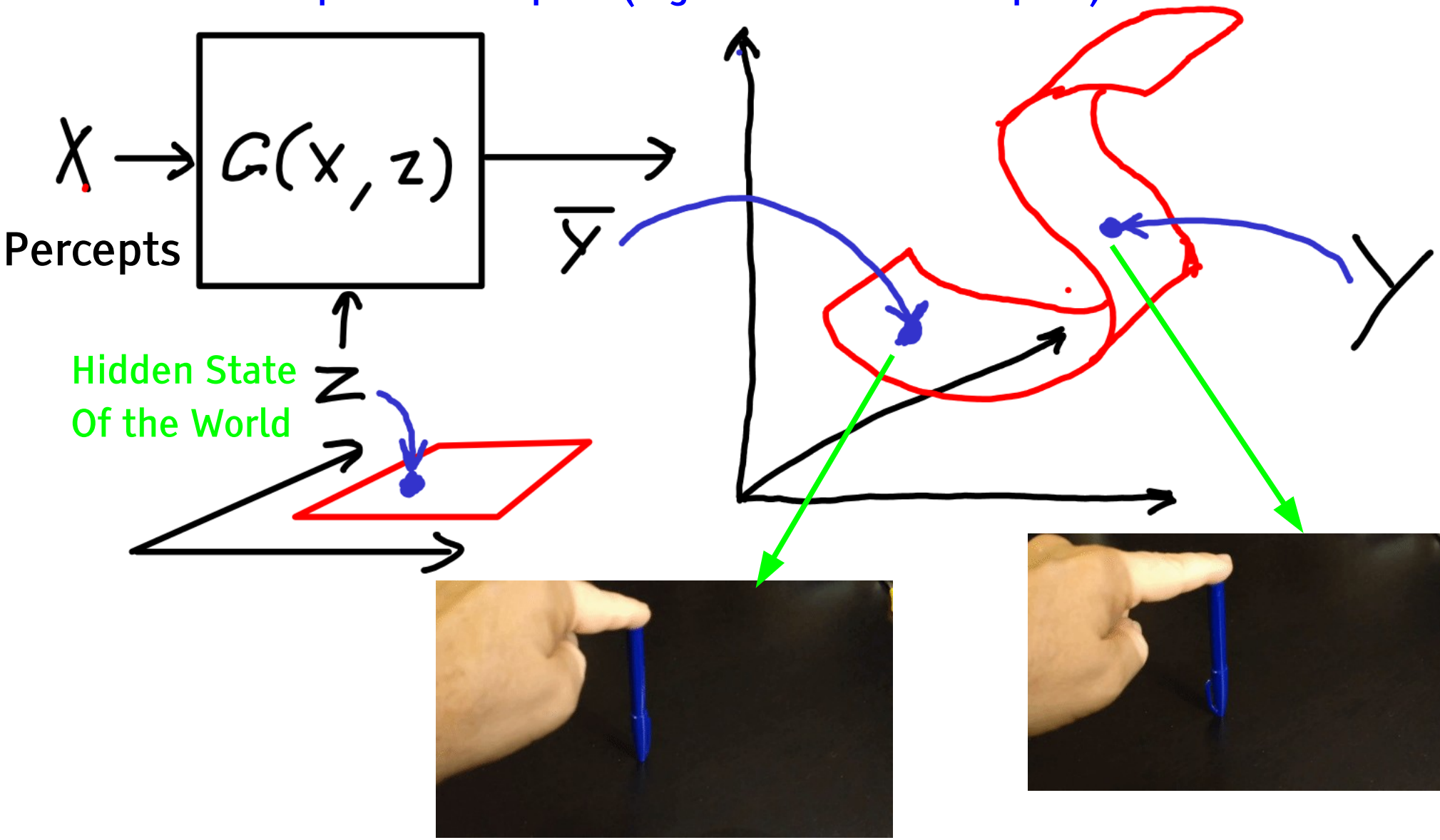
- Sparse coding, sparse auto-encoder, Predictive Sparse Decomposition




Adversarial Training

The Hard Part: Prediction Under Uncertainty

- Invariant prediction: The training samples are merely representatives of a whole set of possible outputs (e.g. a manifold of outputs).



Energy-Based Unsupervised Learning

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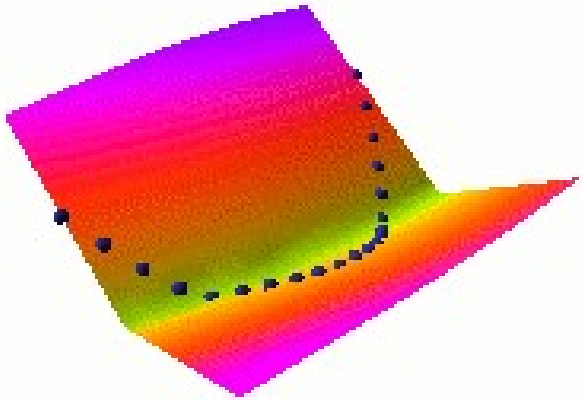
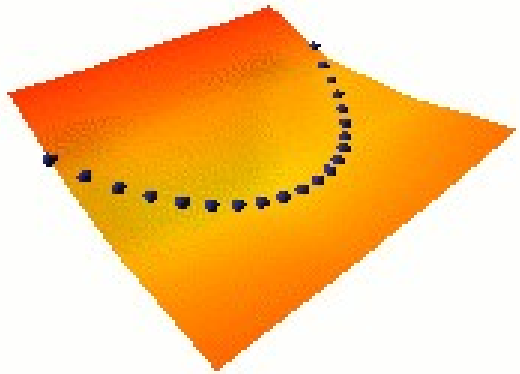
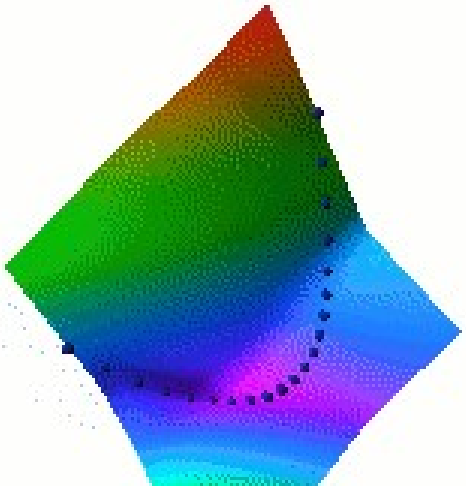
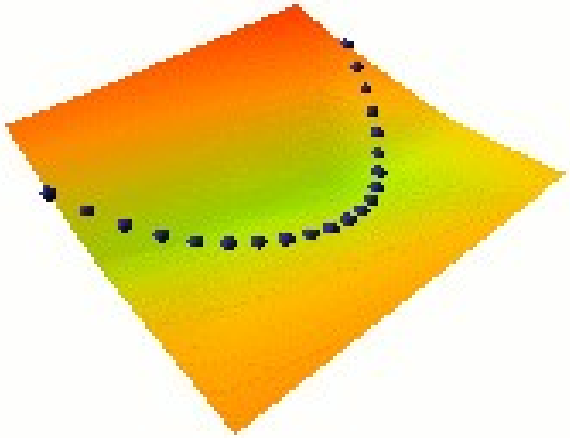


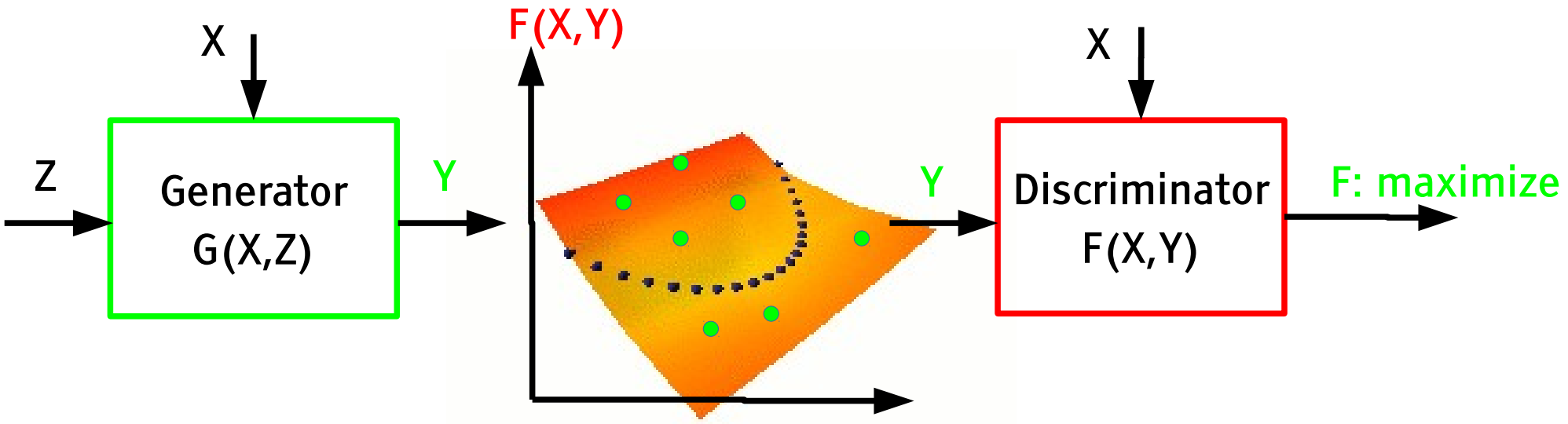


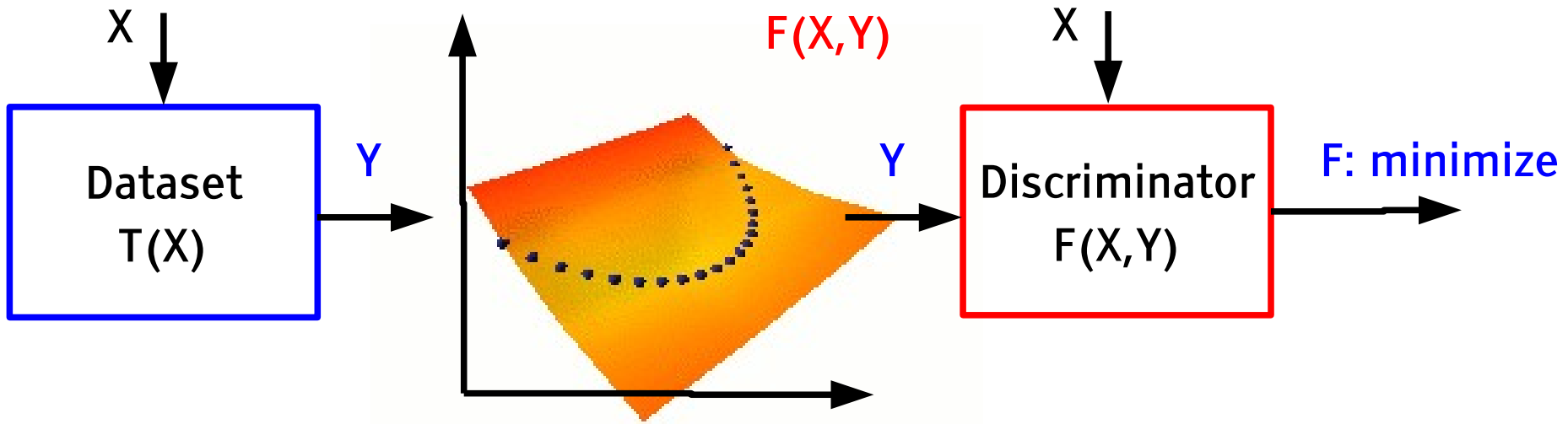




Adversarial Training: A Trainable Objective Function

- **Adversarial Training [Goodfellow et al. NIPS 2014]**
- **Energy-based view of adversarial training: generator picks points to push up**





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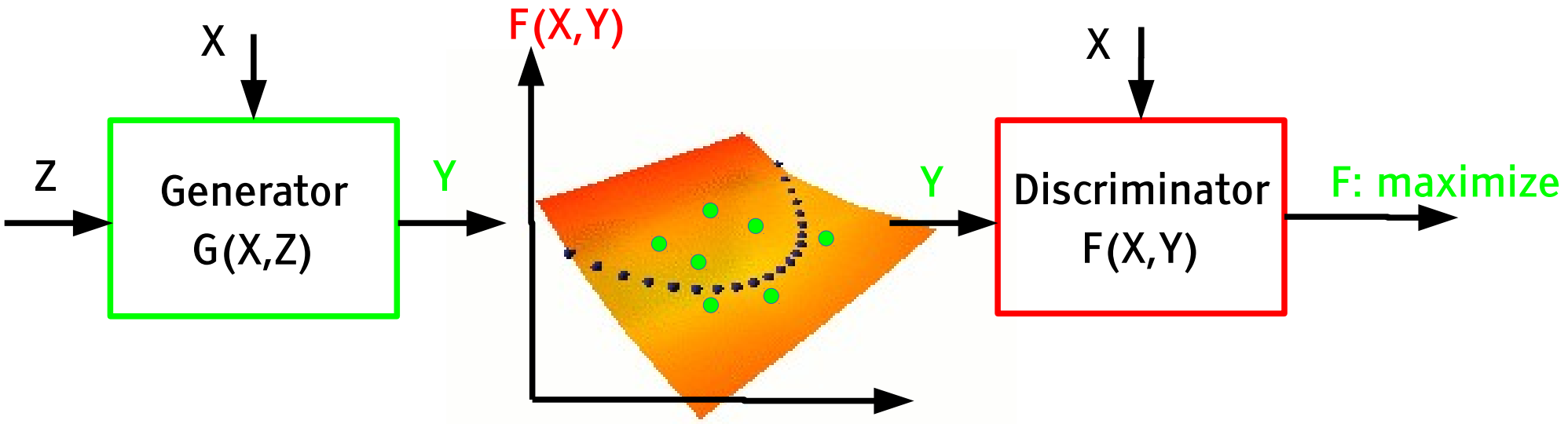
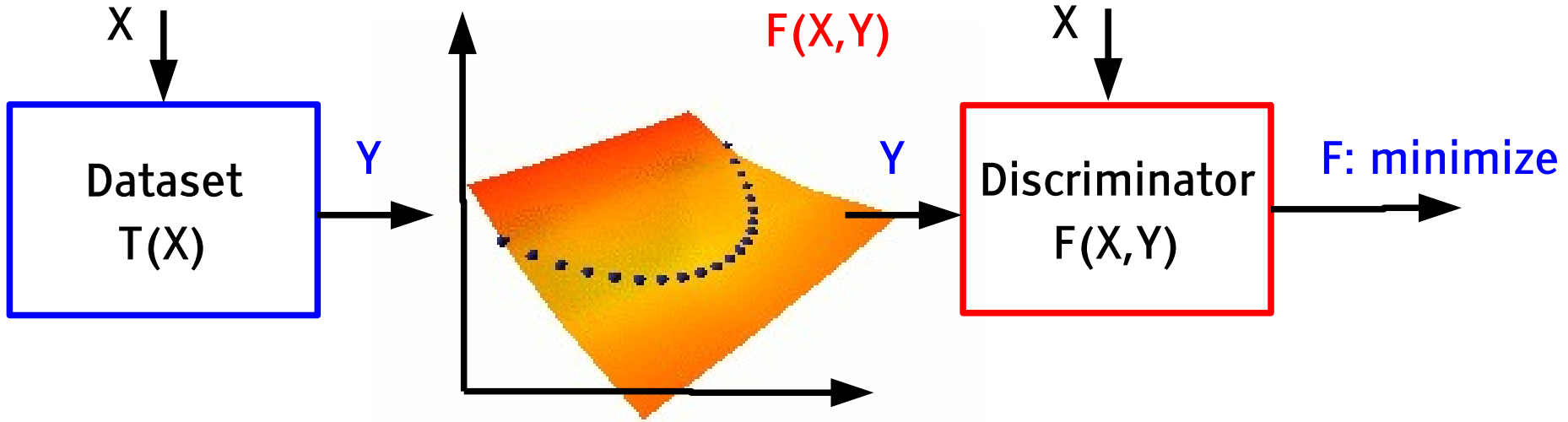
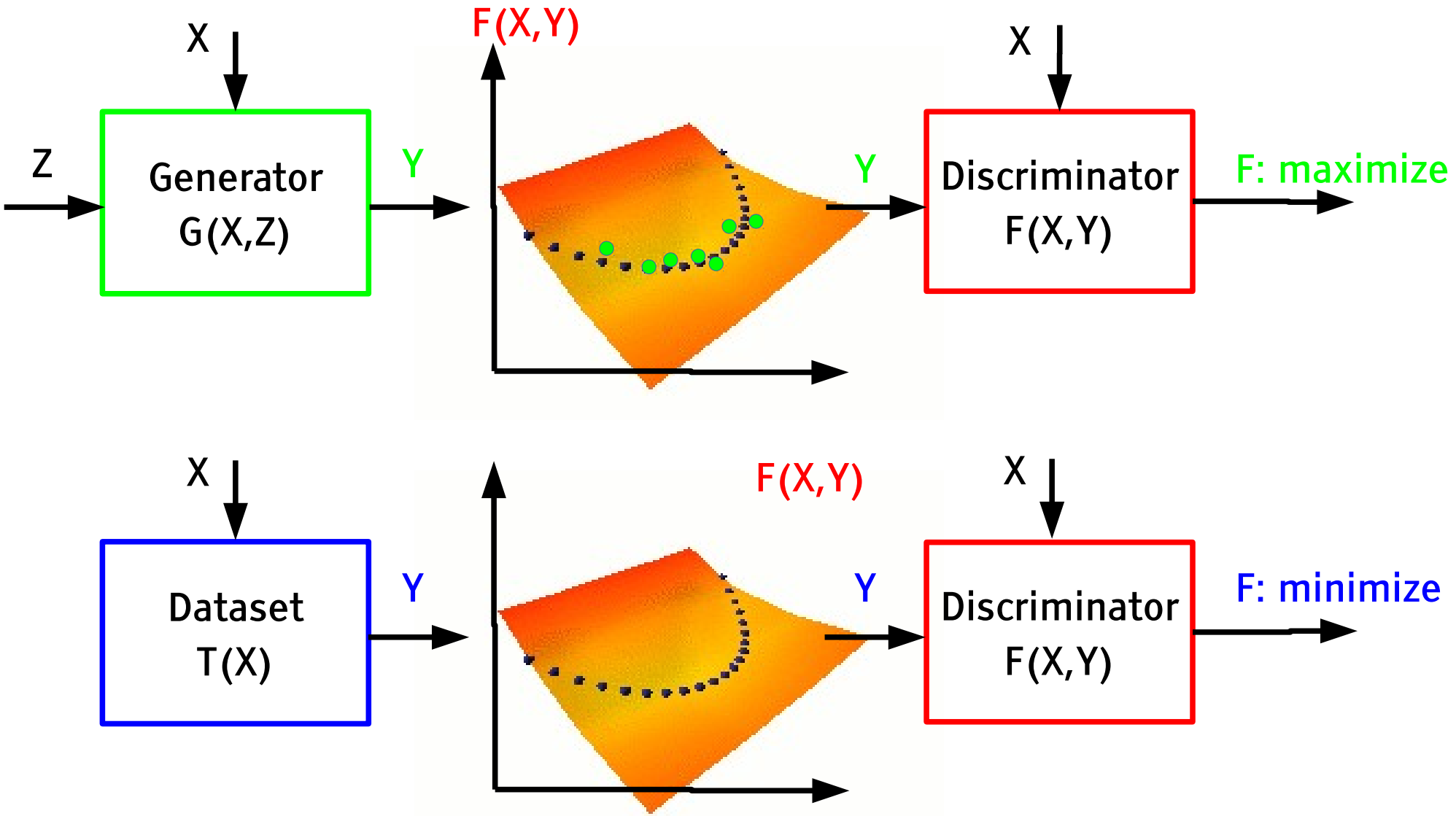




Adversarial Training: A Trainable Objective Function

- **Energy-based GAN [Zhao, Mathieu, LeCun: arXiv:1609.03.126]**

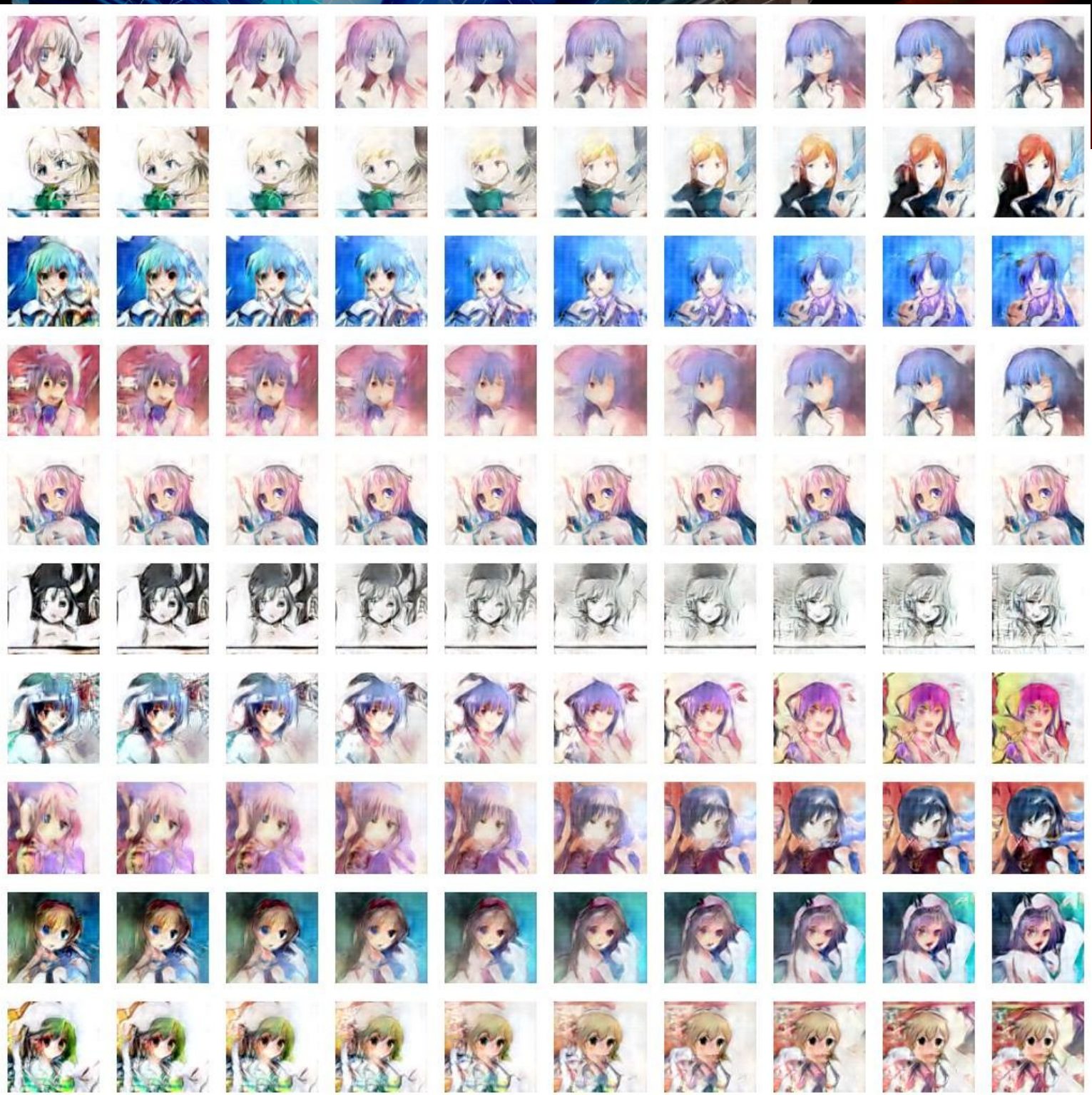


DCGAN: "reverse" ConvNet maps random vectors to images

- DCGAN: adversarial training to generate images.
- [Radford, Metz, Chintala 2015]
  - Input: random numbers; output: bedrooms.

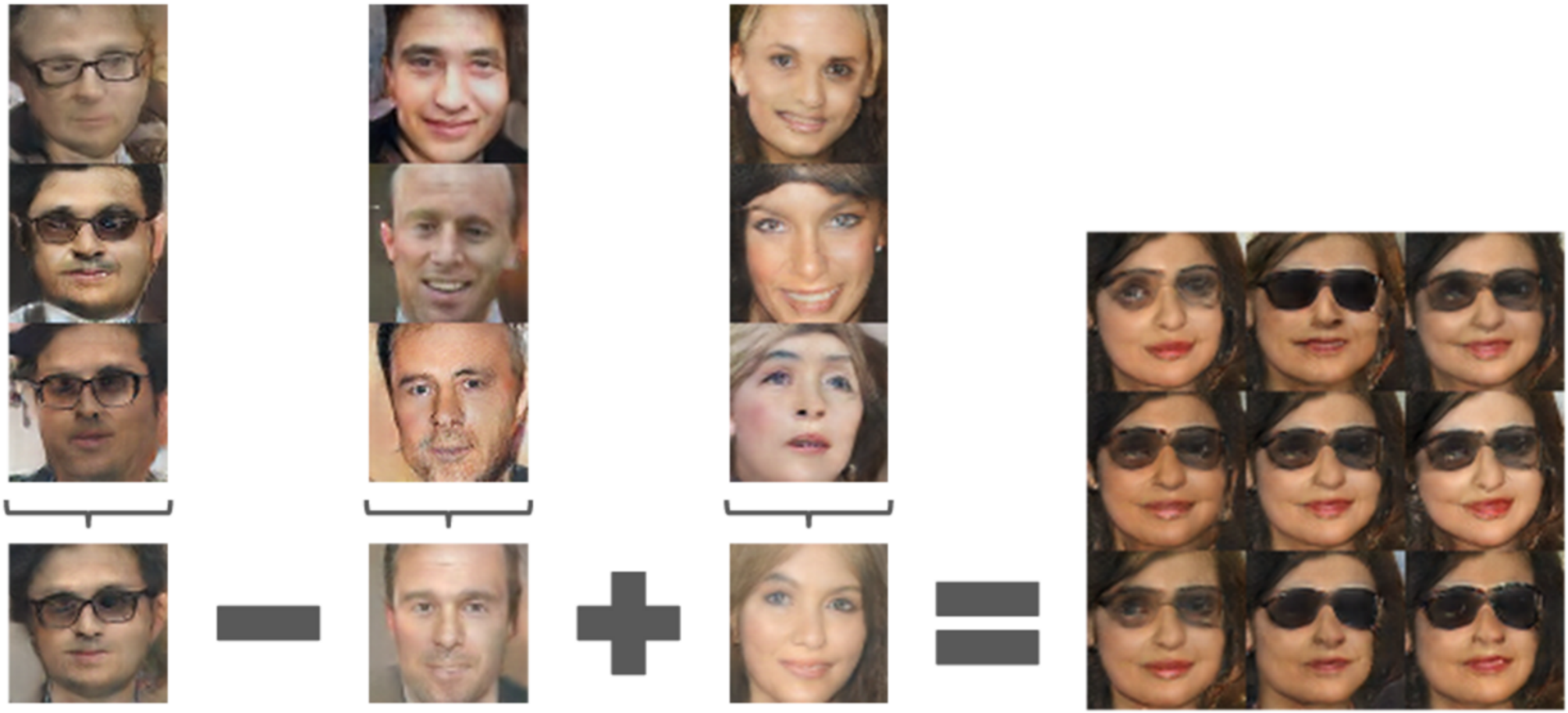
Navigating the Manifold

- DCGAN: adversarial training to generate images.
- Trained on Manga characters
- Interpolates between characters



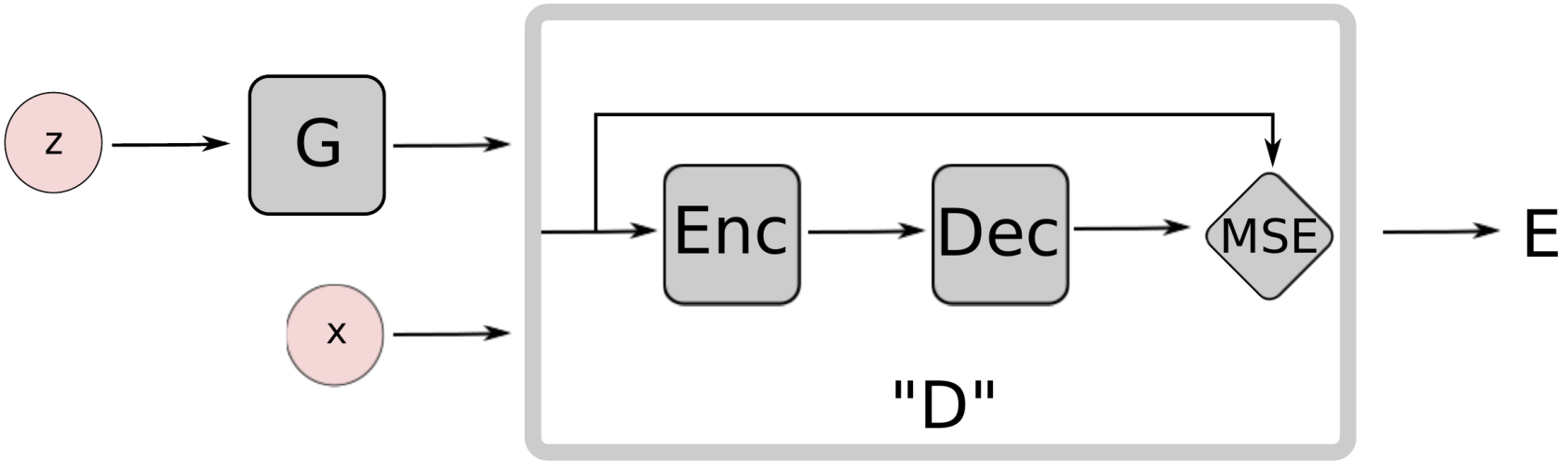
Face Algebra (in DCGAN space)

- DCGAN: adversarial training to generate images.
  - [Radford, Metz, Chintala 2015]



Energy-Based GAN [Zhao, Mathieu, LeCun: arXiv:1609.03.126]

- **Architecture: discriminator is an auto-encoder**



- **Loss functions**

$$f_D(x,z) = D(x) + [m - D\big(G(z)\big)]^+$$
$$= \|Dec\big(Enc(x)\big) - x\| + [m - \|Dec\Big(Enc\big(G(z)\big)\Big) - G(z)\|]^+,$$

$$f_G(z) = \|D\big(G(z)\big)\|$$
$$= \|Dec\Big(Enc\big(G(z)\big)\Big) - G(z)\|$$

EBGAN solutions are Nash Equilibria

- **Loss functions for Discriminator and Generator**

$$\mathcal{L}_D(x,z) = D(x) + [m - D\big(G(z)\big)]^+$$

$$\mathcal{L}_G(z) = D\big(G(z)\big)$$

- **Nash Equilibrium**

We define $V(G,D) = \int_{x,z} \mathcal{L}_D(x,z) p_{data}(x) p_z(z) \mathrm{d}x\mathrm{d}z$ and $U(G,D) = \int_z \mathcal{L}_G(z) p_z(z) \mathrm{d}z$.

$$V(G^*,D^*) \leq V(G^*,D) \qquad \forall D$$

$$U(G^*,D^*) \leq U(G,D^*) \qquad \forall G$$

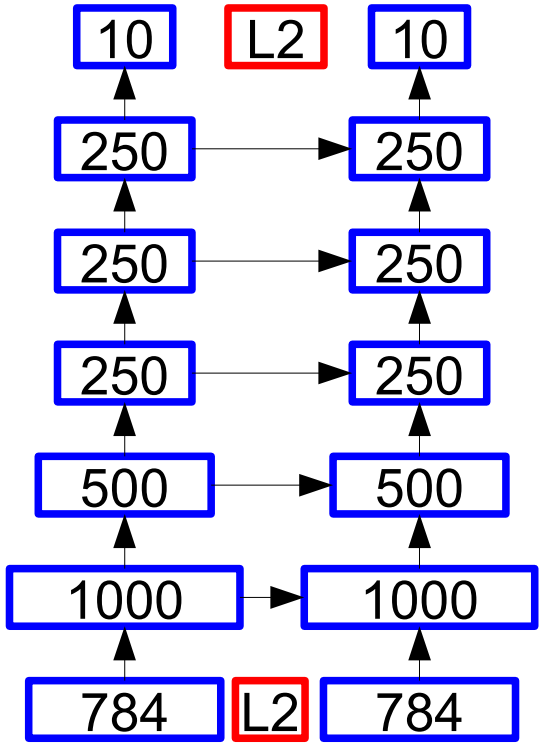
Theorem 1. *If (D^*, G^*) is a Nash equilibrium of the system, then $p_{G^*} = p_{data}$ almost everywhere, and $V(D^*, G^*) = m$.*

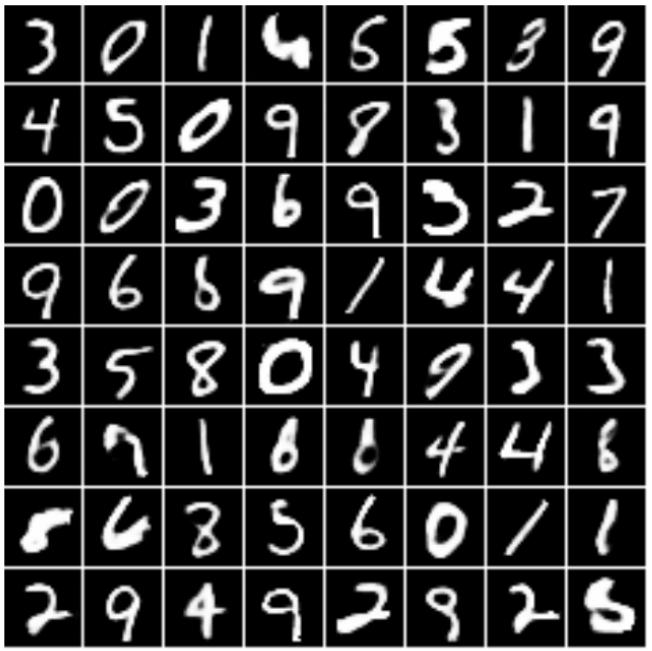
Theorem 2. *Nash equilibrium of this system exists and is characterized by (a) $p_{G^*} = p_{data}$ (almost everywhere) and (b) there exists a constant $\gamma \in [0, m]$ such that $D^*(x) = \gamma$ (almost everywhere).*[1]

EBGAN in which D is a Ladder Network

- **Ladder Network: auto-encoder with skip connections [Rasmus et al 2015]**
- **Permutation-invariant MNIST (fully connected nets)**

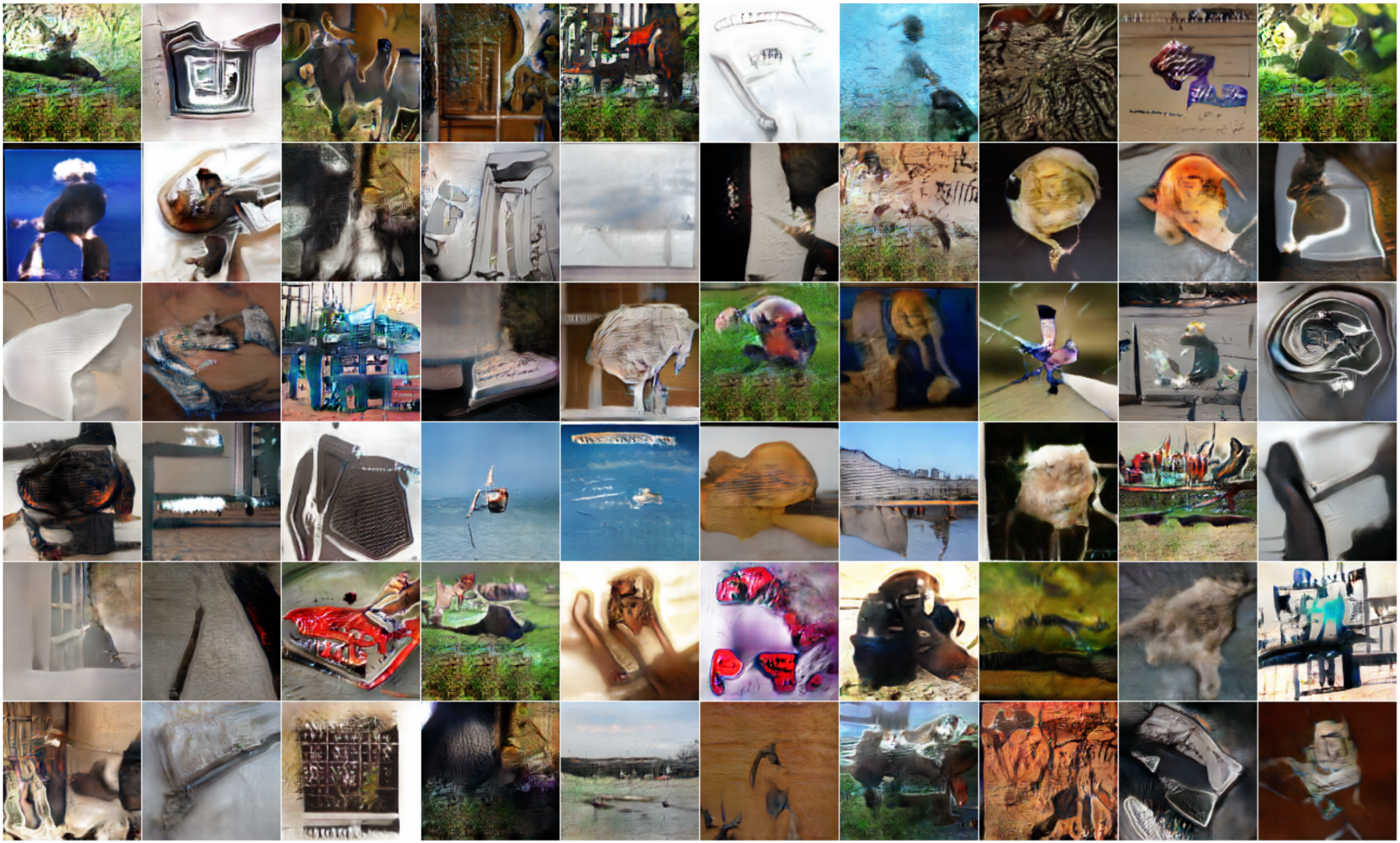
model	100	200	1000
LN bottom-layer-cost, reported in Pezeshki et al. (2015)	1.69±0.18	-	1.05±0.02
LN bottom-layer-cost, reported in Rasmus et al. (2015)	1.09±0.32	-	0.90±0.05
LN bottom-layer-cost, reproduced in this work (see appendix D)	1.36±0.21	1.24±0.09	1.04±0.06
LN bottom-layer-cost within EBGAN framework	**1.04±0.12**	**0.99±0.12**	**0.89±0.04**
Relative percentage improvement	23.5%	20.2%	14.4%





Energy-Based GAN trained on ImageNet at 128x128 pixels

Y LeCun



Energy-Based GAN trained on ImageNet at 256x256 pixels

Y LeCun

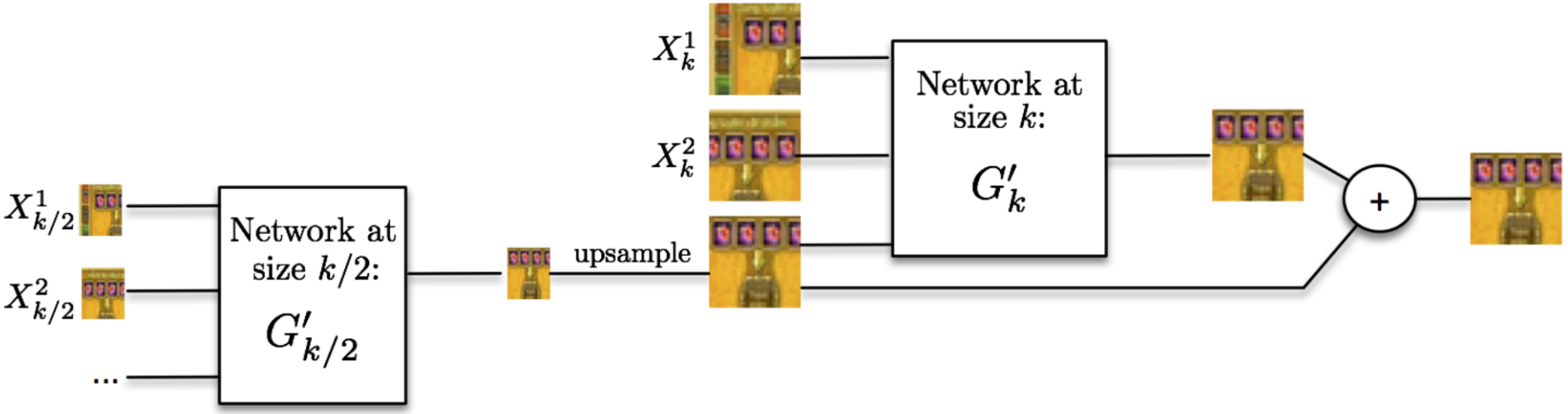
- Trained on dogs


Video Prediction
(with adversarial training)
[Mathieu, Couprie, LeCun ICLR 2016]
arXiv:1511:05440

Multi-Scale ConvNet for Video Prediction

- 4 to 8 frames input → ConvNet → 1 to 8 frames output
- Multi-scale ConvNet, without pooling
- If trained with least square: blurry output

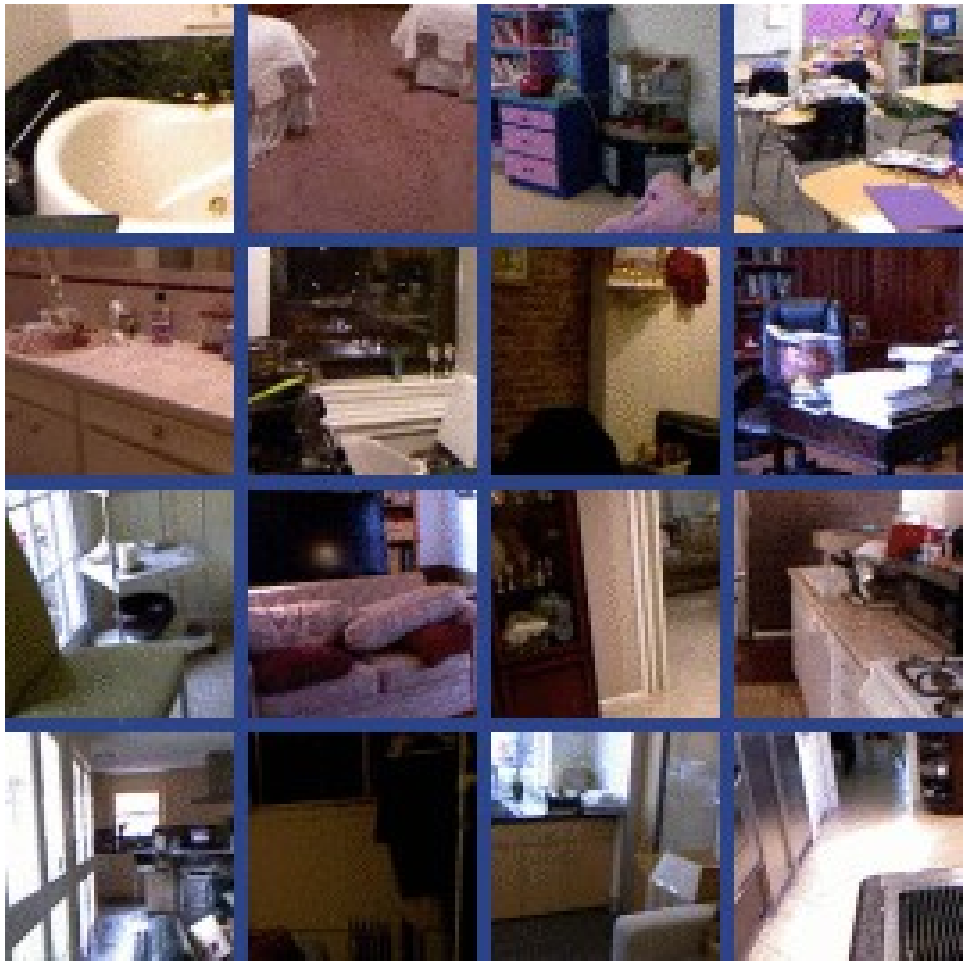
Predictor (multiscale ConvNet Encoder-Decoder)



Predictive Unsupervised Learning

- Our brains are "prediction machines"
- Can we train machines to predict the future?
- Some success with "adversarial training"
  - [Mathieu, Couprie, LeCun arXiv:1511:05440]
- But we are far from a complete solution.

Video Prediction: predicting 5 frames



Video Prediction: predicting 5 frames

Video Prediction: predicting 50 frames