



NEW YORK UNIVERSITY

# The Future of AI + Odds and Ends

Yann LeCun

NYU - Courant Institute & Center for Data Science

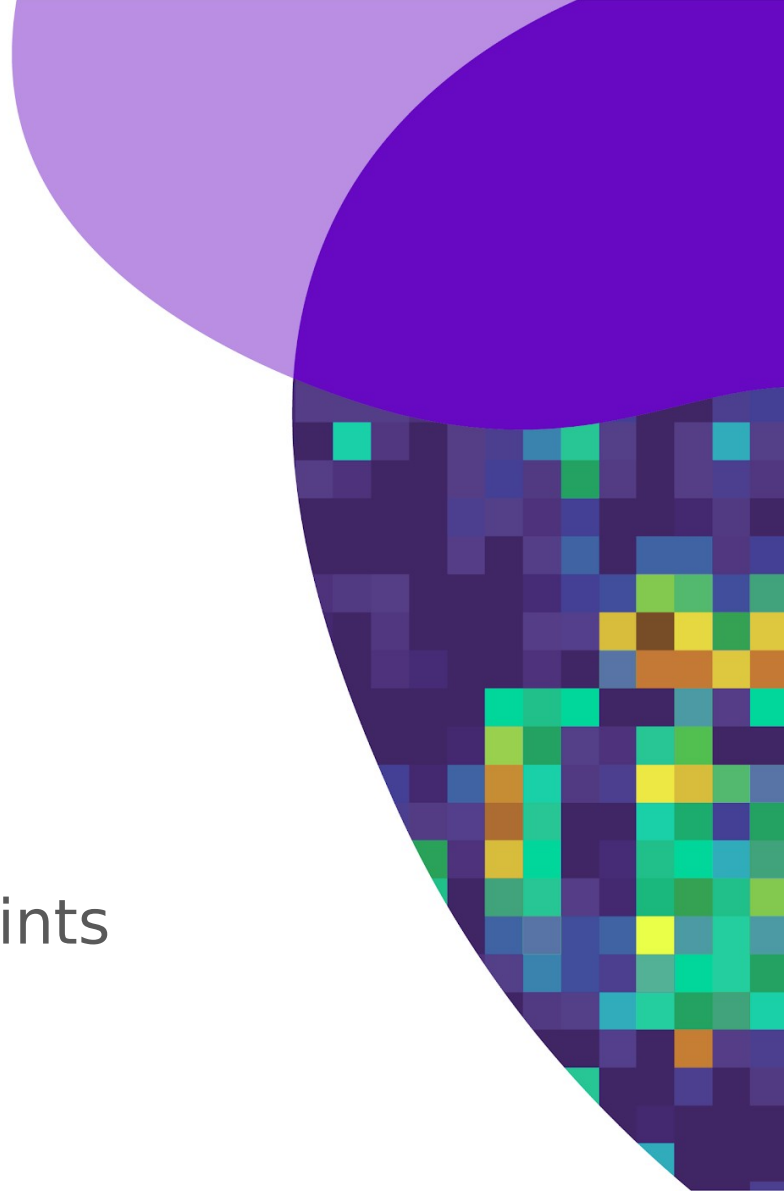
Facebook AI Research

<http://yann.lecun.com>

Deep Learning, NYU, Fall 2021

# Backprop as Lagrangian Optimization

Optimization under constraints



# Reformulating Deep Learning

## ► Loss

$$L(x, y, w) = C(z_K, y) \text{ such that } z_{k+1} = g_k(z_k, w_k), \quad z_0 = x$$

## ► Lagrangian for optimization under constraints

$$L(x, y, z, \lambda, w) = C(z_K, y) + \sum_{k=0}^{K-1} \lambda_k^T (z_{k+1} - g_k(z_k, w_k))$$

## ► Optimality conditions:

$$\frac{\partial L(x, y, z, \lambda, w)}{\partial z_k} = 0, \quad \frac{\partial L(x, y, z, \lambda, w)}{\partial \lambda_k} = 0, \quad \frac{\partial L(x, y, z, \lambda, w)}{\partial w_k} = 0$$

# Reformulating Deep Learning

$$\frac{\partial L(x, y, z, \lambda, w)}{\partial \lambda_k} = z_{k+1} - g_k(z_k, w_k) = 0 \implies z_{k+1} = g_k(z_k, w_k)$$

$$\frac{\partial L(x, y, z, \lambda, w)}{\partial z_k} = \lambda_{k-1}^T - \lambda_k^T \frac{\partial g_{k-1}(z_{k-1}, w_{k-1})}{\partial z_k} = 0 \implies$$

► **Backprop!**

► Lambda is the gradient

$$\lambda_{k-1} = \frac{\partial g_{k-1}(z_{k-1}, w_{k-1})}{\partial z_k}^T \lambda_k$$

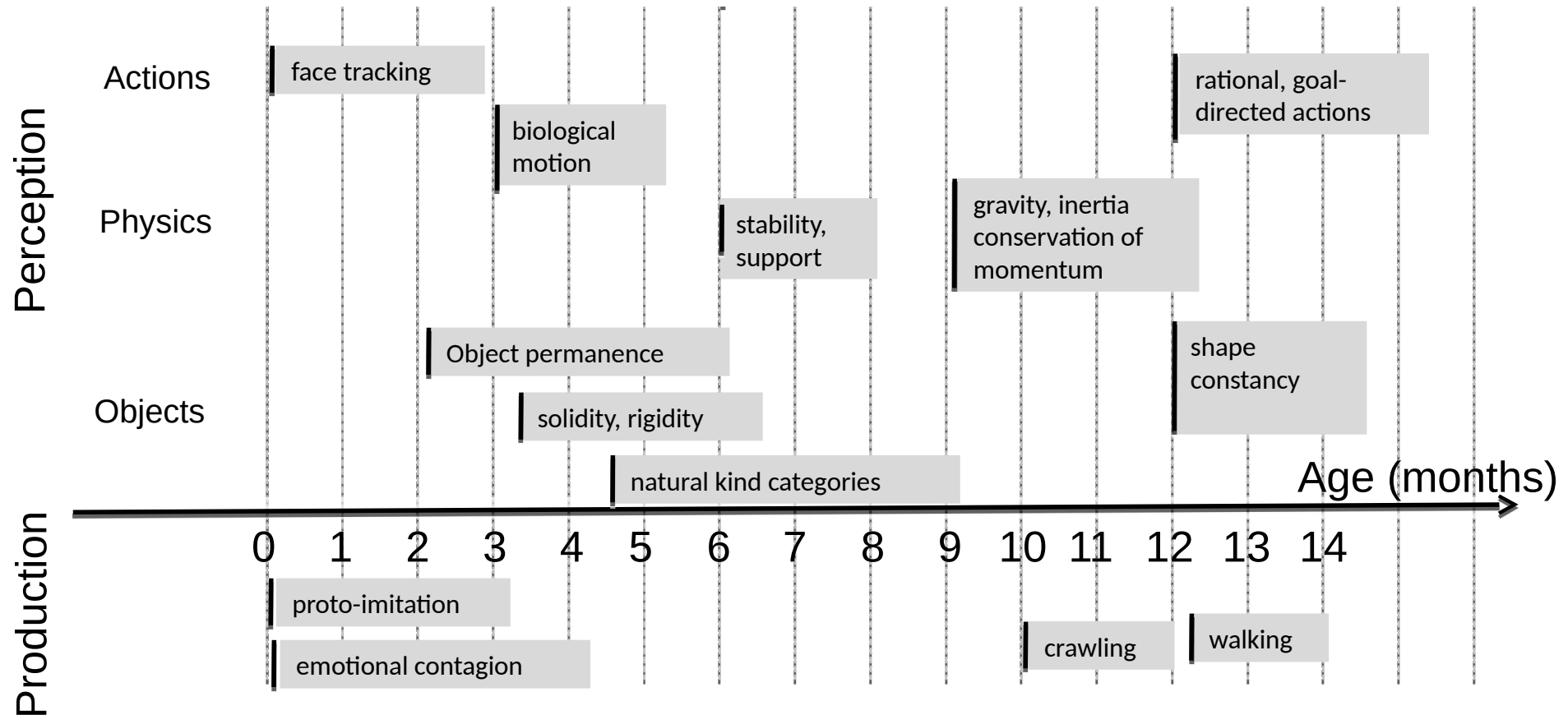
$$\frac{\partial L(x, y, z, \lambda, w)}{\partial w_k} = \lambda_{k+1}^T \frac{\partial g_k(z_k, w_k)}{\partial w_k}$$

# How do humans and animals learn so quickly?

Not supervised.  
Not Reinforced.



# When infants learn models of the world [after Emmanuel Dupoux]



# How do Human and Animal Babies Learn?

- ▶ How do they learn how the world works?
- ▶ Largely by **observation**, with remarkably little interaction (initially).
- ▶ They accumulate enormous amounts of **background knowledge**
  - ▶ About the structure of the world, like intuitive physics.
- ▶ Perhaps **common sense** emerges from this knowledge?



Photos courtesy of  
Emmanuel Dupoux

# From Jitendra Malik's talk

AI systems need to build “mental models”



If the organism carries a ‘small-scale model’ of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and the future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it (Craik, 1943, Ch. 5, p.61)

Commonsense is not just facts, it is a collection of models



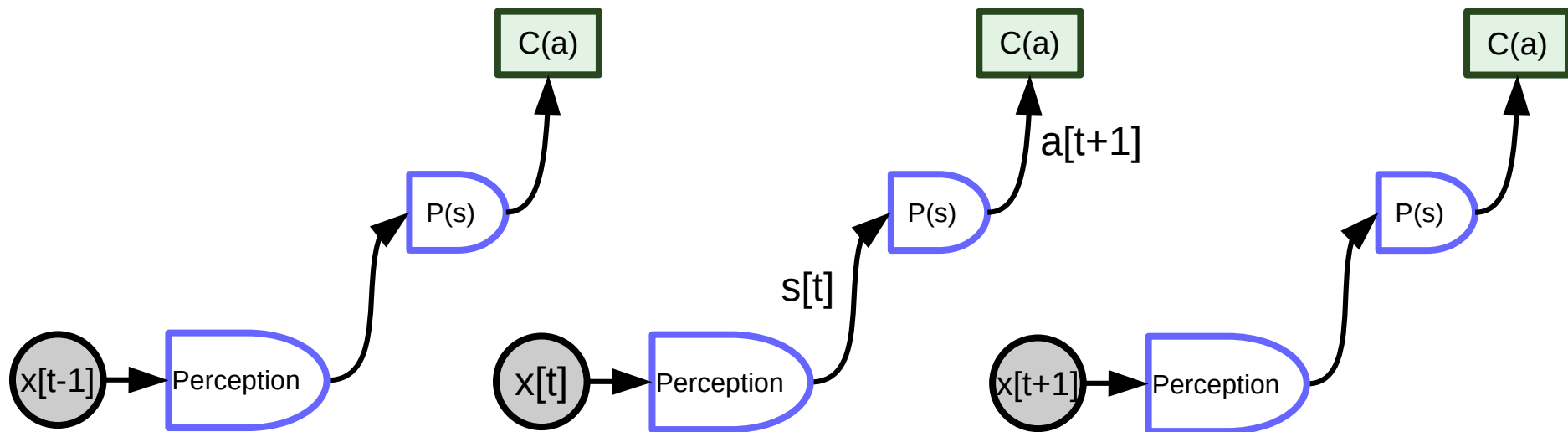


# DL & Control

Learning predictive forward models

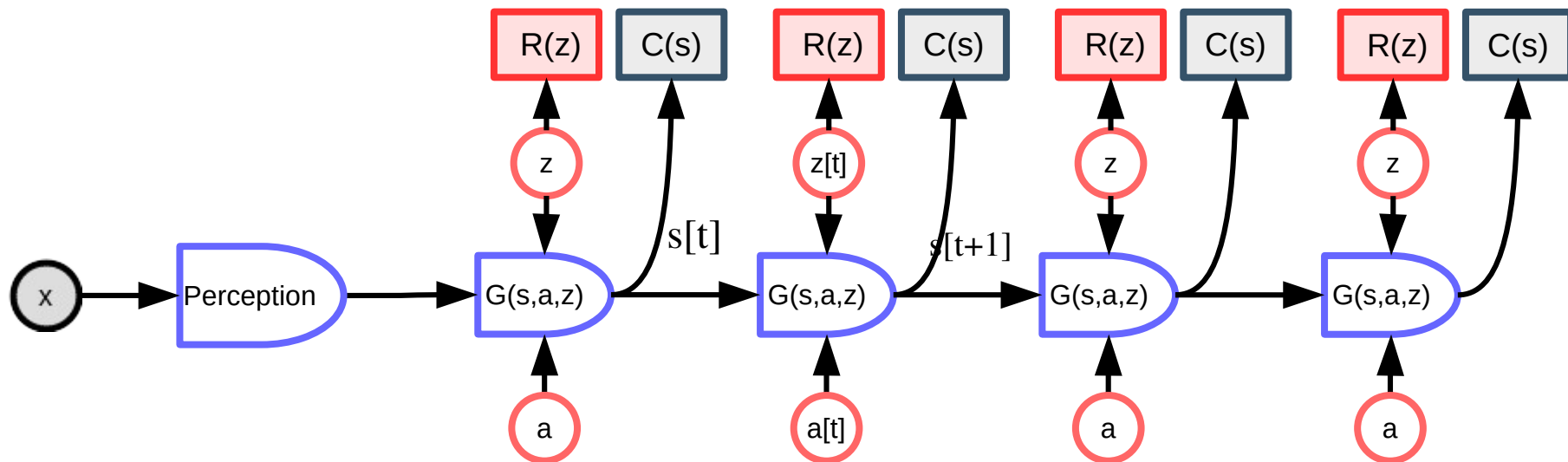
# Model-free RL: $C(s,a)$ is the world (not differentiable)

- ▶ **Cost/Energy:**  $C(a[t])$  is the real world: not differentiable
- ▶ **Policy:**  $a[t] = P(s[t])$



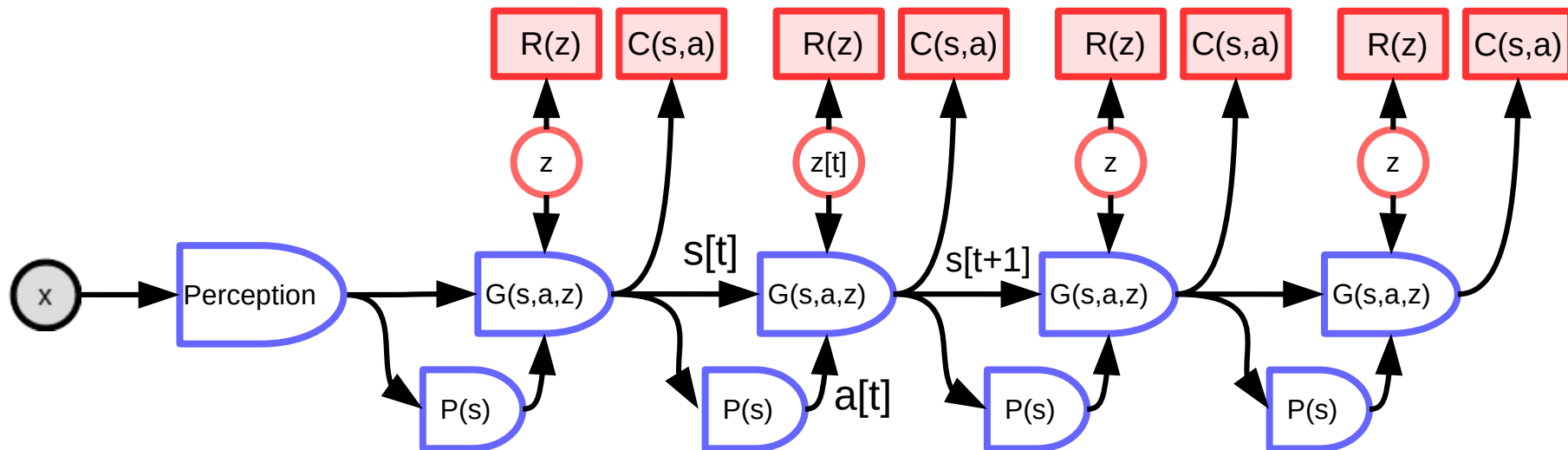
# Model-Based RL: $C(s)$ is the non-differentiable world

- ▶ Forward model:  $s[t+1] = G(s[t], a[t], z[t])$
- ▶ Latent variable  $z$  sampled from  $q(z)$  proportional to  $\exp(-R(z))$
- ▶ Optimize  $(a[1], a[2], \dots, a[T]) = \operatorname{argmin} \sum_t C(s[t])$   
through backprop (== Kelley-Bryson adjoint state method)



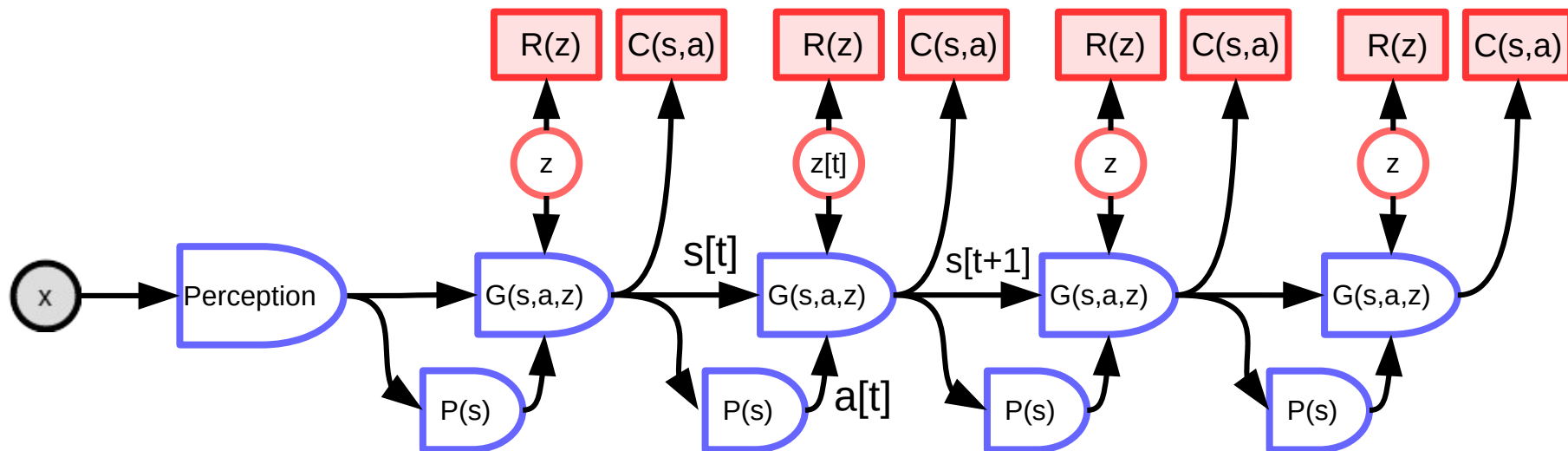
# Model-Based RL

- ▶ Forward model:  $s[t+1] = G(s[t], a[t], z[t])$
- ▶ Cost/Energy:  $f[t] = C(s[t], a[t])$
- ▶ Latent variable  $z$  sampled from  $q(z)$  proportional to  $\exp(-R(z))$
- ▶ Policy:  $a[t] = P(s[t])$



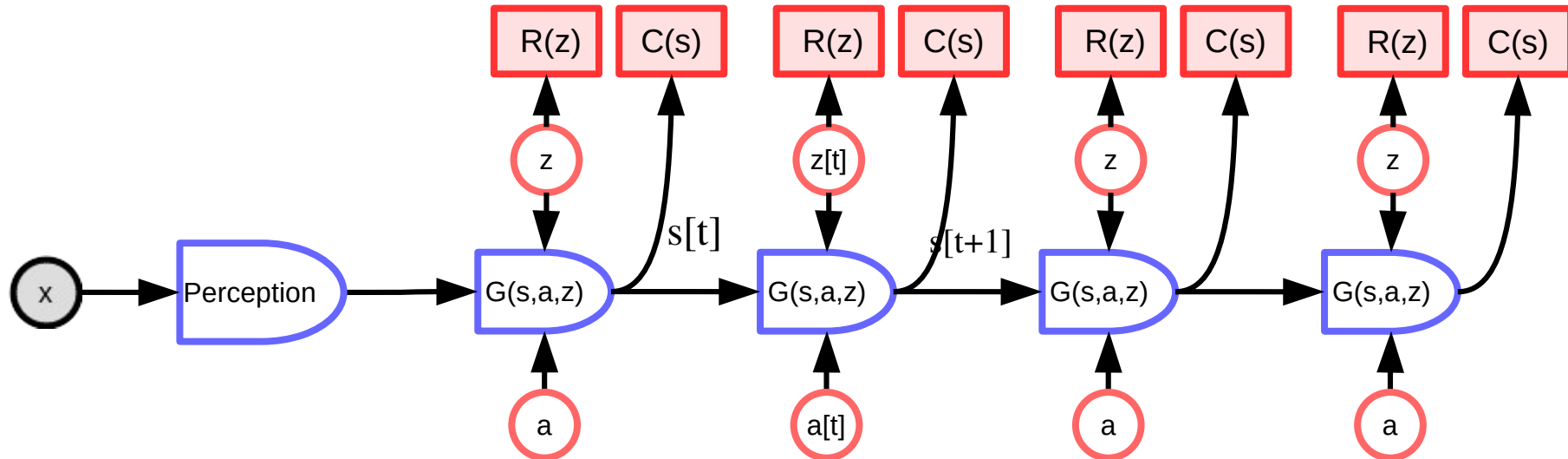
# Model-Based Policy Learning with Intrinsic Objective

- ▶ Forward model:  $s[t+1] = G(s[t], a[t], z[t])$
- ▶ Cost/Energy:  $f[t] = C(s[t], a[t])$  , differentiable!
- ▶ Latent variable  $z$  sampled from  $q(z)$  proportional to  $\exp(-R(z))$
- ▶ Policy:  $a[t] = P(s[t])$



# Model Predictive Control

- ▶ Forward model:  $s[t+1] = G(s[t], a[t], z[t])$
- ▶ Cost/Energy:  $f[t] = C(s[t])$
- ▶ Latent variable  $z$  sampled from  $q(z)$  proportional to  $\exp(-R(z))$
- ▶ Optimize  $(a[1], a[2], \dots, a[T]) = \operatorname{argmin} \sum_t C(s[t])$

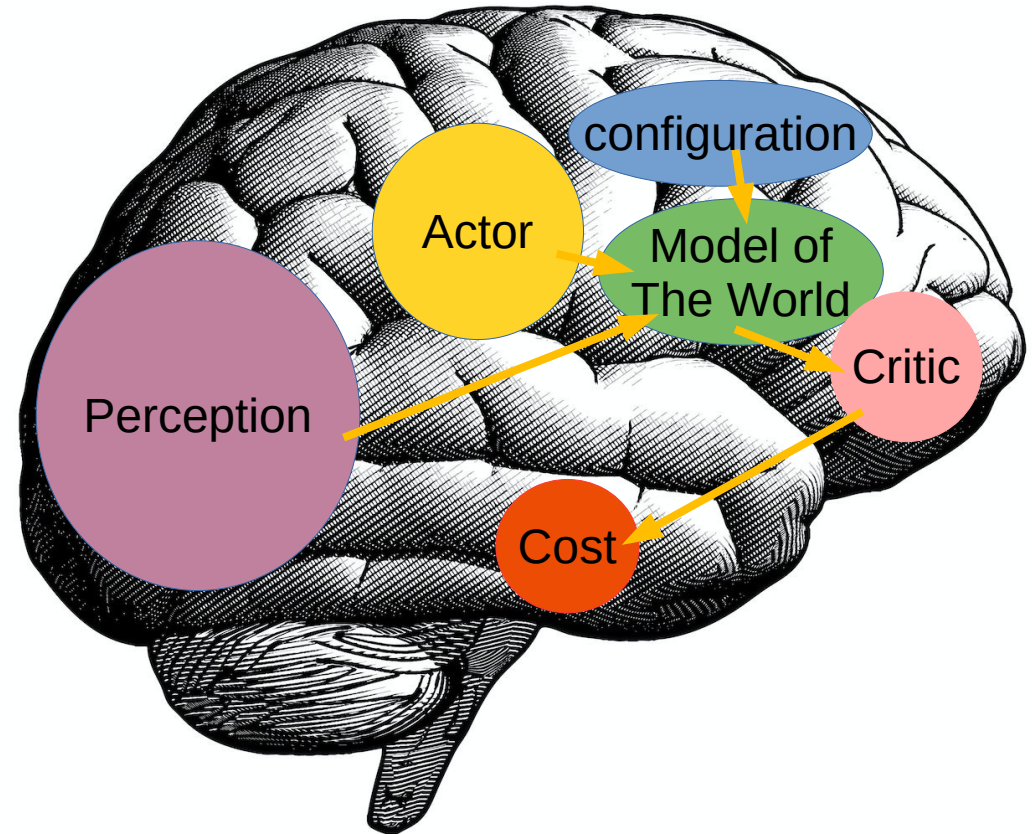


# conclusions

- ▶ **SSL is the future**
  - ▶ Learning hierarchical features in a task-invariant way
  - ▶ Plenty of data, **massive** networks
  - ▶ Learning Forward Models for Model-Based Control
  - ▶ Challenge: handling uncertainty in the prediction: energy-based models
- ▶ **Reasoning/planning through energy minimization**
  - ▶ Energy-Based Models with latent variables
  - ▶ Replace symbols by vectors and logic by continuous functions.
- ▶ **Learning hierarchical representations of action plans**
  - ▶ No idea how to do that!
- ▶ **There is no such thing as AGI.** Intelligence is always specialized.
- ▶ We should talk about rat-level, cat-level, or **human-level AI (HLAI)**.

# Speculation: Architecture for Autonomous Intelligence

- ▶ **World Model**: predicts future states
  - ▶ **Critic**: predicts expected objective
  - ▶ **Cost**: computes objective
  - ▶ **Perception**: estimates world state
  - ▶ **Actor**: computes action
- 
- ▶ Humans only have one world model engine!
- 
- ▶ **Configurator**: configures the world model engine for the situation at hand.
    - ▶ Is this what consciousness is?





# Speculations

- ▶ **Self-Supervised Learning** is the future of AI / ML
- ▶ **Models of the world:** Machines need to learn them (through SSL)
  - ▶ Perhaps common sense will emerge from learning world models
- ▶ **Emotions** are (often) anticipations of outcomes
  - ▶ According to predictions from the model of the world
- ▶ **Reasoning** is finding actions that optimize outcomes
  - ▶ Constraint satisfaction/cost minimization rather than logic
- ▶ **Consciousness** may be the deliberate configuration of our world model?
  - ▶ We only have one (configurable) model of the world
  - ▶ If our brains had infinite capacity, we would not need consciousness
- ▶ **There is no such thing as AGI.** Intelligence is always specialized.
  - ▶ We should talk about rat-level, cat-level, or **human-level AI** (HLAI).