

A polynomial algorithm for the deterministic mean payoff game

Bruno Scherrer

March 17, 2022

Abstract

...

We consider an infinite-horizon game on a directed graph (X, E) between two players, MAX and MIN. For any vertex x , we write $E(x) = \{y; (x, y) \in E\}$ for the set of vertices that can be reached from x by following one edge and we assume $E(x) \neq \emptyset$. The set of vertices $X = \{1, 2, \dots, n\}$ of the graph is partitionned into the sets X_+ and X_- of nodes respectively controlled by MAX and MIN. The game starts in some vertex x_0 . At each time step, the player who controls the current vertex chooses a next vertex by following an edge. So on and so forth, the choices generate an infinitely long trajectory (x_0, x_1, \dots) . In the mean payoff game, the goal of MAX is to maximize

$$\liminf_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^T r(x_t),$$

while that of MIN is to minimize

$$\limsup_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^T r(x_t).$$

As a proxy to solve the mean payoff game, our technical developments will mainly consider the γ -discounted payoff for some $0 \leq \gamma < 1$, where the goal of MAX is to maximize

$$(1 - \gamma) \sum_{t=0}^{\infty} \gamma^t r(x_t)$$

while that of MIN is to minimize this quantity.

literature...

1 Preliminaries

Let M and N be the set of stationary policies for MAX and MIN:

$$\begin{aligned} M &= \{\mu : X_+ \rightarrow X ; \forall x \in X_+, \mu(x) \in E(x)\}, \\ N &= \{\nu : X_- \rightarrow X ; \forall x \in X_-, \nu(x) \in E(x)\}. \end{aligned}$$

For any policies $\mu \in M$ and $\nu \in N$, let us write $P_{\mu, \nu}$ for the transition matrix induced by μ and ν :

$$\begin{aligned} \forall x \in X_+, \forall y \in X, \quad P_{\mu, \nu}(x, y) &= \mathbf{1}_{\mu(x)=y}, \\ \forall x \in X_-, \forall y \in X, \quad P_{\mu, \nu}(x, y) &= \mathbf{1}_{\nu(x)=y}. \end{aligned}$$

Seeing the reward $r : X \rightarrow 0, 1, \dots, R$ and any function $v : X \rightarrow \mathbb{R}$ as vectors of \mathbb{R}^n , consider the following Bellman operators

$$\begin{aligned} T_{\mu,\nu}v &= (1 - \gamma)r + \gamma P_{\mu,\nu}v, \\ T_\mu v &= \min_\nu T_{\mu,\nu}v, \\ \tilde{T}_\nu v &= \max_\mu T_{\mu,\nu}v, \\ Tv &= \max_\mu T_\mu v = \min_\nu \tilde{T}_\nu v. \end{aligned}$$

that are γ -contractions with respect to the max-norm $\|\cdot\|$, defined for all $u \in \mathbb{R}^n$ as $\|u\| = \max_{x \in X} |u(x)|$. For any policies $\mu \in M$ and $\nu \in N$, the value $v_{\mu,\nu}(x)$ obtained by following policies μ and ν satisfies

$$v_{\mu,\nu} = (1 - \gamma) \sum_{t=0}^{\infty} (\gamma P_{\mu,\nu})^t r = (1 - \gamma)(I - \gamma P_{\mu,\nu})^{-1} r,$$

and is the only fixed point of the operator $T_{\mu,\nu}$. Given any policy μ for MAX, the minimal value that MIN can obtain

$$v_\mu = \min_\nu v_{\mu,\nu}$$

is the fixed point of the operator T_μ , and it is well known that any policy ν_+ for MIN such that $T_{\mu,\nu_+}v_\mu = T_\mu v_\mu = v_\mu$ is optimal. Symmetrically, given any policy ν for MIN, the maximal value that MAX can obtain

$$\tilde{v}_\mu = \max_\nu v_{\mu,\nu}$$

is the fixed point of \tilde{T}_ν , and it is well known that any policy μ_+ for MAX such that $T_{\mu_+,\nu}v_\mu = \tilde{T}_\nu \tilde{v}_\nu = \tilde{v}_\nu$ is optimal. The optimal value

$$v_* = \max_\mu \min_\nu v_{\mu,\nu}$$

is the fixed point of the operator T . Let (μ_*, ν_*) be any pair of positional strategies such that $T_{\mu_*,\nu_*}v_* = Tv_*$. It is well-known that (μ_*, ν_*) is optimal.

We shall consider policies that are more complicated than usual stationary policies.

2 A local Bellman equation

The system of equations

$$\forall x, \quad v(x) = [Tv](x),$$

that characterizes the optimal value v_* of the game, is *global* in the sense that it involves the values of *all* the vertices. We shall begin by describing and prove an approximate-optimality equation that has the virtue of being *local* in the sense that it involves only *one* vertex:

Lemma 1. *Let v be any value function that satisfies $v \leq Tv$. If for some x , we have*

$$[T^n v](x) - v(x) \leq \epsilon,$$

Then

$$v_*(x) - [T^n v](x) \leq \frac{\epsilon}{1 - \gamma}.$$

Proof. First, observe that by the monotonicity of T , and since $v \leq Tv$, we have

$$v \leq Tv \leq T^2v \leq \dots \leq T^n v.$$

Let $\vec{\nu} = (\nu_1, \dots, \nu_n)$ be a policy such that

$$T^n v = \tilde{T}_{\vec{\nu}} v.$$

Assume MIN uses $\vec{\nu}$ to play n steps against the optimal policy μ_* of MAX from x . Consider the $n + 1$ vertices visited:

$$x_0 = x, x_1, x_2, \dots, x_n.$$

Since there are n different vertices, by the pigeonhole principle, there necessarily exists $0 \leq i < j \leq n$ such that $x_i = x_j$. Let $\vec{\nu}_p = (\nu_1, \dots, \nu_{i-1})$, $\vec{\nu}_c = (\nu_i, \dots, \nu_{j-1})$ and $\vec{\nu}_{p'} = (\nu_j, \dots, \nu_n)$ so that $\vec{\nu} = \vec{\nu}_p \vec{\nu}_c \vec{\nu}_{p'}$.

Now, assume that against μ_* , MIN uses the non-stationary policy $\vec{\nu}' = \vec{\nu}_p (\vec{\nu}_c)^\infty$. The trajectory is made of a path followed by a cycle of length $j - i$ that is repeated infinitely often:

$$\underbrace{x_0 = x, x_1, x_2, \dots, x_{i-1}}_{\text{path}}, \underbrace{x_i, x_{i+1}, \dots, x_{j-1}}_{\text{cycle}}, \underbrace{x_i, x_{i+1}, \dots, x_{j-1}}_{\text{cycle}}, \dots$$

The value of this game satisfies for any w ,

$$\begin{aligned} v_{\mu_*, \vec{\nu}}(x) - w(x) &= \mathbb{1}_x(T_{\mu_*, \vec{\nu}_p \vec{\nu}_c}(T_{\mu_*, \vec{\nu}_c})^\infty w - w) \\ &= \mathbb{1}_x T_{\mu_*, \vec{\nu}_p \vec{\nu}_c} 0 + \gamma^j \mathbb{1}_{x_i} \sum_{k=0}^{\infty} [(T_{\mu_*, \vec{\nu}_c})^{k+1} w - T_{\mu_*, \vec{\nu}_c}^k w] \\ &= \mathbb{1}_x T_{\mu_*, \vec{\nu}_p \vec{\nu}_c} w + \gamma^j \mathbb{1}_{x_i} \sum_{k=0}^{\infty} \gamma^{(j-i)k} (P_{\mu_*, \vec{\nu}_c})^k (T_{\mu_*, \vec{\nu}_c} w - w) \\ &= \mathbb{1}_x T_{\mu_*, \vec{\nu}_p \vec{\nu}_c} w + \frac{\gamma^j}{1 - \gamma^{j-i}} \mathbb{1}_{x_i} (T_{\mu_*, \vec{\nu}_c} w - w) \\ &\leq \mathbb{1}_x \tilde{T}_{\vec{\nu}_p \vec{\nu}_c} w + \frac{\gamma^j}{1 - \gamma^{j-i}} \mathbb{1}_{x_i} (\tilde{T}_{\vec{\nu}_c} w - w). \end{aligned}$$

Taking $w = \tilde{T}_{\vec{\nu}_{p'}} v$, we obtain

$$\begin{aligned} v_{\mu_*, \vec{\nu}}(x) - [\tilde{T}_{\vec{\nu}_{p'}} v](x) &\leq \mathbb{1}_x (\tilde{T}_{\vec{\nu}_p \vec{\nu}_c} \tilde{T}_{\vec{\nu}_{p'}} v - T_{\vec{\nu}_{p'}} v) + \frac{\gamma^j}{1 - \gamma^{j-i}} \mathbb{1}_{x_i} (\tilde{T}_{\vec{\nu}_c} \tilde{T}_{\vec{\nu}_{p'}} v - \tilde{T}_{\vec{\nu}_{p'}} v) \\ &= \mathbb{1}_x (\tilde{T}_{\vec{\nu}_p \vec{\nu}_c \vec{\nu}_{p'}} v - T_{\vec{\nu}_{p'}} v) + \frac{\gamma^j}{1 - \gamma^{j-i}} \mathbb{1}_{x_i} (\tilde{T}_{\vec{\nu}_c} \tilde{T}_{\vec{\nu}_{p'}} v - \tilde{T}_{\vec{\nu}_{p'}} v) \\ &= \mathbb{1}_x (T^n v - T^{n-j} v) + \frac{\gamma^j}{1 - \gamma^{j-i}} \mathbb{1}_{x_i} (T^{n-i} v - T^{n-j} v) \\ &\leq \mathbb{1}_x (T^n v - v) + \frac{\gamma^j}{1 - \gamma^{j-i}} \mathbb{1}_x (T^n v - v) \\ &\leq \frac{\epsilon}{1 - \gamma}, \end{aligned}$$

where we eventually used the facts that $T^n v - v \leq \epsilon$, $j \geq 1$ and $j - i \geq 1$. The result follows by the fact that $v_*(x) = v_{\mu_*, \nu_*}(x) \leq v_{\mu_*, \vec{\nu}}(x)$ and that $T^n v \geq T^{n-j} v = \tilde{T}_{\vec{\nu}_{p'}} v$. \square

3 Algorithm

We first consider an algorithmic procedure that takes as parameters a threshold ρ and an initial non-stationary policy $\bar{\mu}_0$, and that returns a set of couples of $(x, \bar{\mu}_x)$ of state-policy pairs:

1. (Initialization) Set $k = 0$ and initialize the (solution) set S to the empty set.
2. (Evaluation) Compute the value v_k when MIN plays optimally
3. (Identification of converged states) Determine the set of states

$$C_k = \{x ; \text{adv} \leq (1 - \gamma)\rho\}.$$

4. (Next policy)

Lemma 2. *After at most $\frac{n(v_{\mu_*} - v_{\mu_0})}{\rho}$ iterations, the algorithm stops and returns a policy μ such that*

$$v_*(x) - v_{\bar{\mu}_x}(x) \leq \rho + n(1 - \gamma)R$$

Starting from $\rho_0 = \frac{W}{2}$, let us choose the sequence of parameters

$$\rho_{k+1} = \frac{\rho_k + n(1 - \gamma)R}{2}$$

so that each call to the procedure lasts at most $2n$ iterations.

Then after k iterations, we have

$$\begin{aligned} v_* - v_{\mu_k} &\leq \frac{W}{2^k} + \sum_{i=0}^{k-1} \frac{1}{2^i} (1 - \gamma)nR \\ &\leq \frac{W}{2^k} + 2(1 - \gamma)nR \end{aligned}$$

For the mean payoff game, we have

$$\begin{aligned} \|g_* - g_{\mu_k}\| &\leq 4n(1 - \gamma)R + \|v_* - v_{\mu_k}\| \\ &\leq 6n(1 - \gamma)R + \frac{W}{2^k} \end{aligned}$$

When this is smaller than $\frac{1}{n^2}$, we are done!