Simulation-based Approximate Policy Iteration for Generalized Semi-Markov Decision Processes

Emmanuel Rachelson [1]

Patrick Fabiani [1]
Frédérick Garcia [2]

[1]ONERA-DCSD

[2]INRA-BIA
Toulouse, France

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Plan

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Planning under uncertainty with time dependency.
$\longrightarrow$ planning to coordinate with an uncertain and unstationnary environment.

Planning under uncertainty with time dependency.
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Should we open more lines ?

Planning under uncertainty with time dependency.
$\longrightarrow$ planning to coordinate with an uncertain and unstationnary environment.

Airplanes taxiing management

Planning under uncertainty with time dependency.
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Onboard planning for coordination

Planning under uncertainty with time dependency.
$\longrightarrow$ planning to coordinate with an uncertain and unstationnary environment.

Adding or removing trains ?

Main idea

Why is writing an MDP for the previous problems such a difficult task ?

"Lots of things occur in parallel"

- concurrent phenomena
- partially controlable dynamics

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- concurrent phenomena
- partially controlable dynamics

Typical features

- Continuous time
- Hybrid state spaces
- Large state spaces
- Total reward criteria
- Long trajectories / long episodes

How do we model all this ?

GSMDP, (*Younes et al., 04*)

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GSMP, (*Glynn, 89*)
Several semi-Markov processes affecting the same state space

One process conditionned by the choice of the action undertaken

$$\rightarrow \langle S, E, A, P, F, r \rangle$$

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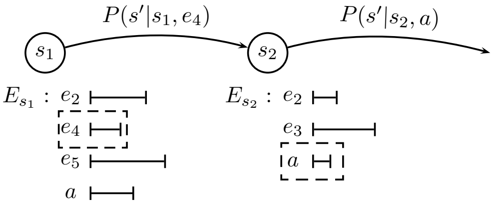

Controling GSMDP

non-Markov behaviour !

$\longrightarrow$ no guarantee of an optimal Markov policy

(*Younes et al., 04*): approximate your model with phase-type (exponential) distributions.

Supplementary variables technique (*Nilsen, 98*). Large dimension state spaces.

Our approach: no hypothesis, simulation-based API.

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1. Time and MDP: motivation and modeling
   - Examples
   - Problem features
   - GSMDP
2. Focusing Policy search in Policy Iteration
   - Policy Iteration algorithms
   - Asynchronous Dynamic Programming
   - Real-Time Policy Iteration
3. Dealing with large dimension, continuous state spaces
   - RL, Monte-Carlo sampling and Statistical Learning
   - The ATPI algorithm (naive version)
   - The ATPI algorithm (complete version)

Policy Iteration

Policy evaluation: V^{π_n}

One-step improvement: π_{n+1}

Policy Iteration

- performs search in policy space
- converges in less iterations than VI
- takes longer than VI

Policy Iteration

Approximate evaluation: V^{π_n}

One-step improvement: π_{n+1}

Asynchronous Dynamic Programming

Bellman backups can be performed in any order, the algorithm eventually reaches the optimal policy.

Example

Asynchronous Value Iteration

$$V_{n+1}(s) \leftarrow \max_{a\in A} r(s,a) + \gamma \sum_{s'\in S} P(s'|s,a)V_n(s')$$

Some states can be updated several times before some others are updated for the first time.

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Example

Asynchronous Policy Iteration

$$\pi_{n+1}(s) \leftarrow \arg\max_{a\in A} r(s,a) + \gamma \sum_{s'\in S} P(s'|s,a) V^{\pi_n}(s')$$

We can choose to update only some states before entering a new evaluation of π step.

(*Barto et al., 95)* Learning to act using real-time dynamic programming.

RTDP

Asynchronous VI with heuristic guidance.
Updated states at step $n+1$ = states visited by the one-step lookahead greedy policy w.r.t V_n.

Is there an equivalent for policy iteration ?
We introduce:

RTPI

At iteration $n+1$, updated states are states visited by the one-step lookahead greedy policy w.r.t V^{π_n}. *ie.* states visited by the application of π_{n+1}.

Practical motivation for RTPI

Motivation: don't want / can't improve the policy everywhere

- too time/resource consuming
- not useful with regard to 'relevant' information gathered

Useful ? Interesting ? Relevant ?
$\longrightarrow$ "Improving the policy in the situations I am likely to encounter today"

In other words ...

Which subset of states for Asynchronous PI ?

The ones visited by policy simulation.

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Simulation-based policy evaluation

Our hypothesis: we have a generative model of the process.
$\rightarrow$ (Monte-Carlo) simulation-based policy evaluation.

Statistical learning

Simulating the policy
$\Leftrightarrow$ Drawing a set of *trajectories*
$\Leftrightarrow$ Finite set of realisations of r.v. $R^{\pi}(s)$

We need to

- abstract (*generalize*) local information from samples
- *compactly* store previous knowledge of $V^{\pi}(s) = E(R^{\pi}(s))$.

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Regression for RL

Reminder:

Approximate evaluation: V^{π_n}

One-step improvement: π_{n+1}

(nearest neighbours, SVR, kLASSO, LWPR)

ATPI

RTPI algorithm on continuous variables with simulation-based policy evaluation + regression.

main:
Input : π_0 or $\tilde{V}_0$, s_0
loop
  $TrainingSet \leftarrow \emptyset$
  for $i = 1$ to N_{sim} **do**
    $\{(s,v)\} \leftarrow \text{simulate}(\tilde{V}, s_0)$
    $TrainingSet \leftarrow TrainingSet \cup \{(s,v)\}$
  end for
  $\tilde{V} \leftarrow \text{TrainApproximator}(TrainingSet)$
end loop

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RTPI algorithm on continuous variables with simulation-based policy evaluation + regression.

simulate$(\tilde{V}, s_0)$**:**
$ExecutionPath \leftarrow \emptyset$
$s \leftarrow s_0$
while horizon not reached **do**
  $action \leftarrow \text{ComputePolicy}(s, \tilde{V})$
  $(s', r) \leftarrow \text{GSMDPstep}(s, action)$
  $ExecutionPath \leftarrow ExecutionPath \cup (s', r)$
end while
convert execution path to $\{(s, v)\}$
return $\{(s, v)\}$

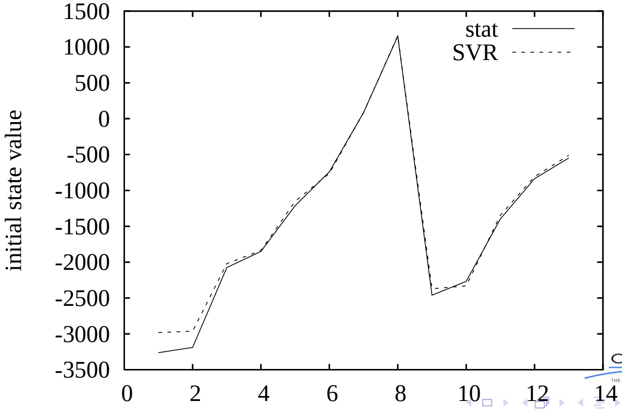
ATPI

RTPI algorithm on continuous variables with simulation-based policy evaluation + regression.

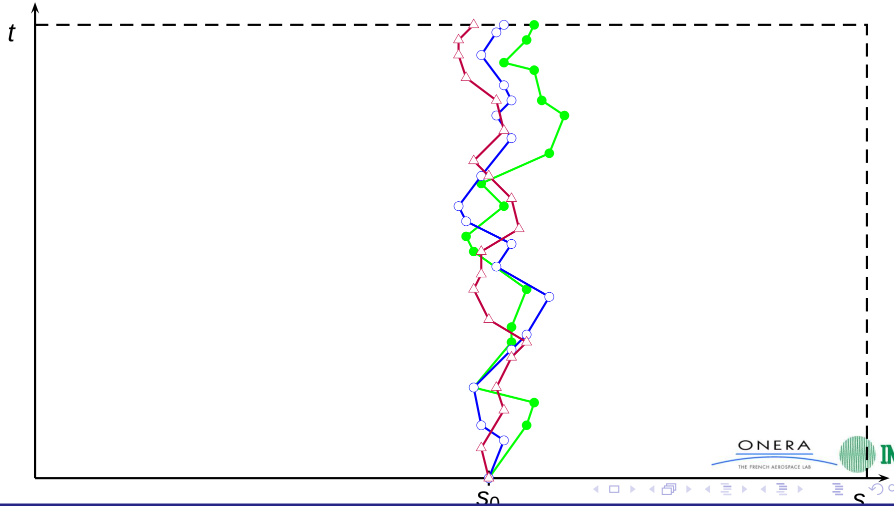
ComputePolicy$(s,\tilde{V})$**:**
for $a \in A$ **do**
  $\tilde{Q}(s,a) = 0$
  for $j = 1$ to $N_{samples}$ **do**
    $(s',r) \leftarrow \text{GSMDPstep}(s,a)$
    $\tilde{Q}(s,a) \leftarrow \tilde{Q}(s,a) + r + \gamma^{t'-t}\tilde{V}(s')$
  end for
  $\tilde{Q}(s,a) \leftarrow \frac{1}{N_{samples}}\tilde{Q}(s,a)$
end for
$action \leftarrow \arg\max_{a \in A} \tilde{Q}(s,a)$
return $action$

Subway problem results

Initial version of online-ATPI with SVR.
Initial policy sets trains to run all day long.



Is there anybody out there ?



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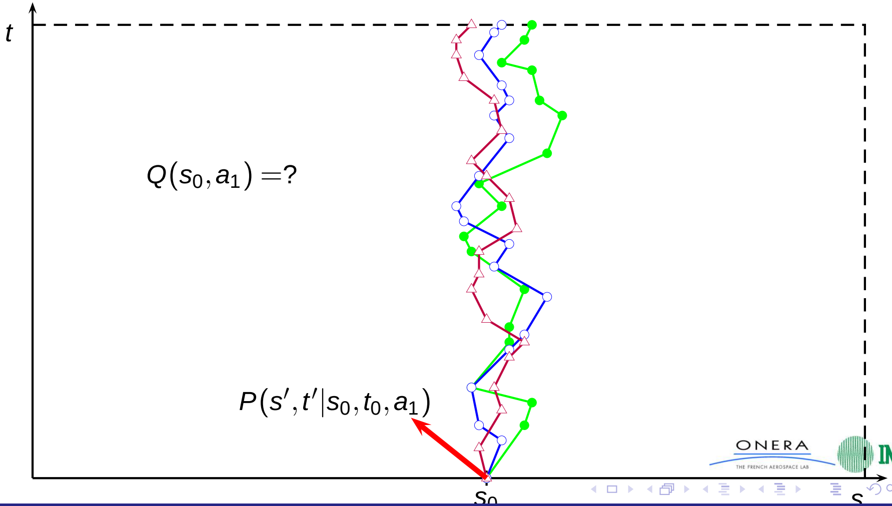

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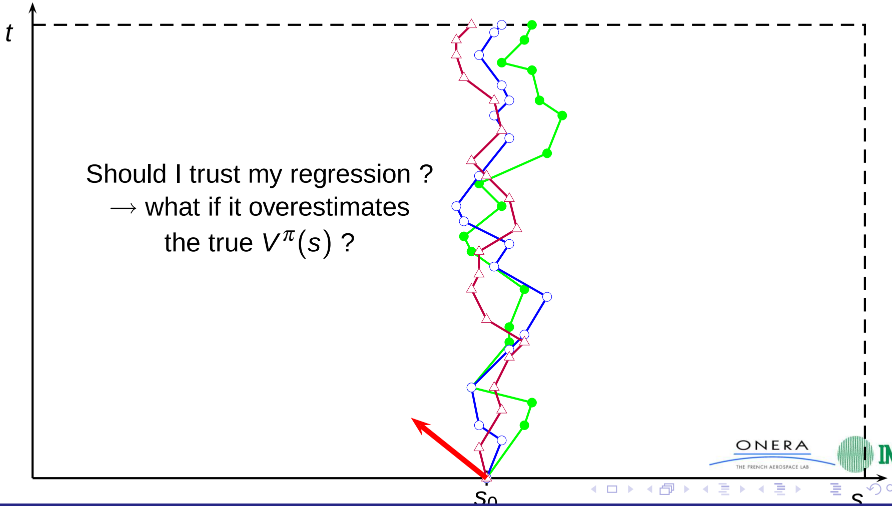

Should I trust my regression ?
$\longrightarrow$ what if it overestimates
the true $V^\pi(s)$?

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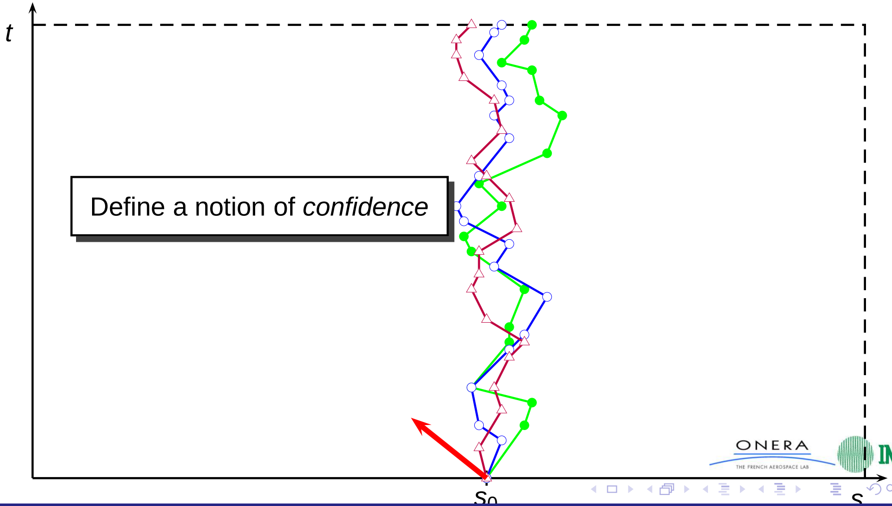

Introducing confidence

- "confidence" $\Leftrightarrow$ having enough points around s
  $\Leftrightarrow$ approaching the sufficient statistics for $V^\pi(s)$
  $\longrightarrow$ approx. measure: pdf of the underlying process.
- What should we do if we are not confident ?
  $\longrightarrow$ generate data – increase the samples' density – simulate
- Storing the policy ?

Same problem for policy storage than for value function:
(*Lagoudakis et al., 03*) RL as Classification.

Full statistical learning problem:
(local incremental) regression (V^π), classification (π),
density estimation (*conf*)

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ATPI - complete version

ATPI

samples $\leftarrow \emptyset$
for $i = 1$ to N_{sim} **do**
  while $t < horizon$ **do**
    estimate Q-values
    $s' \leftarrow$ apply best action
    store (s, a, r, s') in *samples*
  end while
end for
$train\tilde{V}^{\pi}(samples)$
$train\tilde{\pi}(samples)$

ATPI - complete version

estimate $Q(s,a)$

$\tilde{Q}(s,a) \leftarrow 0$

for $i = 1$ to N_a **do**

  $(r,s') \leftarrow$ pick next state

  if $confidence(s') = true$ **then**

    $\tilde{Q}(s,a) \leftarrow \tilde{Q}(s,a) + \frac{r+\tilde{V}^{\pi}(s')}{N_a}$

  else

    $data = simulate(\pi, s')$

    $retrain \tilde{V}^{\pi}(data)$

    $\tilde{Q}(s,a) \leftarrow \tilde{Q}(s,a) + \frac{r+\tilde{V}^{\pi}(s')}{N_a}$

  end if

end for

return $\tilde{Q}(s,a)$

Conclusion

GSMDP Modeling of large scale temporal problems of decision under uncertainty.

RTPI Introduction of a new asynchronous PI method performing partial and incremental state space exploration guided by simulation / local policy improvement.

ATPI Design of a RTPI algorithm for continuous, high dimensional state spaces, exploiting the properties of the time variable and bringing together results from:

- discrete events simulation
- simulation-based policy evaluation
- approximate asynchronous policy iteration
- statistical learning

GiSMoP C++ library

$\longrightarrow$ http://emmanuel.rachelson.free.fr/fr/gismop.html

Future work

RTPI Independent algorithm

- study convergence
- compare with RTDP

ATPI Algorithm improvement and testing

- Even non-parametric methods need some tuning ! (currently: LWPR / MC-SVM / OC-SVM)
- error bounds for API
- other benchmarks

Thank you for your attention !