Reinforcement Learning

6. Direct Policy Search

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Credit: Jan Peters's slides (ICML 2015)
Marc Deisenroth's slides (MLSS 2013)

Overview

Position of the problem

Notations

- State space $\mathcal{S}$
- Action space $\mathcal{A}$
- Transition model $p(s, a, s') \mapsto [0, 1]$
- Reward $r(s)$ bounded

Mainstream RL: based on values

$$V^* : \mathcal{S} \mapsto \mathbf{R} \qquad \pi^*(s) = \underset{a \in \mathcal{A}}{arg\ opt}\left(\sum_{s'} p(s, a, s') V^*(s')\right)$$

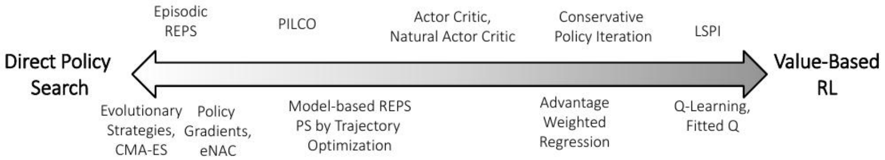
$$Q^* : \mathcal{S} \times \mathcal{A} \mapsto \mathbf{R} \qquad \pi^*(s) = \underset{a \in \mathcal{A}}{arg\ opt}\left(Q^*(s, a)\right)$$

What we want

$$\pi : \mathcal{S} \mapsto \mathcal{A}$$

Aren't we learning something more complex than needed ?...
$\Rightarrow$ Let us consider Direct policy search

From RL to Direct Policy Search



Direct policy search: define

- Search space (representation of solutions)
- Optimization criterion
- Optimization algorithm

Representation

1.Explicit representation ≡ Policy space

π is represented as a function from $\mathcal{S}$ onto $\mathcal{A}$

- Non-parametric representation, e.g. decision tree or random forest
- Parametric representation. Given a function space, π is defined by a vector of parameters θ.

$$\pi_\theta = \begin{cases} \text{Linear function on } \mathcal{S} \\ \text{Radius-based function on } \mathcal{S} \\ \text{(deep) Neural net} \end{cases}$$

E.g. in the linear function case, given $s \in \mathcal{S} = \mathbf{R}^d$ and θ in $\mathbf{R}^d$,

$$\pi_\theta(s) = \langle s, \theta \rangle$$

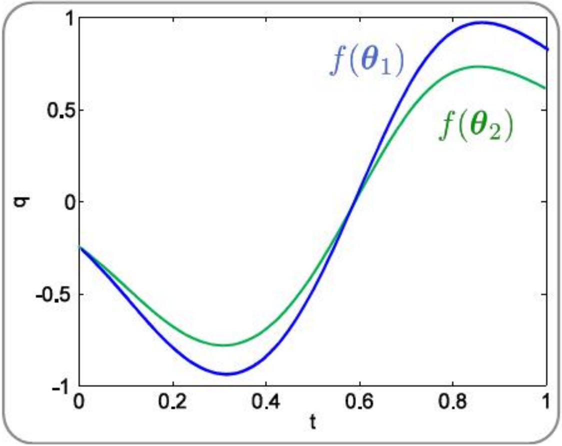
Representation

2. Implicit representation: for example Trajectory generators

$\pi(s)$ is obtained by solving an auxiliary problem. For instance,

- Define desired trajectories
- Trajectory $\tau = f(\theta)$
- Action = getting back to the trajectory given the current state s

Dynamic movement primitives



Direct policy search in RL

Two approaches

- Model-free approaches
- Model-based approaches

History

- Model-free approaches were the first ones; they work well but i) require many examples; ii) these examples must be used in a smart way.
- Model-based approaches are more recent. They proceed by i) modelling the MDP from examples (this learning step has to be smart); ii) using the model as if it were a simulator.
  Important points: the model must give a prediction **and** a confidence interval (will be very important for the exploration).

Overview

The model-free approach

Algorithm

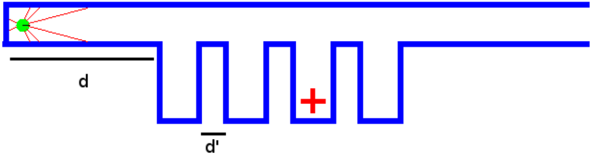
1. Explore: Generate trajectories $\tau_i = (s_{i,t}, a_{i,t})_{t=1}^{T}$ after π_{θ_k}
2. Evaluate:
   - Compute quality of trajectories — Episode-based
   - Compute quality of (state-action) pairs — Step-based
3. Update: compute θ_{k+1}

Two modes

- Episode-based
  - learn a distribution $\mathcal{D}_k$ over Θ
  - draw θ after $\mathcal{D}_k$, generate trajectory, measure its quality
  - bias $\mathcal{D}_k$ toward the high quality regions in Θ space
- Step-based
  - draw a_t from $\pi(s_t, \theta_k)$
  - measure $q_\theta(s, a)$ from the cumulative reward gathered after having visited (s, a)

Model-free Episode-based DPS. PROS

Getting rid of Markovian assumption



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Model-free Episode-based DPS. PROS

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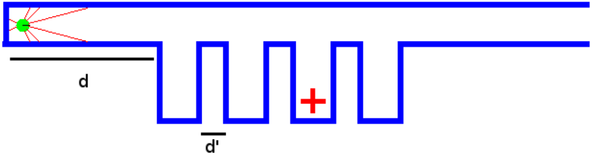

- Rover on Mars: take a picture of region 1, region 2, ...

PROS, 2

Hopes of scalability

- With respect to continuous state space
- No divergence even under function approximation

Tackling more ambitious goals

also see Evolutionary RL

- Partial observability does not hurt convergence (though increases computational cost)
- Optimize controller (software) and also morphology of the robot (hardware);
- Possibly consider co-operation of several robots...

Model-free Episode-based DPS. CONS

Lost the global optimum properties

- Not a well-posed optimization problem in general
- Lost the Bellman equation $\Rightarrow$ larger variance of solutions

A noisy optimization problem

- Policy $\pi \rightarrow$ a distribution over the trajectories (depending on starting point, on noise in the environment, sensors, actuators...)
- $V(\theta) =_{def} \mathbf{E}\left[\sum_t \gamma^t r_{t+1} | \theta\right]$ or

$$V(\theta) =_{def} \mathbf{E}_\theta \left[J(\text{ trajectory })\right]$$

- In practice

$$V(\theta) \approx \frac{1}{K} \sum_{i=1}^{K} J(\text{ trajectory }_i)$$

How many trajectories are needed ?

Requires tons of examples

CONS, 2

The in-situ *vs* in-silico dilemma

- In-situ: launch the robot in the real-life and observe what happens
- In-silico: use a simulator
    - But is the simulator realistic ???

The exploration *vs* exploitation dilemma

- For generating the new trajectories
- For updating the current solution θ

$$\theta_{t+1} = \theta_t - \alpha_t \nabla V(\theta)$$

Very sensitive to the learning rate α_t.

Overview

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2. Direct policy search in RL
   - The model-free approach
     - Gradient-based approaches
     - Distribution-based approaches
     - Exponentially weighted approaches
   - The model-based approach
3. Evolutionary Robotics
   - Search space
   - Objective
   - Evolution of morphology
   - Intrinsic rewards

Cumulative value, gradient

The cumulative discounted value

$$V(s_0) = r(s) + \sum_{t=1} \gamma^t r(s_t)$$

with s_{t+1} next state after s_t for policy π_θ

The gradient

$$\frac{\partial V(s_0,\theta)}{\partial \theta} \approx \frac{V(s_0,\theta+\epsilon) - V(s_0,\theta-\epsilon)}{2\epsilon}$$

- Model $p(s_{t+1}|s_t, a_t, \theta)$ not required but useful
- Laaarge variance ! many samples needed.

A trick

- Using a simulator: Fix the random seed and reset
- No variance of $V(s_0, \theta)$, much smaller variance of its gradient

Average value, gradient

No discount: long term average reward

$$V(s) = \lim_{T \to \infty} \frac{1}{T} \mathbf{E} \left[\sum_t r(s_t) | s_0 = s \right]$$

Assumption: ergodic Markov chain

(After a while, the initial state does not matter).

- $V(s)$ does not depend on s
- One can estimate the percentage of time spent in state s

$$q(\theta, s) = Pr_\theta(S = s)$$

Yields another value to optimize

$$V(\theta) = \mathbf{E}_\theta[r(S)] = \sum_s r(s) q(\theta, s)$$

Model-free Direct Policy Search.

Algorithm

1. $V(\theta) = \mathbf{E}_\theta[r(S)] = \sum_s r(s)q(\theta, s)$
2. Compute or estimate the gradient $\nabla V(\theta)$
3. $\theta_{t+1} = \theta_t + \alpha_t \nabla V(\theta)$

Computing the derivative (*)

$$\nabla V = \nabla \left(\sum_s r(s)q(\theta, s) \right) = \sum_s r(s)\nabla q(\theta, s)$$

$$= \mathbf{E}_{S,\theta}\left[r(S)\frac{\nabla q(\theta, S)}{q(\theta, S)} \right]$$

$$= \mathbf{E}_{S,\theta}\left[r(S)\nabla log\, q(\theta, S) \right]$$

Unbiased estimate of the gradient ($\widehat{\text{integral}}$ = empirical sum)

$$\hat{\nabla} V = \frac{1}{N}\sum_i r(s_i)\frac{\nabla q(\theta, s_i)}{q(\theta, s_i)}$$

(*) Explanations next slide

Analytical reformulations

Expectation and empirical averages

$$\mathbf{E}[f] = \int f(x)dp(x) = \int f(x)p(x)dx \approx \frac{1}{n}\sum_{i=1}^{n} f(x_i)$$

Expectation under different distributions

$$\int_{p(s)} g(s)ds = \int_S \frac{g(s)}{p(s)}ds$$

Gradients

$$\frac{\nabla q(x)}{q(x)} = \nabla(log(q(x))$$

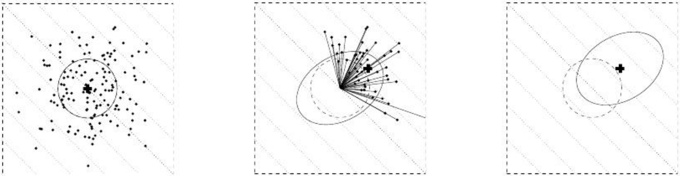
Distribution-based optimization

The Gaussian case

see CMA-ES

$$\theta \sim \mathcal{D}_k = \mathcal{N}(\mu_k, \Sigma_k)$$

- easy to adapt μ_k
- Computationally heavy to adapt Σ_k
- does not scale up to high dimensions (> 200)



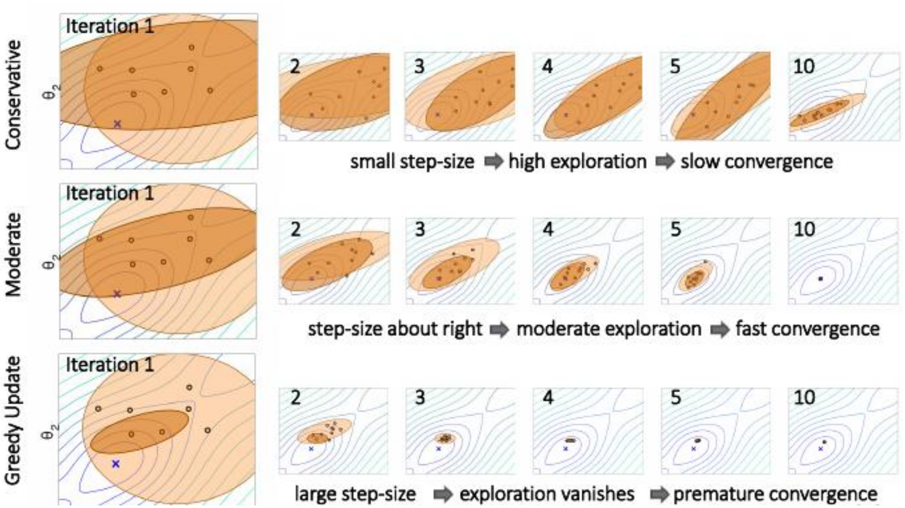
$\boldsymbol{y}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{C})\,,\ \mathbf{C} = \mathbf{I}$
$\boldsymbol{x}_i = \boldsymbol{m} + \sigma\, \boldsymbol{y}_i,\ \sigma = 1$

$\mathbf{C}_\mu = \frac{1}{\mu} \sum \boldsymbol{y}_{i:\lambda} \boldsymbol{y}_{i:\lambda}^{\mathrm{T}}$
$\mathbf{C} \leftarrow (1-1) \times \mathbf{C} + 1 \times \mathbf{C}_\mu$

$\boldsymbol{m}_{\text{new}} \leftarrow \boldsymbol{m} + \frac{1}{\mu} \sum \boldsymbol{y}_{i:\lambda}$

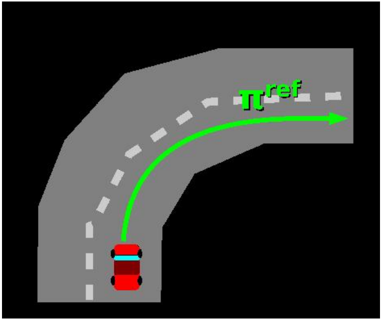
- Invariances under monotonous transform of optimization criterion and affine transf. of Θ.
- A particular case of Information Geometry Optimization

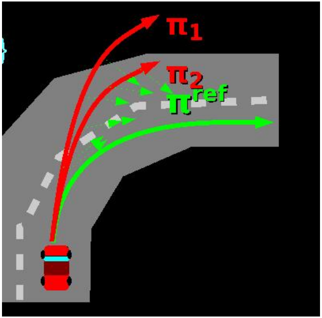
Effects of step size



Danger

Must stay close to the known regions...





In the distribution space

Adapt $\mathcal{D}_k$ *and* stay close to the data distribution

How: add a distance term to the objective

$$\mathcal{F}(\theta) = V(\theta) + KL(\theta \| q)$$

The KL divergence among distributions

$$KL(p||q) = \sum_x p(x) \frac{q(x)}{p(x)}$$

Information-theoretic "distance" among distributions

- Positive

$$KL(p||q) > 0$$

- Identity of indiscernibles

$$KL(p||q) = 0 \Leftrightarrow p = q$$

- Not symmetric (hence not a distance)

$$KL(p||q) \neq KL(q||p)$$

Minimizing $KL(p||q)$

- if $q = 0$ must have $p = 0$ $\rightarrow$ no wild exploration
- KL is minimized, everything else being equal, if entropy(p) maximized $\rightarrow$ enforce exploration

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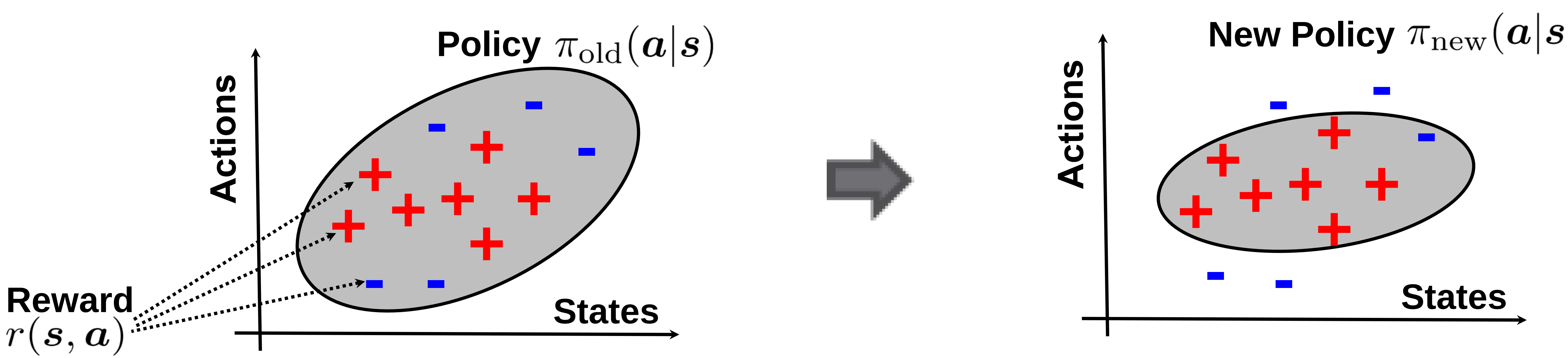
Success Matching Principle

> “When learning from a set of their own trials in iterated decision problems, humans attempt to match **not the best taken action** but the **reward-weighted frequency** of their actions and outcomes” [Arrow, 1958].

Success-Matching: policy reweighting by success probability *f(r)*

$$\pi_{\text{new}}(\boldsymbol{a}|\boldsymbol{s}) \propto f(r(\boldsymbol{s},\boldsymbol{a}))\pi_{\text{old}}(\boldsymbol{a}|\boldsymbol{s})$$



+ Succes (high reward) **- Failure (low reward)**

Principle

$$\pi_{new}(a|s) \propto \text{ Success } (s, a, \theta).\pi_{old}(a|s)$$

Different computation of "Success"

- $\theta \sim \mathcal{D}_k$ generates trajectory, evaluation $V(\theta)$
- Transform evaluation into (non-negative) probability w_k
- Find mixture policy π_{k+1}

$$p(a|s) \propto \sum w_k p(a|s, \theta_k)$$

- Find θ_{k+1} accounting for π_{k+1}
- Update $\mathcal{D}_k$, iterate

Computing the weights

$$w_k = exp\left(\beta(V(\theta) - minV(\theta)\right)$$

β: temperature of optimization simulated annealing

Example

$$= exp\left(10\frac{V(\theta) - minV(\theta)}{maxV(\theta) - minV(\theta)}\right)$$

Updating the distribution

The Gaussian case

$$\mathcal{D}_k = \mathcal{N}(\mu_k, \Sigma_k)$$

Updating the mean

$$\mu_{k+1} = \frac{\sum_i w_{k,i} \theta_{k,i}}{\sum_i w_{k,i}}$$

Updating the covariance

$$\Sigma_{k+1} = \frac{\sum_i w_{k,i} (\theta_{k,i} - \mu).(\theta_{k,i} - \mu)^t)}{\sum_i w_{k,i}}$$

With A^t the transpose of matrix A.

Model-free Direct Policy Search, summary

Algorithm

- Define the criterion to be optimized (cumulative value, average value)
- Define the search space (Θ: parametric representation of π)
- Optimize it: $\theta_k \rightarrow \theta_k + 1$
  - Using gradient approaches
  - Updating a distribution $\mathcal{D}_k$ on Θ
  - In the step-based mode or success matching case:
    find next best $q^*_{k+1}(s, a)$; find θ_{k+1} such that $Q^\pi = q^*_{k+1}$

Pros

- It works

Cons

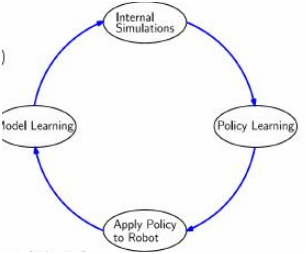
- Requires tons of examples
- Optimization process difficult to tune:
  - Learning rate difficult to adjust
  - Regularization (e.g. using KL divergence) badly needed and difficult to adjust

Overview

Direct Policy Search. The model-based approach

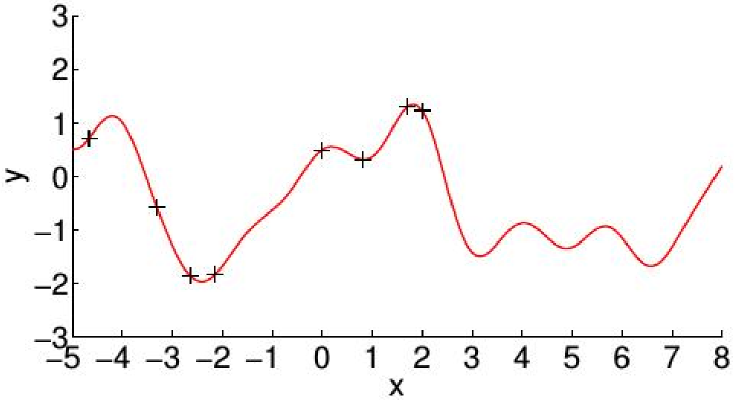
Algorithm

1. Use data $\tau_i = (s_{i,t}, a_{i,t})_{t=1}^{T}$ to learn a forward model $\hat{p}(s'|s,a)$
2. Use the model as a simulator
3. Optimize policy
4. (Use policy on robot and improve the model)



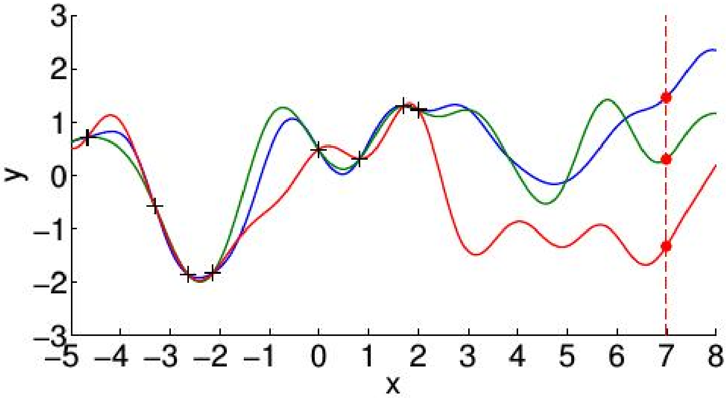
Learning the model

Modeling



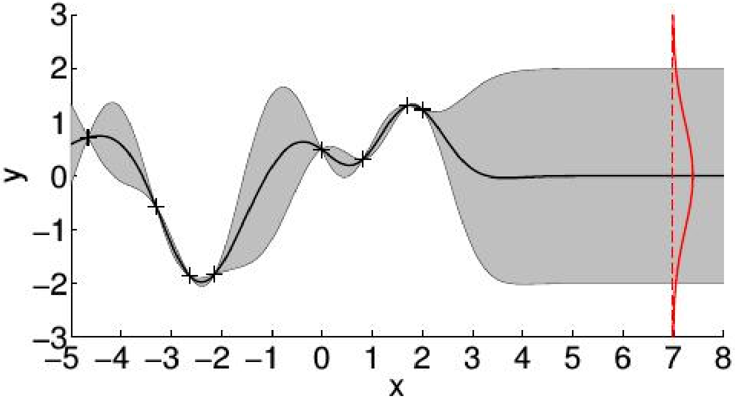
Learning the model

Modeling and predicting



Learning the model

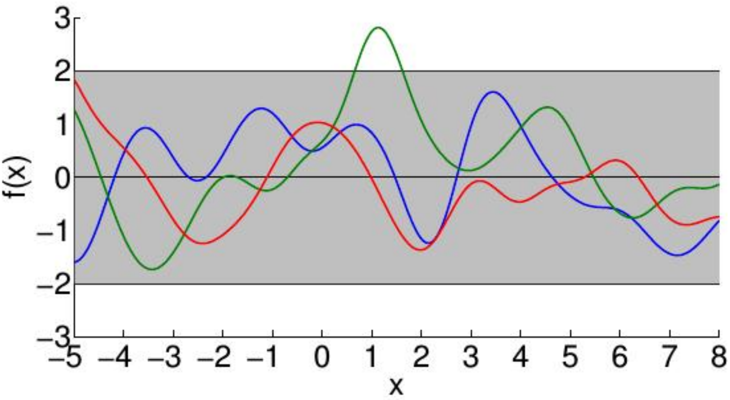
Modeling



When optimizing a model: very useful to have a measure of uncertainty on the prediction

Learning the model, 2

Gaussian Processes http://www.gaussianprocess.org/



Prior belief about the function

Learning the model, 2

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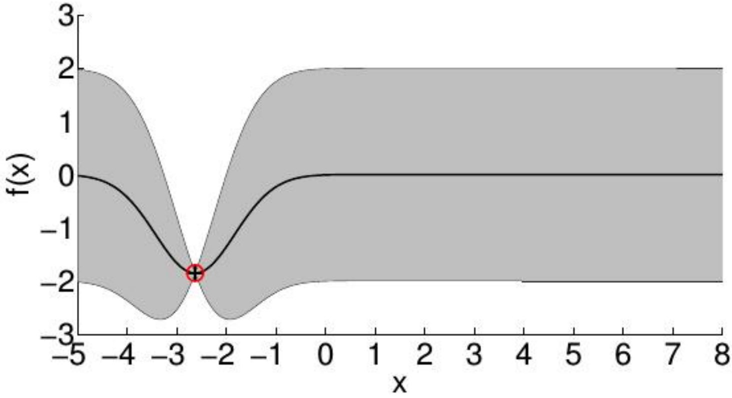

Posterior belief about the function

Learning the model, 2

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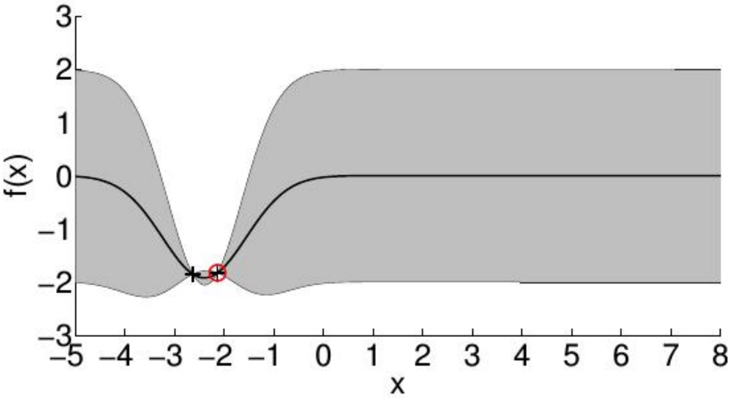

Posterior belief about the function

Learning the model, 2

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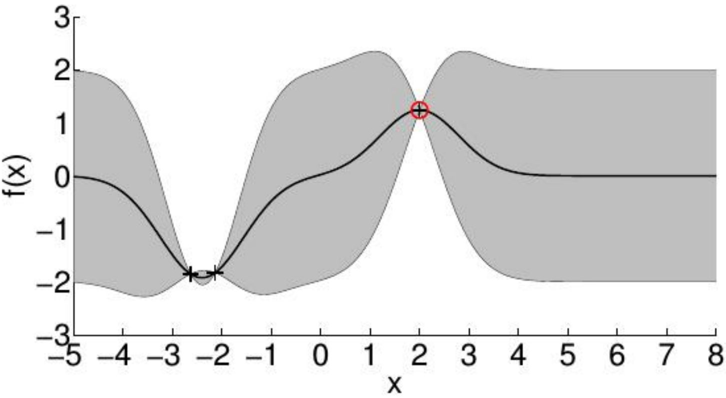

Posterior belief about the function

Learning the model, 2

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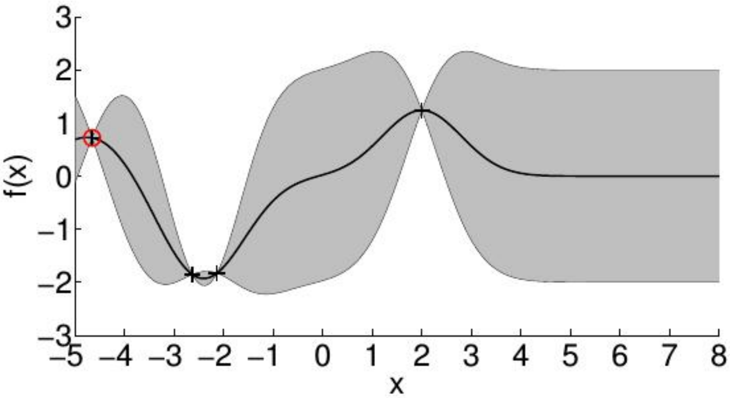

Posterior belief about the function

Learning the model, 2

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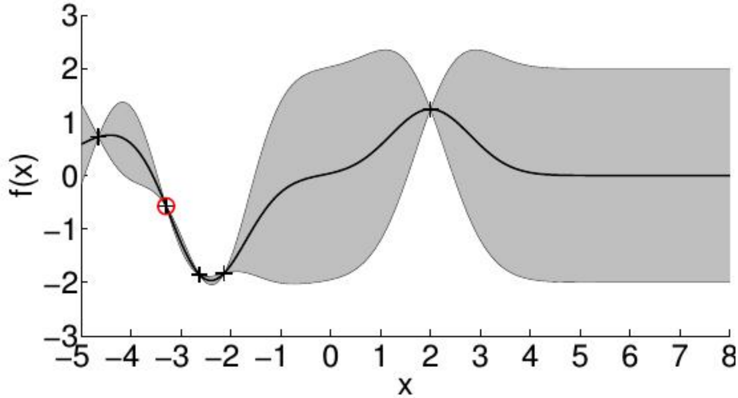

Posterior belief about the function

Learning the model, 2

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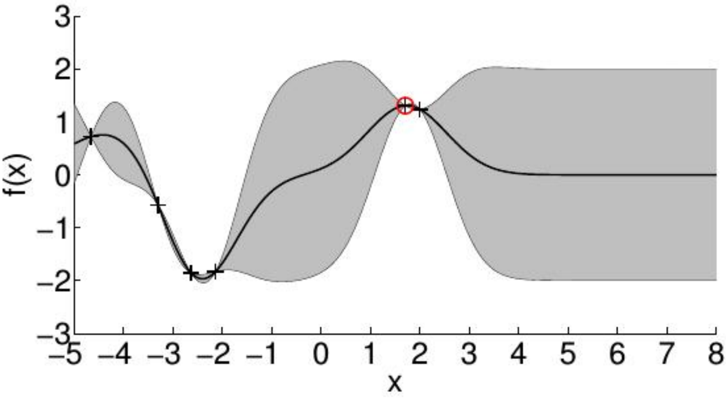

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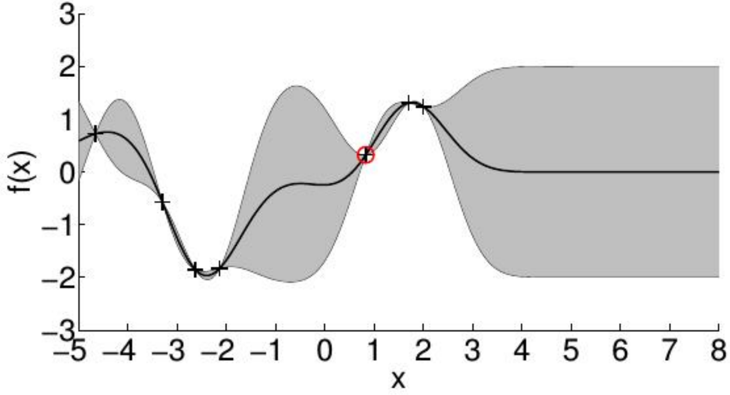

Posterior belief about the function

Learning the model, 2

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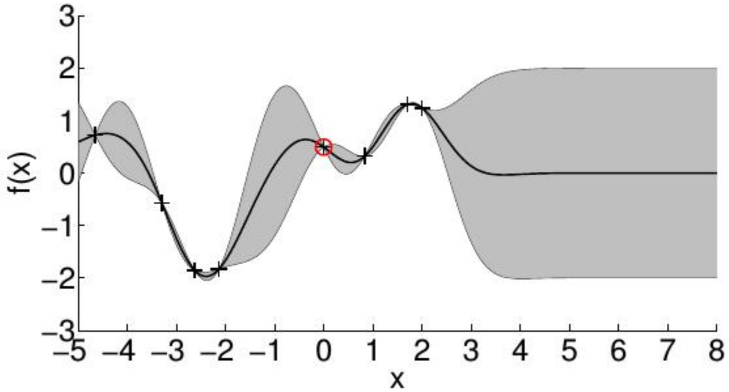

Posterior belief about the function

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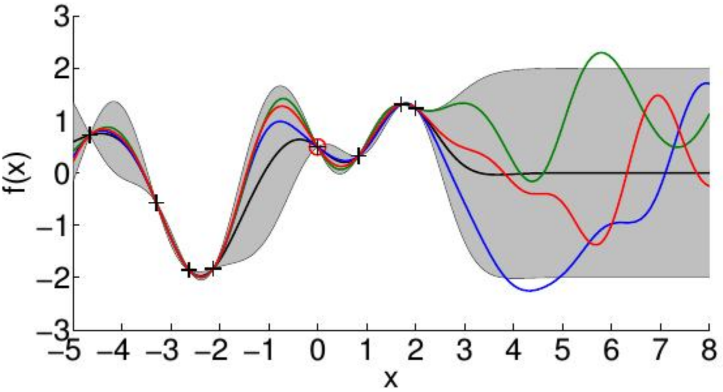


Posterior belief about the function

Computing the gradient

Given

- Forward model

$$s_{t+1} = f(s_t, a_t)$$

- Differentiable policy

$$a = \pi(s_t, \theta)$$

It comes

$$V(\theta) = \sum_t \gamma^t r_{t+1}$$

Exact gradient computation

$$\frac{\partial V(\theta)}{\partial \theta} = \sum_t \gamma^t \frac{\partial r_{t+1}}{\partial \theta}$$

$$= \sum_t \gamma^t \frac{\partial r_{t+1}}{\partial s_{t+1}} . \frac{\partial s_{t+1}}{\partial \theta}$$

$$= \sum_t \gamma^t \frac{\partial r_{t+1}}{\partial s_{t+1}} \left(\frac{\partial s_{t+1}}{\partial s_t} . \frac{\partial s_t}{\partial \theta} + \frac{\partial s_{t+1}}{\partial a_t} . \frac{\partial a_t}{\partial \theta} \right)$$

Model-based Direct Policy Search, summary

Algorithm

- Learn a model (prediction and confidence interval)
- Derive the gradient of the policy return
- Optimize it standard gradient optimization, e.g. BFGS

Pros

- Sample efficient (= does not require tons of examples)
- Fast (standard gradient-based optimization)
- Best ever results on some applications (pendulum on a car, picking up objects, controlling throttle valves)

Cons

- Gaussian processes (modelling also the confidence interval) hardly scale up: in $O(n^3)$, with n the number of examples
- Require specific parametrizations of the policy and the reward function
- Only works if the model is good (otherwise, disaster)

Overview

Evolutionary Robotics

1. Select the search space Θ
2. Define the objective function $\mathcal{F}(\theta)$ in simulation or in-situ
   Sky is the limit: controller; morphology of the robot; co-operation of several robots...
3. Optimize: Evolutionary Computation (EC) and variants
4. Test the found solution reality gap

Search Space, 1

Neural Nets

- Universal approximators; continuity; generalization hoped for.
- Fast computation
- Can include priors in the structure
- Feedforward architecture: reactive policy
- Recurrent architecture: internal state
  encoding memory (fast vanishing)

Critical issues

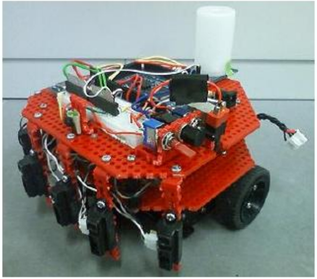
- Find the structure: structured EC much more difficult
- See *NeuroEvolution of Augmented Topology* (NEAT) and HyperNEAT
  Stanley Miikkulainen, 2002

Other options

- Finite state automaton (find states; write rules; optimize thresholds...)
  The Braitenberg controller.
- Genetic programming (optimization of programs)

Example: Swarm robots moving in column formation

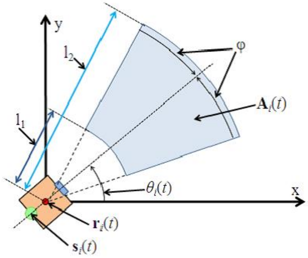
Robot



Robotic swarm, 2

Representation

Constants		
	l1	blind zone
	l2	sensor range
	ϕ	Vision angular range
Variables(t)		
	$r(t), s(t)$	positions
	$\theta(t)$	angular direction



Example of a (almost manual) controller

CONTROLLER OF A ROBOT

Info. from the image sensors	Info. from the IR sensors		
	$0 \leqq x_{\mathrm{IR}} < \beta_0$	$\beta_0 \leqq x_{\mathrm{IR}} < \beta$	$\beta \leqq x_{\mathrm{IR}}$
$0 \leqq x_{\mathrm{image}} \leqq \alpha$	move backward or turn right	turn left	
$\alpha < x_{\mathrm{image}} < (19 - \alpha)$	move backward or turn right	stop	move forward
$\alpha \leqq x_{\mathrm{image}} \leqq 19$	move backward or turn right	turn right	
preceding robot NOT FOUND	move backward or turn right	move forward	

Toward defining $\mathcal{F}$

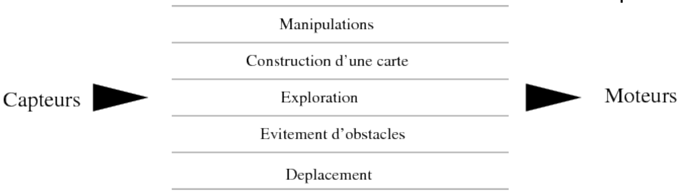
- The i-th robot follows the k-th robot at time t iff the center of gravity of k belongs to the perception range of i ($\mathbf{s}_k(t) \in \mathbf{A}_i(t)$).
- The i-th robot is a leader if i) it does not follow any other robot; ii) there exists at least one robot following it.
- A column is a subset $\{i_1, \ldots i_K\}$ such that robot i_{k+1} follows robot i_k and robot i_1 is a leader.
- A deadlock is a subset $\{i_1, \ldots i_K\}$ such that robot i_{k+1} follows robot i_k and robot i_1 follows robot i_K.

Overview

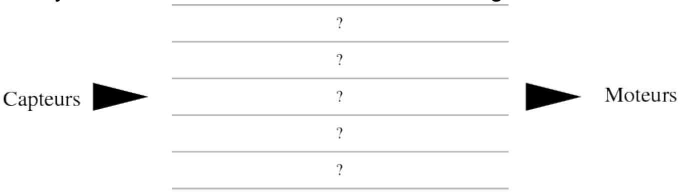
Optimization criterion

The promise: no need to decompose the goal

- Behavioral robotics — hand crafted decomposition

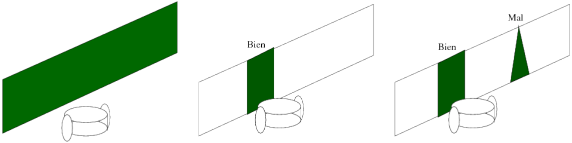


- Evolutionary robotics — emergence of a structure



In practice: bootstrap

- All initial (random) individuals are just incompetent
- Fitness landscape: Needle in the Haystack ? (doesn't work)
- Start with something simple
- Switch to more complex *during evolution*
- Example: visual recognition



Optimization criterion, 2

- Fonctional vs behavioral

  state of controller vs distance walked
- Implicit vs explicit

  Survival vs Distance to socket
- Internal vs external information

  Sensors, ground truth
- Co-evolution: e.g. predator/prey

  performance depends on the other robots

State of art

- Standard: function, explicit, external variables
- In-situ: behavioral, implicit, internal variables
- Interactive: behavioral, explicit, external variables

Optimization criterion, 3

Fitness shaping

- Obstacle avoidance
- Obstacle avoidance, and move !
- Obstacle avoidance, and (non circular) move !!

Finally

Floreano Nolfi 2000

$$\mathcal{F}(\theta) = \int_{T_{exp.}} A(1 - \sqrt{\Delta B})(1 - i)$$

- A sum of wheel speed $r_i \in [-0.5, 0.5]$

→ move

- $\Delta B = |r_1 + r_2|$

→ ahead

- i maximum (normalised) of sensor values

→ obstacle avoidance

Behavioral, internal variables, explicit

Result analysis

- First generations
  - Most rotate
  - Best ones slowly go forward
  - No obstacle avoidance
  - Perf. depends on starting point
- After $\approx$ 20 gen.
  - Obstacle avoidance
  - No rotation
- Thereafter, gradually speed up

Result analysis, 2

- Max. speed 48mm/s (true max = 80)

Inertia, bad sensors

- Never stuck in a corner

contrary to Braitenberg

Going further

- Changing environment
- Changing robotic platform

Limitations

- From simulation to real-world — Reality gap !
- Opportunism of evolution
- Roboticists not impressed...

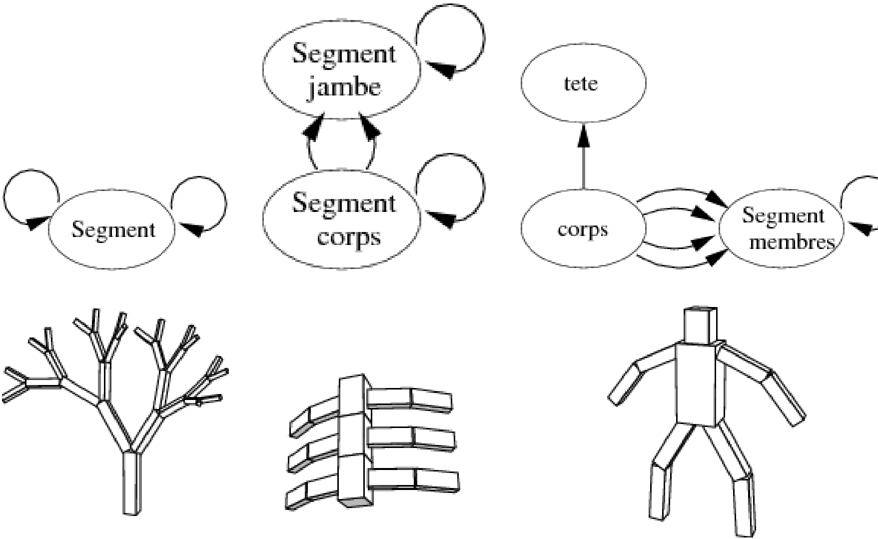
Carl Sims

Goal

- Evolve both morphology and controller
- using a grammar (oriented graph)
- Heavy computational cost

  simulation, several days on Connection Machine – 65000 proc.
- Evolving locomotion (walk, swim, jump)
- and competitive co-evolution (catch an object)

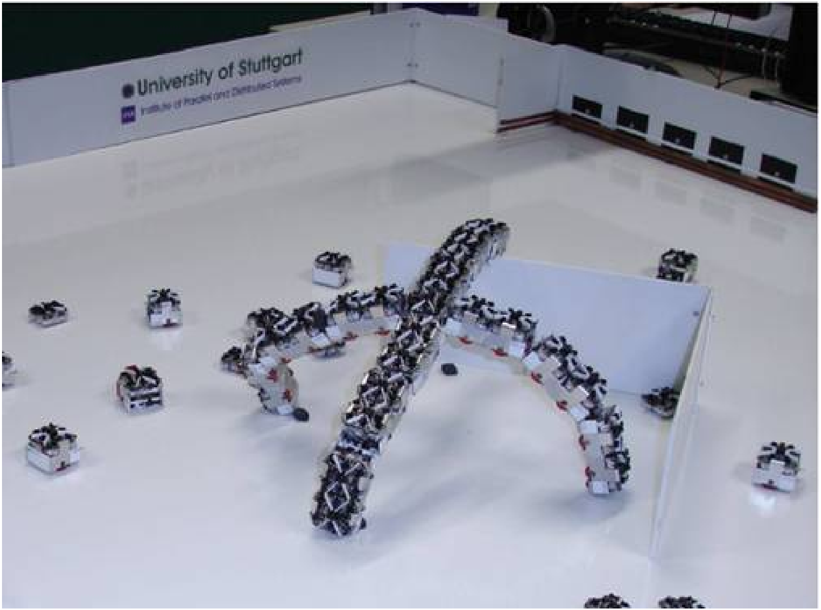
The creatures, Karl Sims



Video: https://www.youtube.com/watch?v=JBgG_VSP7f8

Overview

Context



Internal rewards

Delarboulas et al., PPSN 2010

Requirements

1. No simulation
2. On-board training
   - Frugal (computation, memory)
   - No ground truth
3. Providing "interesting results"

"Human – robot communication"

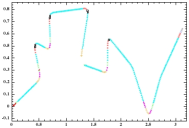
Goal: self-driven Robots : **Defining instincts**

Starting from (almost) nothing

Robot ≡ a data stream

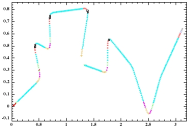
$$t \rightarrow x[t] = (sensor[t], motor[t])$$

Trajectory = $\{x[t], t = 1 \ldots T\}$



Robot trajectory

Starting from (almost) nothing



Robot trajectory

Robot $\equiv$ a data stream

$$t \rightarrow x[t] = (sensor[t], motor[t])$$

Trajectory = $\{x[t], t = 1 \dots T\}$

Computing the quantity of information of the stream
Given $x_1, \dots x_n$, visited with frequency $p_1 \dots p_n$,

$$Entropy(trajectory) = -\sum_{i=1}^{n} p_i \log p_i$$

Conjecture

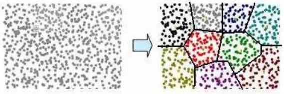
Controller quality $\propto$ Quantity of information of the stream

Building sensori-motor states

Avoiding trivial solutions...
If sensors and motors are continuous / high dimensional

- then all vectors $x[t]$ are different
- then $\forall i, p_i = 1/T$; $Entropy = \log T$

... requires generalization
From the sensori-motor stream
to clusters



Clusters in sensori-motor space ($\mathbb{R}^2$)

sequence of points in $\mathbb{R}^d$
sensori-motor states

Trajectory $\rightarrow$
$x_1 x_2 x_3 x_1 \ldots$

Clustering

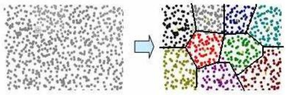
k-Means

1. Draw k points $x[t_i]$
2. Define a partition $\mathcal{C}$ in k subsets C_i — Voronoï cells

$$C_i = \{x / d(x, x[t_i]) < d(x, x[t_j]), j \neq i\}$$

ϵ-Means

1. Init : $\mathcal{C} = \{\}$ — Initial site list
2. For $t = 1$ to T — loop on trajectory
   - If $d(x[t], \mathcal{C}) > \epsilon$, $\mathcal{C} \leftarrow \mathcal{C} \cup \{x[t]\}$



Curiosity Instinct

Search space

- Neural Net, 1 hidden layer.

Definition

- Controller F + environment $\rightarrow$ Trajectory
- Apply Clustering on Trajectory
- For each C_i, compute its frequency p_i

$$\mathcal{F}(F) = -\sum_{i=1}^{n} p_i * \log(p_i)$$

Curiosity instinct: Maximizing Controller IQ

Properties

- Penalizes inaction: a single state → entropy = 0
- Robust w.r.t. sensor noise (outliers count for very little)
- Computable online, on-board (use ϵ-clustering)
- Evolvable onboard

Limitations: does not work if

- Environment too poor
  (in desert, a single state → entropy = 0)
- Environment too rich
  (if all states are distinct, *Fitness*(controller) $= \log T$)

both under and over-stimulation are counter-effective.

From curiosity to discovery

Intuition

- An individual learns sensori-motor states ($x[t_i]$ center of C_i)
- The SMSs can be transmitted to offspring
- giving the offspring an access to “history”
- The offspring can try to “make something different”

fitness(offspring) = Entropy(Trajectory(ancestors $\bigcup$ offspring))

NB: does not require to keep the trajectory of all ancestors.
One only needs to store $\{C_i, n_i\}$

From curiosity to discovery

Cultural evolution transmits genome + "culture"

1. parent = (controller genome, $(C_1, n_1), \ldots (C_K, n_K)$)
2. Perturb parent controller $\rightarrow$ offspring controller
3. Run the offspring controller and record $x[1], \ldots x[T]$
4. Run ϵ-clustering variant.

$$Fitness(offspring) = -\sum_{i=1}^{\ell} p_i \log p_i$$

ϵ-clustering variant

Algorithm

1. Init : $\mathcal{C} = \{(C_1, n_1), \ldots (C_K, n_K))\}$ Initial site list
2. For $t = 1$ to T *loop on trajectory*
   - If $d(x[t], \mathcal{C}) > \epsilon$, $\mathcal{C} \leftarrow \mathcal{C} \cup \{x[t]\}$
3. Define $p_i = n_i / \sum_j n_j$

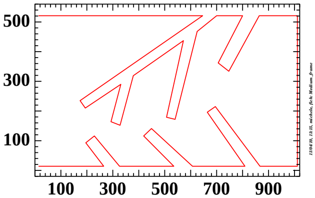
$$Fitness(offspring) = -\sum_{i=1}^{\ell} p_i \log p_i$$

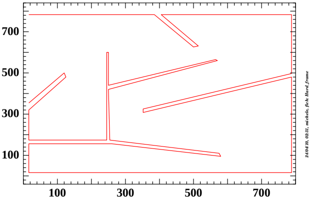
Validation

Experimental setting

Robot = Cortex M3, 8 infra-red sensors, 2 motors.
Controller space = ML Perceptron, 10 hidden neurons.

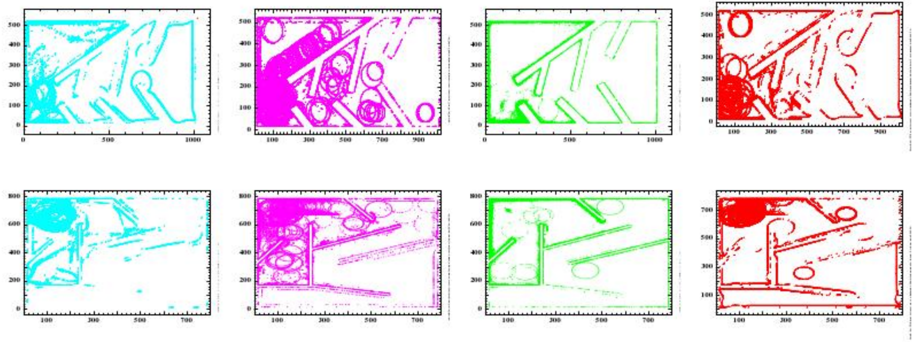
Medium and Hard Arenas





Validation, 2

Plot points in hard arena visited 10 times or more by the 100 best individuals.



Nolfi & Floreano Lehman & Stanley Curiosity Discovery

PPSN 2010

Partial conclusions

Entropy-minimization

- computable on-board;

  no need of prior knowledge/ground truth
- yields “interesting” behavior
- needs stimulating environment

See also

- Robust Intrinsic Motivation

  Baranes & Oudeyer 05,07; Oudeyer, NIPS 2012