

# Verified Algorithms for Solving Markov Decision Processes

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## Abstract

We present a formalization of algorithms for solving Markov Decision Processes (MDPs) with formal guarantees on the optimality of their solutions. In particular we build on our analysis of the Bellman operator for discounted infinite horizon MDPs. From the iterator rule on the Bellman operator we directly derive executable value iteration and policy iteration algorithms to iteratively solve finite MDPs. We also prove correct optimized versions of value iteration that use matrix splittings to improve the convergence rate. In particular, we formally verify Gauss-Seidel value iteration and modified policy iteration. The algorithms are evaluated on two standard examples from the literature, namely, inventory management and gridworld. Our formalization covers most of chapter 6 in Puterman’s book [1].

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```

theory Value-Iteration
  imports MDP-Rewards.MDP-reward
begin

context MDP-att- $\mathcal{L}$ 
begin

```

## 1 Value Iteration

In the previous sections we derived that repeated application of  $\mathcal{L}_b$  to any bounded function from states to the reals converges to the optimal value of the MDP  $\nu_b\text{-opt}$ .

We can turn this procedure into an algorithm that computes not only an approximation of  $\nu_b\text{-opt}$  but also a policy that is arbitrarily close to optimal.

Most of the proofs rely on the assumption that the supremum in  $\mathcal{L}_b$  can always be attained.

The following lemma shows that the relation we use to prove termination of the value iteration algorithm decreases in each step. In essence, the distance of the estimate to the optimal value decreases by a factor of at least  $l$  per iteration.

**lemma** *vi-rel-dec*:

**assumes**  $l \neq 0 \ \mathcal{L}_b \ v \neq \nu_b\text{-opt}$

**shows**  $\lceil \log (1 / l) (\text{dist } (\mathcal{L}_b \ v) \ \nu_b\text{-opt}) - c \rceil < \lceil \log (1 / l) (\text{dist } v \ \nu_b\text{-opt}) - c \rceil$

*<proof>*

**lemma** *dist- $\mathcal{L}_b$ -lt-dist-opt*:  $\text{dist } v (\mathcal{L}_b \ v) \leq 2 * \text{dist } v \ \nu_b\text{-opt}$

*<proof>*

**abbreviation** *term-measure*  $\equiv (\lambda(\text{eps}, v).$

*if*  $v = \nu_b\text{-opt} \vee l = 0$

*then* 0

*else*  $\text{nat } (\text{ceiling } (\log (1/l) (\text{dist } v \ \nu_b\text{-opt}) - \log (1/l) (\text{eps} * (1-l) / (8 * l))))$

**function** *value-iteration* ::  $\text{real} \Rightarrow ('s \Rightarrow_b \text{real}) \Rightarrow ('s \Rightarrow_b \text{real})$  **where**

*value-iteration eps v =*

*(if  $2 * l * \text{dist } v (\mathcal{L}_b \ v) < \text{eps} * (1-l) \vee \text{eps} \leq 0$  then  $\mathcal{L}_b \ v$  else *value-iteration eps* ( $\mathcal{L}_b \ v$ ))*

*<proof>*

**termination**

*<proof>*

The distance between an estimate for the value and the optimal value can be bounded with respect to the distance between the estimate and the result of applying it to  $\mathcal{L}_b$

**lemma** *contraction- $\mathcal{L}$ -dist*:  $(1 - l) * \text{dist } v \ \nu_b\text{-opt} \leq \text{dist } v (\mathcal{L}_b \ v)$

*<proof>*

**lemma** *dist- $\mathcal{L}_b$ -opt-eps*:

**assumes**  $\text{eps} > 0 \ 2 * l * \text{dist } v (\mathcal{L}_b \ v) < \text{eps} * (1-l)$

**shows**  $\text{dist } (\mathcal{L}_b \ v) \ \nu_b\text{-opt} < \text{eps} / 2$

*<proof>*

The estimates above allow to give a bound on the error of *value-iteration*.

**declare** *value-iteration.simps*[*simp del*]

**lemma** *value-iteration-error*:

**assumes**  $\text{eps} > 0$

**shows**  $\text{dist} (\text{value-iteration } \text{eps } v) \nu_b\text{-opt} < \text{eps} / 2$

$\langle \text{proof} \rangle$

After the value iteration terminates, one can easily obtain a stationary deterministic epsilon-optimal policy.

Such a policy does not exist in general, attainment of the supremum in  $\mathcal{L}_b$  is required.

**definition** *find-policy*  $(v :: 's \Rightarrow_b \text{real}) s = \text{arg-max-on } (\lambda a. L_a a v s) (A s)$

**definition** *vi-policy*  $\text{eps } v = \text{find-policy } (\text{value-iteration } \text{eps } v)$

We formalize the attainment of the supremum using a predicate *has-arg-max*.

**abbreviation**  $\text{vi } u \ n \equiv (\mathcal{L}_b \ \widetilde{\sim}_n) u$

**lemma**  *$\mathcal{L}_b$ -iter-mono*:

**assumes**  $u \leq v$  **shows**  $\text{vi } u \ n \leq \text{vi } v \ n$

$\langle \text{proof} \rangle$

**lemma**

**assumes**  $\text{vi } v \ (\text{Suc } n) \leq \text{vi } v \ n$

**shows**  $\text{vi } v \ (\text{Suc } n + m) \leq \text{vi } v \ (n + m)$

$\langle \text{proof} \rangle$

**lemma**

**assumes**  $\text{vi } v \ n \leq \text{vi } v \ (\text{Suc } n)$

**shows**  $\text{vi } v \ (n + m) \leq \text{vi } v \ (\text{Suc } n + m)$

$\langle \text{proof} \rangle$

**lemma**  $\text{vi } v \longrightarrow \nu_b\text{-opt}$

$\langle \text{proof} \rangle$

**lemma**  $(\lambda n. \text{dist } (\text{vi } v \ (\text{Suc } n)) (\text{vi } v \ n)) \longrightarrow 0$

$\langle \text{proof} \rangle$

**end**

**context** *MDP-att- $\mathcal{L}$*

**begin**

The error of the resulting policy is bounded by the distance from its value to the value computed by the value iteration plus the error in the value iteration itself. We show that both are less than  $\text{eps} / (2::'b)$  when the algorithm terminates.

**lemma** *find-policy-error-bound*:

**assumes**  $\text{eps} > 0 \ 2 * l * \text{dist } v (\mathcal{L}_b \ v) < \text{eps} * (1-l)$   
**shows**  $\text{dist } (\nu_b \ (\text{mk-stationary-det } (\text{find-policy } (\mathcal{L}_b \ v)))) \ \nu_{b\text{-opt}} < \text{eps}$   
 $\langle \text{proof} \rangle$

**lemma** *vi-policy-opt*:

**assumes**  $0 < \text{eps}$   
**shows**  $\text{dist } (\nu_b \ (\text{mk-stationary-det } (\text{vi-policy } \text{eps } v))) \ \nu_{b\text{-opt}} < \text{eps}$   
 $\langle \text{proof} \rangle$

**lemma** *lemma-6-3-1-d*:

**assumes**  $\text{eps} > 0$   
**assumes**  $2 * l * \text{dist } (vi \ v \ (\text{Suc } n)) \ (vi \ v \ n) < \text{eps} * (1-l)$   
**shows**  $\text{dist } (vi \ v \ (\text{Suc } n)) \ \nu_{b\text{-opt}} < \text{eps} / 2$   
 $\langle \text{proof} \rangle$

**end**

**context** *MDP-act* **begin**

**definition** *find-policy'* ( $v :: 's \Rightarrow_b \text{real}$ )  $s = \text{arb-act } (\text{opt-acts } v \ s)$

**definition** *vi-policy'*  $\text{eps } v = \text{find-policy}' \ (\text{value-iteration } \text{eps } v)$

**lemma** *find-policy'-error-bound*:

**assumes**  $\text{eps} > 0 \ 2 * l * \text{dist } v (\mathcal{L}_b \ v) < \text{eps} * (1-l)$   
**shows**  $\text{dist } (\nu_b \ (\text{mk-stationary-det } (\text{find-policy}' (\mathcal{L}_b \ v)))) \ \nu_{b\text{-opt}} < \text{eps}$   
 $\langle \text{proof} \rangle$

**lemma** *vi-policy'-opt*:

**assumes**  $\text{eps} > 0 \ l > 0$   
**shows**  $\text{dist } (\nu_b \ (\text{mk-stationary-det } (\text{vi-policy}' \ \text{eps } v))) \ \nu_{b\text{-opt}} < \text{eps}$   
 $\langle \text{proof} \rangle$

**end**

**end**

**theory** *Policy-Iteration*

**imports** *MDP-Rewards.MDP-reward*

**begin**

## 2 Policy Iteration

The Policy Iteration algorithms provides another way to find optimal policies under the expected total reward criterion. It differs from Value Iteration in that it continuously improves an initial guess for an optimal decision rule. Its execution can be subdivided into two alternating steps: policy evaluation and policy improvement.

Policy evaluation means the calculation of the value of the current decision rule.

During the improvement phase, we choose the decision rule with the maximum value for  $L$ , while we prefer to keep the old action selection in case of ties.

**context** *MDP-att- $\mathcal{L}$*  **begin**

**definition** *policy-eval*  $d = \nu_b$  (*mk-stationary-det*  $d$ )  
**end**

**context** *MDP-act*

**begin**

**definition** *policy-improvement*  $d \ v \ s =$  (  
  *if is-arg-max* ( $\lambda a. L_a \ a \ (apply-bfun \ v) \ s$ ) ( $\lambda a. a \in A \ s$ ) ( $d \ s$ )  
  *then*  $d \ s$   
  *else arb-act* (*opt-acts*  $v \ s$ ))

**definition** *policy-step*  $d = policy-improvement \ d \ (policy-eval \ d)$

**function** *policy-iteration*  $:: ('s \Rightarrow 'a) \Rightarrow ('s \Rightarrow 'a)$  **where**  
  *policy-iteration*  $d =$  (  
    *let*  $d' = policy-step \ d$  *in*  
    *if*  $d = d' \vee \neg is-dec-det \ d$  *then*  $d$  *else* *policy-iteration*  $d'$ )  
   $\langle proof \rangle$

The policy iteration algorithm as stated above does require that the supremum in  $\mathcal{L}_b$  is always attained.

Each policy improvement returns a valid decision rule.

**lemma** *is-dec-det-pi*: *is-dec-det* (*policy-improvement*  $d \ v$ )  
 $\langle proof \rangle$

**lemma** *policy-improvement-is-dec-det*:  $d \in D_D \implies policy-improvement \ d \ v \in D_D$   
 $\langle proof \rangle$

**lemma** *policy-improvement-improving*:  
  **assumes**  $d \in D_D$

**shows**  $\nu$ -improving  $v$  ( $mk\text{-}dec\text{-}det$  ( $policy\text{-}improvement$   $d$   $v$ ))  
 $\langle proof \rangle$

**lemma** *eval-policy-step-L*:

**assumes**  $is\text{-}dec\text{-}det$   $d$   
**shows**  $L$  ( $mk\text{-}dec\text{-}det$  ( $policy\text{-}step$   $d$ )) ( $policy\text{-}eval$   $d$ ) =  $\mathcal{L}_b$  ( $policy\text{-}eval$   $d$ )  
 $\langle proof \rangle$

The sequence of policies generated by policy iteration has monotonically increasing discounted reward.

**lemma** *policy-eval-mon*:

**assumes**  $is\text{-}dec\text{-}det$   $d$   
**shows**  $policy\text{-}eval$   $d \leq policy\text{-}eval$  ( $policy\text{-}step$   $d$ )  
 $\langle proof \rangle$

If policy iteration terminates, i.e.  $d = policy\text{-}step$   $d$ , then it does so with optimal value.

**lemma** *policy-step-eq-imp-opt*:

**assumes**  $is\text{-}dec\text{-}det$   $d$   $d = policy\text{-}step$   $d$   
**shows**  $\nu_b$  ( $mk\text{-}stationary$  ( $mk\text{-}dec\text{-}det$   $d$ )) =  $\nu_b\text{-}opt$   
 $\langle proof \rangle$

**end**

We prove termination of policy iteration only if both the state and action sets are finite.

**locale** *MDP-PI-finite* = *MDP-act*  $A$   $K$   $r$   $l$  *arb-act*

**for**  
 $A$  **and**  
 $K :: 's :: countable \times 'a :: countable \Rightarrow 's$  *pmf* **and**  $r$   $l$  *arb-act* +  
**assumes**  $fin\text{-}states$ :  $finite$  ( $UNIV :: 's$  *set*) **and**  $fin\text{-}actions$ :  $\bigwedge s. finite$  ( $A$   $s$ )  
**begin**

If the state and action sets are both finite, then so is the set of deterministic decision rules  $D_D$

**lemma** *finite- $D_D[simp]$* :  $finite$   $D_D$   
 $\langle proof \rangle$

**lemma** *finite-rel*:  $finite$   $\{(u, v). is\text{-}dec\text{-}det$   $u \wedge is\text{-}dec\text{-}det$   $v \wedge \nu_b$  ( $mk\text{-}stationary\text{-}det$   $u$ ) >  $\nu_b$  ( $mk\text{-}stationary\text{-}det$   $v$ )\}  
 $\langle proof \rangle$

This auxiliary lemma shows that policy iteration terminates if no improvement to the value of the policy could be made, as then the policy remains unchanged.

**lemma** *eval-eq-imp-policy-eq*:

**assumes** *policy-eval*  $d = \text{policy-eval } (\text{policy-step } d)$  *is-dec-det*  $d$

**shows**  $d = \text{policy-step } d$

$\langle \text{proof} \rangle$

We are now ready to prove termination in the context of finite state-action spaces. Intuitively, the algorithm terminates as there are only finitely many decision rules, and in each recursive call the value of the decision rule increases.

**termination** *policy-iteration*

$\langle \text{proof} \rangle$

The termination proof gives us access to the induction rule/simplification lemmas associated with the *policy-iteration* definition. Thus we can prove that the algorithm finds an optimal policy.

**lemma** *is-dec-det-pi'*:  $d \in D_D \implies \text{is-dec-det } (\text{policy-iteration } d)$

$\langle \text{proof} \rangle$

**lemma** *pi-pi[simp]*:  $d \in D_D \implies \text{policy-step } (\text{policy-iteration } d) = \text{policy-iteration } d$

$\langle \text{proof} \rangle$

**lemma** *policy-iteration-correct*:

$d \in D_D \implies \nu_b (\text{mk-stationary-det } (\text{policy-iteration } d)) = \nu_b\text{-opt}$

$\langle \text{proof} \rangle$

**end**

**context** *MDP-finite-type* **begin**

The following proofs concern code generation, i.e. how to represent  $\mathcal{P}_1$  as a matrix.

**sublocale** *MDP-att- $\mathcal{L}$*

$\langle \text{proof} \rangle$

**definition** *fun-to-matrix*  $f = \text{matrix } (\lambda v. (\chi j. f (\text{vec-nth } v) j))$

**definition** *Ek-mat*  $d = \text{fun-to-matrix } (\lambda v. ((\mathcal{P}_1 \ d) (Bfun \ v)))$

**definition** *nu-inv-mat*  $d = \text{fun-to-matrix } ((\lambda v. ((\text{id-blifun} - l *_R \mathcal{P}_1 \ d) (Bfun \ v))))$

**definition** *nu-mat*  $d = \text{fun-to-matrix } (\lambda v. ((\sum i. (l *_R \mathcal{P}_1 \ d) \ \frown \ i) (Bfun \ v)))$

**lemma** *apply-nu-inv-mat*:

$(\text{id-blifun} - l *_R \mathcal{P}_1 \ d) \ v = Bfun \ (\lambda i. ((\text{nu-inv-mat } d) * v (\text{vec-lambda } v)) \ \$ \ i)$

$\langle \text{proof} \rangle$

**lemma** *bounded-linear-vec-lambda*: *bounded-linear*  $(\lambda x. \text{vec-lambda } (x :: 's \Rightarrow_b \text{real}))$



$\langle proof \rangle$

**lemma** *bounded-linear-vec-lambda-blinfun*:  
**fixes**  $f :: ('s \Rightarrow_b \text{real}) \Rightarrow_L ('s \Rightarrow_b \text{real})$   
**shows** *bounded-linear*  $(\lambda v. \text{vec-lambda } (\text{apply-bfun } (\text{blinfun-apply } f$   
 $(\text{bfun.Bfun } ((\$) v))))$   
 $\langle proof \rangle$

**lemma** *invertible-nu-inv-max*: *invertible*  $(\text{nu-inv-mat } d)$   
 $\langle proof \rangle$

**end**

**definition** *least-arg-max*  $f P = (\text{LEAST } x. \text{is-arg-max } f P x)$

**locale** *MDP-ord* = *MDP-finite-type*  $A K r l$   
**for**  $A$  **and**  
 $K :: 's :: \{\text{finite}, \text{wellorder}\} \times 'a :: \{\text{finite}, \text{wellorder}\} \Rightarrow 's \text{ pmf}$   
**and**  $r l$   
**begin**

**lemma**  *$\mathcal{L}$ -fin-eq-det*:  $\mathcal{L} v s = (\bigsqcup a \in A s. L_a a v s)$   
 $\langle proof \rangle$

**lemma**  *$\mathcal{L}_b$ -fin-eq-det*:  $\mathcal{L}_b v s = (\bigsqcup a \in A s. L_a a v s)$   
 $\langle proof \rangle$

**sublocale** *MDP-PI-finite*  $A K r l \lambda X. \text{Least } (\lambda x. x \in X)$   
 $\langle proof \rangle$

**end**

**end**

**theory** *Modified-Policy-Iteration*  
**imports**  
*Policy-Iteration*  
*Value-Iteration*  
**begin**

### 3 Modified Policy Iteration

**locale** *MDP-MPI* = *MDP-finite-type*  $A K r l + \text{MDP-act } A K r l$   
 $\text{arb-act}$   
**for**  $A$  **and**  $K :: 's :: \text{finite} \times 'a :: \text{finite} \Rightarrow 's \text{ pmf}$  **and**  $r l \text{ arb-act}$   
**begin**

### 3.1 The Advantage Function $B$

**definition**  $B \ v \ s = (\bigsqcup d \in D_R. (r\text{-dec } d \ s + (l *_R \mathcal{P}_1 \ d - id\text{-blinfun}) \ v \ s))$

The function  $B$  denotes the advantage of choosing the optimal action vs. the current value estimate

**lemma**  $B\text{-eq-}\mathcal{L}$ :  $B \ v \ s = \mathcal{L} \ v \ s - v \ s$   
 $\langle proof \rangle$

$B$  is a bounded function.

**lift-definition**  $B_b :: ('s \Rightarrow_b \text{real}) \Rightarrow 's \Rightarrow_b \text{real}$  is  $B$   
 $\langle proof \rangle$

**lemma**  $B_b\text{-eq-}\mathcal{L}_b$ :  $B_b \ v = \mathcal{L}_b \ v - v$   
 $\langle proof \rangle$

**lemma**  $\mathcal{L}_b\text{-eq-SUP-}L_a$ :  $\mathcal{L}_b \ v \ s = (\bigsqcup a \in A \ s. L_a \ a \ v \ s)$   
 $\langle proof \rangle$

### 3.2 Optimization of the Value Function over Multiple Steps

**definition**  $U \ m \ v \ s = (\bigsqcup d \in D_R. (\nu_b\text{-fin } (mk\text{-stationary } d) \ m + ((l *_R \mathcal{P}_1 \ d) \widetilde{\sim} m) \ v) \ s)$

$U$  expresses the value estimate obtained by optimizing the first  $m$  steps and afterwards using the current estimate.

**lemma**  $U\text{-zero } [simp]$ :  $U \ 0 \ v = v$   
 $\langle proof \rangle$

**lemma**  $U\text{-one-eq-}\mathcal{L}$ :  $U \ 1 \ v \ s = \mathcal{L} \ v \ s$   
 $\langle proof \rangle$

**lift-definition**  $U_b :: \text{nat} \Rightarrow ('s \Rightarrow_b \text{real}) \Rightarrow ('s \Rightarrow_b \text{real})$  is  $U$   
 $\langle proof \rangle$

**lemma**  $U_b\text{-contraction}$ :  $\text{dist } (U_b \ m \ v) (U_b \ m \ u) \leq l \wedge m * \text{dist } v \ u$   
 $\langle proof \rangle$

**lemma**  $U_b\text{-conv}$ :  
 $\exists! v. U_b \ (Suc \ m) \ v = v$   
 $(\lambda n. (U_b \ (Suc \ m) \ \widetilde{\sim} n) \ v) \longrightarrow (THE \ v. U_b \ (Suc \ m) \ v = v)$   
 $\langle proof \rangle$

**lemma**  $U_b\text{-convergent}$ :  $\text{convergent } (\lambda n. (U_b \ (Suc \ m) \ \widetilde{\sim} n) \ v)$   
 $\langle proof \rangle$

**lemma**  $U_b\text{-mono}$ :

**assumes**  $v \leq u$   
**shows**  $U_b \ m \ v \leq U_b \ m \ u$   
 $\langle proof \rangle$

**lemma**  $U_b\text{-le-}\mathcal{L}_b$ :  $U_b \ m \ v \leq (\mathcal{L}_b \ \frown m) \ v$   
 $\langle proof \rangle$

**lemma**  $L\text{-iter-le-}U_b$ :  
**assumes**  $d \in D_R$   
**shows**  $(L \ d \ \frown m) \ v \leq U_b \ m \ v$   
 $\langle proof \rangle$

**lemma**  $\lim\text{-}U_b$ :  $\lim (\lambda n. (U_b \ (Suc \ m) \ \frown n) \ v) = \nu_b\text{-opt}$   
 $\langle proof \rangle$

**lemma**  $U_b\text{-tendsto}$ :  $(\lambda n. (U_b \ (Suc \ m) \ \frown n) \ v) \longrightarrow \nu_b\text{-opt}$   
 $\langle proof \rangle$

**lemma**  $U_b\text{-fix-unique}$ :  $U_b \ (Suc \ m) \ v = v \longleftrightarrow v = \nu_b\text{-opt}$   
 $\langle proof \rangle$

**lemma**  $\text{dist-}U_b\text{-opt}$ :  $\text{dist} \ (U_b \ m \ v) \ \nu_b\text{-opt} \leq l \ \frown m * \text{dist} \ v \ \nu_b\text{-opt}$   
 $\langle proof \rangle$

### 3.3 Expressing a Single Step of Modified Policy Iteration

The function  $W$  equals the value computed by the Modified Policy Iteration Algorithm in a single iteration. The right hand addend in the definition describes the advantage of using the optimal action for the first  $m$  steps.

**definition**  $W \ d \ m \ v = v + (\sum i < m. (l *_{\mathcal{R}} \mathcal{P}_1 \ d) \ \frown i) \ (B_b \ v)$

**lemma**  $W\text{-eq-}L\text{-iter}$ :  
**assumes**  $\nu\text{-improving} \ v \ d$   
**shows**  $W \ d \ m \ v = (L \ d \ \frown m) \ v$   
 $\langle proof \rangle$

**lemma**  $W\text{-le-}U_b$ :  
**assumes**  $v \leq u \ \nu\text{-improving} \ v \ d$   
**shows**  $W \ d \ m \ v \leq U_b \ m \ u$   
 $\langle proof \rangle$

**lemma**  $W\text{-ge-}\mathcal{L}_b$ :  
**assumes**  $v \leq u \ 0 \leq B_b \ u \ \nu\text{-improving} \ u \ d'$

**shows**  $\mathcal{L}_b v \leq W d' (Suc m) u$   
 $\langle proof \rangle$

**lemma**  $B_b$ -le:

**assumes**  $\nu$ -improving  $v d$   
**shows**  $B_b v + (l *_R \mathcal{P}_1 d - id\text{-}blinfun) (u - v) \leq B_b u$   
 $\langle proof \rangle$

**lemma**  $\mathcal{L}_b$ -W-ge:

**assumes**  $u \leq \mathcal{L}_b u$   $\nu$ -improving  $u d$   
**shows**  $W d m u \leq \mathcal{L}_b (W d m u)$   
 $\langle proof \rangle$

### 3.4 Computing the Bellman Operator over Multiple Steps

**definition**  $L\text{-}pow :: ('s \Rightarrow_b real) \Rightarrow ('s \Rightarrow 'a) \Rightarrow nat \Rightarrow ('s \Rightarrow_b real)$   
**where**

$L\text{-}pow v d m = (L (mk\text{-}dec\text{-}det d) \text{~}\!\!\sim\!\!\sim Suc m) v$

**lemma**  $sum\text{-}telescope'$ :  $(\sum i \leq k. f (Suc i) - f i) = f (Suc k) - (f 0$   
 $:: 'c :: ab\text{-}group\text{-}add)$   
 $\langle proof \rangle$

**lemma**  $L\text{-}pow\text{-}eq$ :

**assumes**  $\nu$ -improving  $v (mk\text{-}dec\text{-}det d)$   
**shows**  $L\text{-}pow v d m = v + (\sum i \leq m. ((l *_R \mathcal{P}_1 (mk\text{-}dec\text{-}det d)) \text{~}\!\!\sim\!\!\sim i))$   
 $(B_b v)$   
 $\langle proof \rangle$

**lemma**  $L\text{-}pow\text{-}eq\text{-}W$ :

**assumes**  $d \in D_D$   
**shows**  $L\text{-}pow v (policy\text{-}improvement d v) m = W (mk\text{-}dec\text{-}det$   
 $(policy\text{-}improvement d v)) (Suc m) v$   
 $\langle proof \rangle$

**lemma**  $L\text{-}pow\text{-}\mathcal{L}_b\text{-}mono\text{-}inv$ :

**assumes**  $d \in D_D$   $v \leq \mathcal{L}_b v$   
**shows**  $L\text{-}pow v (policy\text{-}improvement d v) m \leq \mathcal{L}_b (L\text{-}pow v (policy\text{-}improvement$   
 $d v) m)$   
 $\langle proof \rangle$

### 3.5 The Modified Policy Iteration Algorithm

**context**

**fixes**  $d0 :: 's \Rightarrow 'a$   
**fixes**  $v0 :: 's \Rightarrow_b real$   
**fixes**  $m :: nat \Rightarrow ('s \Rightarrow_b real) \Rightarrow nat$

**assumes**  $d0$ :  $d0 \in D_D$   
**begin**

We first define a function that executes the algorithm for  $n$  steps.

**fun**  $mpi :: nat \Rightarrow ((s \Rightarrow 'a) \times (s \Rightarrow_b real))$  **where**  
 $mpi\ 0 = (policy-improvement\ d0\ v0, v0) \mid$   
 $mpi\ (Suc\ n) =$   
 $(let\ (d, v) = mpi\ n; v' = L-pow\ v\ d\ (m\ n\ v)\ in$   
 $(policy-improvement\ d\ v', v'))$

**definition**  $mpi-val\ n = snd\ (mpi\ n)$

**definition**  $mpi-pol\ n = fst\ (mpi\ n)$

**lemma**  $mpi-pol-zero[simp]$ :  $mpi-pol\ 0 = policy-improvement\ d0\ v0$   
 $\langle proof \rangle$

**lemma**  $mpi-pol-Suc$ :  $mpi-pol\ (Suc\ n) = policy-improvement\ (mpi-pol\ n)\ (mpi-val\ (Suc\ n))$   
 $\langle proof \rangle$

**lemma**  $mpi-pol-is-dec-det$ :  $mpi-pol\ n \in D_D$   
 $\langle proof \rangle$

**lemma**  $\nu-improving-mpi-pol$ :  $\nu-improving\ (mpi-val\ n)\ (mk-dec-det\ (mpi-pol\ n))$   
 $\langle proof \rangle$

**lemma**  $mpi-val-zero[simp]$ :  $mpi-val\ 0 = v0$   
 $\langle proof \rangle$

**lemma**  $mpi-val-Suc$ :  $mpi-val\ (Suc\ n) = L-pow\ (mpi-val\ n)\ (mpi-pol\ n)\ (m\ n\ (mpi-val\ n))$   
 $\langle proof \rangle$

**lemma**  $mpi-val-eq$ :  $mpi-val\ (Suc\ n) =$   
 $mpi-val\ n + (\sum i \leq m\ n\ (mpi-val\ n). (l *_R \mathcal{P}_1\ (mk-dec-det\ (mpi-pol\ n))) \frown i)\ (B_b\ (mpi-val\ n))$   
 $\langle proof \rangle$

Value Iteration is a special case of MPI where  $\forall n\ v. m\ n\ v = 0$ .

**lemma**  $mpi-includes-value-it$ :  
**assumes**  $\forall n\ v. m\ n\ v = 0$   
**shows**  $mpi-val\ (Suc\ n) = \mathcal{L}_b\ (mpi-val\ n)$   
 $\langle proof \rangle$

### 3.6 Convergence Proof

We define the sequence  $w$  as an upper bound for the values of MPI.

**fun**  $w$  **where**

$w \ 0 = v0 \mid$

$w \ (Suc \ n) = U_b \ (Suc \ (m \ n \ (mpi-val \ n))) \ (w \ n)$

**lemma**  $dist-\nu_b-opt$ :  $dist \ (w \ (Suc \ n)) \ \nu_b-opt \leq l * dist \ (w \ n) \ \nu_b-opt$   
 $\langle proof \rangle$

**lemma**  $dist-\nu_b-opt-n$ :  $dist \ (w \ n) \ \nu_b-opt \leq l^n * dist \ v0 \ \nu_b-opt$   
 $\langle proof \rangle$

**lemma**  $w-conv$ :  $w \longrightarrow \nu_b-opt$   
 $\langle proof \rangle$

MPI converges monotonically to the optimal value from below. The iterates are sandwiched between  $\mathcal{L}_b$  from below and  $U_b$  from above.

**theorem**  $mpi-conv$ :

**assumes**  $v0 \leq \mathcal{L}_b \ v0$

**shows**  $mpi-val \longrightarrow \nu_b-opt$  **and**  $\bigwedge n. mpi-val \ n \leq mpi-val \ (Suc \ n)$

$\langle proof \rangle$

### 3.7 $\epsilon$ -Optimality

This gives an upper bound on the error of MPI.

**lemma**  $mpi-pol-eps-opt$ :

**assumes**  $2 * l * dist \ (mpi-val \ n) \ (\mathcal{L}_b \ (mpi-val \ n)) < eps * (1 - l)$

$eps > 0$

**shows**  $dist \ (\nu_b \ (mk-stationary-det \ (mpi-pol \ n))) \ (\mathcal{L}_b \ (mpi-val \ n)) \leq$

$eps / 2$

$\langle proof \rangle$

**lemma**  $mpi-pol-opt$ :

**assumes**  $2 * l * dist \ (mpi-val \ n) \ (\mathcal{L}_b \ (mpi-val \ n)) < eps * (1 - l)$

$eps > 0$

**shows**  $dist \ (\nu_b \ (mk-stationary-det \ (mpi-pol \ n))) \ (\nu_b-opt) < eps$

$\langle proof \rangle$

**lemma**  $mpi-val-term-ex$ :

**assumes**  $v0 \leq \mathcal{L}_b \ v0 \ eps > 0$

**shows**  $\exists n. 2 * l * dist \ (mpi-val \ n) \ (\mathcal{L}_b \ (mpi-val \ n)) < eps * (1 - l)$

$\langle proof \rangle$

**end**

### 3.8 Unbounded MPI

**context**

**fixes**  $eps \ \delta :: real$  **and**  $M :: nat$

**begin**

**function** (*domintros*) *mpi-algo* **where** *mpi-algo* *d v m* = (  
 if  $2 * l * \text{dist } v (\mathcal{L}_b \ v) < \text{eps} * (1 - l)$   
 then (*policy-improvement* *d v*, *v*)  
 else *mpi-algo* (*policy-improvement* *d v*) (*L-pow* *v* (*policy-improvement*  
*d v*) (*m 0 v*)) ( $\lambda n. m \ (\text{Suc } n)$ ))  
*<proof>*)

We define a tailrecursive version of *mpi* which more closely resembles *mpi-algo*.

**fun** *mpi'* **where**  
*mpi'* *d v 0 m* = (*policy-improvement* *d v*, *v*) |  
*mpi'* *d v (Suc n) m* = (  
 let *d'* = *policy-improvement* *d v*; *v'* = *L-pow* *v d' (m 0 v)* in *mpi'* *d'*  
*v' n* ( $\lambda n. m \ (\text{Suc } n)$ ))

**lemma** *mpi-Suc'*:  
**assumes**  $d \in D_D$   
**shows** *mpi* *d v m (Suc n)* = *mpi* (*policy-improvement* *d v*) (*L-pow* *v*  
(*policy-improvement* *d v*) (*m 0 v*)) ( $\lambda a. m \ (\text{Suc } a)$ ) *n*  
*<proof>*

**lemma**  
**assumes**  $d \in D_D$   
**shows** *mpi* *d v m n* = *mpi'* *d v n m*  
*<proof>*

**lemma** *termination-mpi-algo*:  
**assumes**  $\text{eps} > 0 \ d \in D_D \ v \leq \mathcal{L}_b \ v$   
**shows** *mpi-algo-dom* (*d*, *v*, *m*)  
*<proof>*

**abbreviation** *mpi-alg-rec* *d v m*  $\equiv$   
 (if  $2 * l * \text{dist } v (\mathcal{L}_b \ v) < \text{eps} * (1 - l)$  then (*policy-improvement*  
*d v*, *v*)  
 else *mpi-algo* (*policy-improvement* *d v*) (*L-pow* *v* (*policy-improvement*  
*d v*) (*m 0 v*))  
 ( $\lambda n. m \ (\text{Suc } n)$ ))

**lemma** *mpi-algo-def'*:  
**assumes**  $d \in D_D \ v \leq \mathcal{L}_b \ v \ \text{eps} > 0$   
**shows** *mpi-algo* *d v m* = *mpi-alg-rec* *d v m*  
*<proof>*

**lemma** *mpi-algo-eq-mpi*:  
**assumes**  $d \in D_D \ v \leq \mathcal{L}_b \ v \ \text{eps} > 0$   
**shows** *mpi-algo* *d v m* = *mpi* *d v m* (*LEAST* *n*.  $2 * l * \text{dist} \ (\text{mpi-val}$   
*d v m n*) ( $\mathcal{L}_b \ (\text{mpi-val } d \ v \ m \ n)) < \text{eps} * (1 - l)$ )  
*<proof>*

**lemma** *mpi-algo-opt*:  
**assumes**  $v0 \leq \mathcal{L}_b$   $v0 \text{ eps} > 0$   $d \in D_D$   
**shows**  $\text{dist } (\nu_b \text{ (mk-stationary-det (fst (mpi-algo d v0 m)))) } \nu_b\text{-opt}$   
 $< \text{eps}$   
 $\langle \text{proof} \rangle$

**end**

### 3.9 Initial Value Estimate *v0-mpi*

We define an initial estimate of the value function for which Modified Policy Iteration always terminates.

**abbreviation**  $r\text{-min} \equiv (\bigcap s' \text{ a. } r(s', a))$

**definition**  $v0\text{-mpi } s = r\text{-min} / (1 - l)$

**lift-definition**  $v0\text{-mpi}_b :: 's \Rightarrow_b \text{real}$  **is**  $v0\text{-mpi}$   
 $\langle \text{proof} \rangle$

**lemma**  $v0\text{-mpi}_b\text{-le-}\mathcal{L}_b$ :  $v0\text{-mpi}_b \leq \mathcal{L}_b$   $v0\text{-mpi}_b$   
 $\langle \text{proof} \rangle$

### 3.10 An Instance of Modified Policy Iteration with a Valid Conservative Initial Value Estimate

**definition**  $\text{mpi-user } \text{eps } m =$  (  
 $\text{if } \text{eps} \leq 0 \text{ then undefined else mpi-algo } \text{eps } (\lambda x. \text{arb-act } (A \ x))$   
 $v0\text{-mpi}_b \ m)$

**lemma** *mpi-user-eq*:  
**assumes**  $\text{eps} > 0$   
**shows**  $\text{mpi-user } \text{eps} = \text{mpi-alg-rec } \text{eps } (\lambda x. \text{arb-act } (A \ x)) \ v0\text{-mpi}_b$   
 $\langle \text{proof} \rangle$

**lemma** *mpi-user-opt*:  
**assumes**  $\text{eps} > 0$   
**shows**  $\text{dist } (\nu_b \text{ (mk-stationary-det (fst (mpi-user } \text{eps } n)))) \nu_b\text{-opt} <$   
 $\text{eps}$   
 $\langle \text{proof} \rangle$

**end**

**end**  
**theory** *Matrix-Util*  
**imports** *HOL-Analysis.Analysis*  
**begin**



## 4 Matrices

**proposition** *scalar-matrix-assoc*:  
**fixes**  $C :: ('b::\text{real-algebra-1})^m \times n$   
**shows**  $k *_R (C ** D) = C ** (k *_R D)$   
 $\langle \text{proof} \rangle$

### 4.1 Nonnegative Matrices

**lemma** *nonneg-matrix-nonneg* [dest]:  $0 \leq m \implies 0 \leq m \$ i \$ j$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-mult-mono*:  
**assumes**  $0 \leq E \ 0 \leq C \ (E :: \text{real}^c \times c) \leq B \ C \leq D$   
**shows**  $E ** C \leq B ** D$   
 $\langle \text{proof} \rangle$

**lemma** *nonneg-matrix-mult*:  $0 \leq (C :: ('b::\{\text{field}, \text{ordered-ring}\})^{\wedge} \times \wedge)$   
 $\implies 0 \leq D \implies 0 \leq C ** D$   
 $\langle \text{proof} \rangle$

**lemma** *zero-le-mat-iff* [simp]:  $0 \leq \text{mat } (x :: 'c :: \{\text{zero}, \text{order}\}) \longleftrightarrow$   
 $0 \leq x$   
 $\langle \text{proof} \rangle$

**lemma** *nonneg-mat-ge-zero*:  $0 \leq Q \implies 0 \leq v \implies 0 \leq Q * v \ (v ::$   
 $\text{real}^c \times c)$   
 $\langle \text{proof} \rangle$

**lemma** *nonneg-mat-mono*:  $0 \leq Q \implies u \leq v \implies Q * v \ u \leq Q * v \ (v$   
 $:: \text{real}^c \times c)$   
 $\langle \text{proof} \rangle$

**lemma** *nonneg-mult-imp-nonneg-mat*:  
**assumes**  $\bigwedge v. v \geq 0 \implies X * v \ v \geq 0$   
**shows**  $X \geq (0 :: \text{real}^{\wedge} \times \wedge)$   
 $\langle \text{proof} \rangle$

**lemma** *nonneg-mat-iff*:  
 $(X \geq (0 :: \text{real}^{\wedge} \times \wedge)) \longleftrightarrow (\forall v. v \geq 0 \longrightarrow X * v \ v \geq 0)$   
 $\langle \text{proof} \rangle$

**lemma** *mat-le-iff*:  $(X \leq Y) \longleftrightarrow (\forall x \geq 0. (X :: \text{real}^{\wedge} \times \wedge) * v \ x \leq Y * v$   
 $x)$   
 $\langle \text{proof} \rangle$

### 4.2 Matrix Powers

**primrec** *matpow* ::  $'a::\text{semiring-1}^n \times n \Rightarrow \text{nat} \Rightarrow 'a^{\wedge} n \times n$  **where**  
*matpow-0*:  $\text{matpow } A \ 0 = \text{mat } 1 \mid$

*matpow-Suc*:  $\text{matpow } A \text{ (Suc } n) = (\text{matpow } A \text{ } n) ** A$

**lemma** *nonneg-matpow*:  $0 \leq X \implies 0 \leq \text{matpow } (X :: \text{real } ^\wedge - ^\wedge -) \text{ } i$   
 $\langle \text{proof} \rangle$

**lemma** *matpow-mono*:  $0 \leq C \implies C \leq D \implies \text{matpow } (C :: \text{real } ^\wedge - ^\wedge -)$   
 $n \leq \text{matpow } D \text{ } n$   
 $\langle \text{proof} \rangle$

**lemma** *matpow-scaleR*:  $\text{matpow } (c *_R (X :: 'b :: \text{real-algebra-1 } ^\wedge - ^\wedge -))$   
 $n = (c ^\wedge n) *_R (\text{matpow } X) \text{ } n$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-vector-mult-code'*:  $(X *_v x) \$ i = (\sum_{j \in UNIV}. X \$ j \$ i$   
 $\$ j * x \$ j)$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-vector-mult-mono*:  $(0 :: \text{real } ^\wedge - ^\wedge -) \leq X \implies 0 \leq v \implies X$   
 $\leq Y \implies X *_v v \leq Y *_v v$   
 $\langle \text{proof} \rangle$

### 4.3 Triangular Matrices

**definition** *lower-triangular-mat*  $X \longleftrightarrow (\forall i \ j. (i :: 'b :: \{\text{finite}, \text{linorder}\})$   
 $< j \longrightarrow X \$ i \$ j = 0)$

**definition** *strict-lower-triangular-mat*  $X \longleftrightarrow (\forall i \ j. (i :: 'b :: \{\text{finite},$   
 $\text{linorder}\}) \leq j \longrightarrow X \$ i \$ j = 0)$

**definition** *upper-triangular-mat*  $X \longleftrightarrow (\forall i \ j. j < i \longrightarrow X \$ i \$ j =$   
 $0)$

**lemma** *stlI*: *strict-lower-triangular-mat*  $X \implies \text{lower-triangular-mat}$   
 $X$   
 $\langle \text{proof} \rangle$

**lemma** *lower-triangular-mat-mat*: *lower-triangular-mat*  $(\text{mat } x)$   
 $\langle \text{proof} \rangle$

**lemma** *lower-triangular-mult*:  
**assumes** *lower-triangular-mat*  $X$  *lower-triangular-mat*  $Y$   
**shows** *lower-triangular-mat*  $(X ** Y)$   
 $\langle \text{proof} \rangle$

**lemma** *lower-triangular-pow*:  
**assumes** *lower-triangular-mat*  $X$   
**shows** *lower-triangular-mat*  $(\text{matpow } X \text{ } i)$   
 $\langle \text{proof} \rangle$

**lemma** *lower-triangular-suminf*:  
**assumes**  $\bigwedge i. \text{lower-triangular-mat } (f \ i) \text{ summable } (f \ :: \text{ nat} \Rightarrow 'b::\text{real-normed-vector}^{\wedge} \text{-}\wedge)$   
**shows**  $\text{lower-triangular-mat } (\sum i. f \ i)$   
 $\langle \text{proof} \rangle$

**lemma** *lower-triangular-pow-eq*:  
**assumes**  $\text{lower-triangular-mat } X \ \text{lower-triangular-mat } Y \ \bigwedge s'. s' \leq s \Rightarrow \text{row } s' \ X = \text{row } s' \ Y \ s' \leq s$   
**shows**  $\text{row } s' \ (\text{matpow } X \ i) = \text{row } s' \ (\text{matpow } Y \ i)$   
 $\langle \text{proof} \rangle$

**lemma** *lower-triangular-mat-mult*:  
**assumes**  $\text{lower-triangular-mat } M \ \bigwedge i. i \leq j \Rightarrow v \ \$ \ i = v' \ \$ \ i$   
**shows**  $(M * v \ v) \ \$ \ j = (M * v \ v') \ \$ \ j$   
 $\langle \text{proof} \rangle$

#### 4.4 Inverses

**lemma** *matrix-inv*:  
**assumes** *invertible*  $M$   
**shows** *matrix-inv-left*:  $\text{matrix-inv } M ** M = \text{mat } 1$   
**and** *matrix-inv-right*:  $M ** \text{matrix-inv } M = \text{mat } 1$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-inv-unique*:  
**fixes**  $A::'a::\{\text{semiring-1}\}^{\wedge} n^{\wedge} n$   
**assumes**  $AB: A ** B = \text{mat } 1$  **and**  $BA: B ** A = \text{mat } 1$   
**shows**  $\text{matrix-inv } A = B$   
 $\langle \text{proof} \rangle$

**end**  
**theory** *Blinfun-Matrix*  
**imports**  
 $\text{MDP-Rewards.Blinfun-Util}$   
 $\text{Matrix-Util}$   
**begin**

## 5 Bounded Linear Functions and Matrices

**definition** *blinfun-to-matrix*  $(f :: ('b::\text{finite} \Rightarrow_b \text{real}) \Rightarrow_L ('c::\text{finite} \Rightarrow_b -)) =$   
 $\text{matrix } (\lambda v. (\chi \ j. f \ (Bfun \ ((\$) \ v)) \ j))$

**definition** *matrix-to-blinfun*  $X = \text{Blinfun } (\lambda v. Bfun \ (\lambda i. (X * v \ (\chi \ i. (\text{apply-bfun } v \ i)))) \ \$ \ i))$

**lemma** *plus-vec-eq*:  $(\chi \ i. f \ i + g \ i) = (\chi \ i. f \ i) + (\chi \ i. g \ i)$

$\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-mult*: *matrix-to-blinfun*  $m$  ( $v :: 'c::\text{finite} \Rightarrow_{\text{b}} \text{real}$ )  $i = (m * v (\chi \ i. \ v \ i)) \$ i$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-mult*: (*blinfun-to-matrix*  $f * v (\chi \ i. \ \text{apply-bfun } v \ i)$ )  $\$ i = f \ v \ i$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-mult'*: (*blinfun-to-matrix*  $f * v \ v$ )  $\$ i = f$   
(*Bfun* ( $\lambda i. \ v \ \$ i$ ))  $i$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-mult''*: (*blinfun-to-matrix*  $f * v \ v$ ) = ( $\chi \ i. \ f$   
(*Bfun* ( $\lambda i. \ v \ \$ i$ ))  $i$ )  
 $\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-inv*: *matrix-to-blinfun* (*blinfun-to-matrix*  $f$ )  
=  $f$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-add*: *blinfun-to-matrix* ( $f + g$ ) = *blinfun-to-matrix*  
 $f + \text{blinfun-to-matrix } g$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-diff*: *blinfun-to-matrix* ( $f - g$ ) = *blinfun-to-matrix*  
 $f - \text{blinfun-to-matrix } g$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-scaleR*: *blinfun-to-matrix* ( $c *_R f$ ) =  $c *_R$   
*blinfun-to-matrix*  $f$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-add*:  
*matrix-to-blinfun* (( $f :: \text{real}^{\wedge-}$ ) +  $g$ ) = *matrix-to-blinfun*  $f + \text{ma-}$   
*trix-to-blinfun*  $g$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-diff*:  
*matrix-to-blinfun* (( $f :: \text{real}^{\wedge-}$ ) -  $g$ ) = *matrix-to-blinfun*  $f - \text{ma-}$   
*trix-to-blinfun*  $g$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-scaleR*:  
*matrix-to-blinfun* ( $c *_R (f :: \text{real}^{\wedge-})$ ) =  $c *_R \text{matrix-to-blinfun } f$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-comp*: *matrix-to-blinfun* (( $m :: \text{real}^{\wedge-}$ ) \*\*

$n) = (\text{matrix-to-blinfun } m) \circ_L (\text{matrix-to-blinfun } n)$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-comp*:  $\text{blinfun-to-matrix } (f \circ_L g) = (\text{blinfun-to-matrix } f) ** (\text{blinfun-to-matrix } g)$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-id*:  $\text{blinfun-to-matrix } \text{id-blinfun} = \text{mat } 1$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-id*:  $\text{matrix-to-blinfun } (\text{mat } 1 :: (\text{real} \hat{-} \hat{-})) = \text{id-blinfun}$   
 $\langle \text{proof} \rangle$

**lemma** *matrix-to-blinfun-inv<sub>L</sub>*:  
**assumes** *invertible*  $m$   
**shows**  $\text{matrix-to-blinfun } (\text{matrix-inv } (m :: \text{real} \hat{-} \hat{-})) = \text{inv}_L (\text{matrix-to-blinfun } m)$   
 $\text{invertible}_L (\text{matrix-to-blinfun } m)$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-inverse*:  
**assumes** *invertible<sub>L</sub>*  $X$   
**shows**  $\text{invertible } (\text{blinfun-to-matrix } (X :: ('b::\text{finite} \Rightarrow_b \text{real}) \Rightarrow_L 'c::\text{finite} \Rightarrow_b \text{real}))$   
 $\text{blinfun-to-matrix } (\text{inv}_L X) = \text{matrix-inv } (\text{blinfun-to-matrix } X)$   
 $\langle \text{proof} \rangle$

**lemma** *blinfun-to-matrix-inv[simp]*:  $\text{blinfun-to-matrix } (\text{matrix-to-blinfun } f) = f$   
 $\langle \text{proof} \rangle$

**lemma** *invertible-invertible<sub>L</sub>-I*:  $\text{invertible } (\text{blinfun-to-matrix } f) \implies \text{invertible}_L f$   
 $\text{invertible}_L (\text{matrix-to-blinfun } X) \implies \text{invertible } (X :: \text{real} \hat{-} \hat{-})$   
 $\langle \text{proof} \rangle$

**lemma** *bounded-linear-blinfun-to-matrix*:  $\text{bounded-linear } (\text{blinfun-to-matrix } :: ('a \Rightarrow_b \text{real}) \Rightarrow_L ('b \Rightarrow_b \text{real}) \Rightarrow \text{real} \hat{-} 'a \hat{-} 'b)$   
 $\langle \text{proof} \rangle$

**lemma** *summable-blinfun-to-matrix*:  
**assumes** *summable*  $(f :: \text{nat} \Rightarrow ('c::\text{finite} \Rightarrow_b -) \Rightarrow_L ('c \Rightarrow_b -))$   
**shows**  $\text{summable } (\lambda i. \text{blinfun-to-matrix } (f i))$   
 $\langle \text{proof} \rangle$

**abbreviation** *nonneg-blinfun*  $Q \equiv 0 \leq (\text{blinfun-to-matrix } Q)$

**lemma** *nonneg-blinfun-mono*:  $\text{nonneg-blinfun } Q \implies u \leq v \implies Q\ u \leq Q\ v$   
 ⟨proof⟩

**lemma** *nonneg-blinfun-nonneg*:  $\text{nonneg-blinfun } Q \implies 0 \leq v \implies 0 \leq Q\ v$   
 ⟨proof⟩

**lemma** *nonneg-id-blinfun*:  $\text{nonneg-blinfun id-blinfun}$   
 ⟨proof⟩

**lemma** *norm-nonneg-blinfun-one*:  
**assumes**  $0 \leq \text{blinfun-to-matrix } X$   
**shows**  $\text{norm } X = \text{norm } (\text{blinfun-apply } X\ 1)$   
 ⟨proof⟩

**lemma** *matrix-le-norm-mono*:  
**assumes**  $0 \leq (\text{blinfun-to-matrix } C)$   
**and**  $(\text{blinfun-to-matrix } C) \leq (\text{blinfun-to-matrix } D)$   
**shows**  $\text{norm } C \leq \text{norm } D$   
 ⟨proof⟩

**lemma** *blinfun-to-matrix-matpow*:  $\text{blinfun-to-matrix } (X \text{ ^^ } i) = \text{mat-pow } (\text{blinfun-to-matrix } X)\ i$   
 ⟨proof⟩

**lemma** *nonneg-blinfun-iff*:  $\text{nonneg-blinfun } X \longleftrightarrow (\forall v \geq 0. X\ v \geq 0)$   
 ⟨proof⟩

**lemma** *blinfun-apply-mono*:  $(0::\text{real}^{\wedge}\text{-}\wedge) \leq \text{blinfun-to-matrix } X \implies 0 \leq v \implies \text{blinfun-to-matrix } X \leq \text{blinfun-to-matrix } Y \implies X\ v \leq Y\ v$   
 ⟨proof⟩

**end**

**theory** *Splitting-Methods*  
**imports**  
   *Blinfun-Matrix*  
   *Value-Iteration*  
   *Policy-Iteration*  
**begin**

## 6 Value Iteration using Splitting Methods

### 6.1 Regular Splittings for Matrices and Bounded Linear Functions

**definition** *is-splitting-mat*  $X\ Q\ R \longleftrightarrow$

$$X = Q - R \wedge \text{invertible } Q \wedge 0 \leq \text{matrix-inv } Q \wedge 0 \leq R$$

**definition** *is-splitting-blin*  $X \ Q \ R \longleftrightarrow \text{is-splitting-mat } (\text{blinfun-to-matrix } X) \ (\text{blinfun-to-matrix } Q) \ (\text{blinfun-to-matrix } R)$

**lemma** *is-splitting-blin-def'*: *is-splitting-blin*  $X \ Q \ R \longleftrightarrow$

$X = Q - R \wedge \text{invertible}_L \ Q \wedge \text{nonneg-blinfun } (\text{inv}_L \ Q) \wedge \text{non-neg-blinfun } R$   
 $\langle \text{proof} \rangle$

**lemma** *is-splitting-blinD[dest]*:

**assumes** *is-splitting-blin*  $X \ Q \ R$   
**shows**  $X = Q - R \wedge \text{invertible}_L \ Q \wedge \text{nonneg-blinfun } (\text{inv}_L \ Q) \wedge \text{non-neg-blinfun } R$   
 $\langle \text{proof} \rangle$

## 6.2 Splitting Methods for MDPs

**locale** *MDP-QR* = *MDP-finite-type*  $A \ K \ r \ l$

**for**  $A :: 's :: \text{finite} \Rightarrow ('a :: \text{finite}) \text{ set}$   
**and**  $K :: ('s \times 'a) \Rightarrow 's \text{ pmf}$   
**and**  $r \ l +$   
**fixes**  $Q :: ('s \Rightarrow 'a) \Rightarrow ('s \Rightarrow_b \text{real}) \Rightarrow_L ('s \Rightarrow_b \text{real})$   
**fixes**  $R :: ('s \Rightarrow 'a) \Rightarrow ('s \Rightarrow_b \text{real}) \Rightarrow_L ('s \Rightarrow_b \text{real})$   
**assumes** *is-splitting*:  $\bigwedge d. d \in D_D \Longrightarrow \text{is-splitting-blin } (\text{id-blinfun} - l *_R \mathcal{P}_1 (\text{mk-dec-det } d)) (Q \ d) (R \ d)$   
**assumes** *QR-contraction*:  $(\bigsqcup_{d \in D_D} \text{norm } (\text{inv}_L (Q \ d) \ o_L \ R \ d)) < 1$   
**assumes** *arg-max-ex-split*:  $\exists d. \forall s. \text{is-arg-max } (\lambda d. \text{inv}_L (Q \ d) (r\text{-dec}_b (\text{mk-dec-det } d) + R \ d \ v) \ s) (\lambda d. d \in D_D) \ d$   
**begin**

**lemma** *inv-Q-mono*:  $d \in D_D \Longrightarrow u \leq v \Longrightarrow (\text{inv}_L (Q \ d)) \ u \leq (\text{inv}_L (Q \ d)) \ v$   
 $\langle \text{proof} \rangle$

**lemma** *splitting-eq*:  $d \in D_D \Longrightarrow Q \ d - R \ d = (\text{id-blinfun} - l *_R \mathcal{P}_1 (\text{mk-dec-det } d))$   
 $\langle \text{proof} \rangle$

**lemma** *Q-nonneg*:  $d \in D_D \Longrightarrow 0 \leq v \Longrightarrow 0 \leq \text{inv}_L (Q \ d) \ v$   
 $\langle \text{proof} \rangle$

**lemma** *Q-invertible*:  $d \in D_D \Longrightarrow \text{invertible}_L (Q \ d)$   
 $\langle \text{proof} \rangle$

**lemma** *R-nonneg*:  $d \in D_D \Longrightarrow 0 \leq v \Longrightarrow 0 \leq R \ d \ v$   
 $\langle \text{proof} \rangle$

**lemma** *R-mono*:  $d \in D_D \implies u \leq v \implies (R\ d)\ u \leq (R\ d)\ v$   
 $\langle \text{proof} \rangle$

**lemma** *QR-nonneg*:  $d \in D_D \implies 0 \leq v \implies 0 \leq (\text{inv}_L\ (Q\ d)\ o_L\ R\ d)\ v$   
 $\langle \text{proof} \rangle$

**lemma** *QR-mono*:  $d \in D_D \implies u \leq v \implies (\text{inv}_L\ (Q\ d)\ o_L\ R\ d)\ u \leq (\text{inv}_L\ (Q\ d)\ o_L\ R\ d)\ v$   
 $\langle \text{proof} \rangle$

**lemma** *norm-QR-less-one*:  $d \in D_D \implies \text{norm}\ (\text{inv}_L\ (Q\ d)\ o_L\ R\ d) < 1$   
 $\langle \text{proof} \rangle$

**lemma** *splitting*:  $d \in D_D \implies \text{id-blinfun} - l *_R \mathcal{P}_1\ (\text{mk-dec-det}\ d) = Q\ d - R\ d$   
 $\langle \text{proof} \rangle$

### 6.3 Discount Factor *QR-disc*

**abbreviation** *QR-disc*  $\equiv (\bigsqcup d \in D_D. \text{norm}\ (\text{inv}_L\ (Q\ d)\ o_L\ R\ d))$

**lemma** *QR-le-QR-disc*:  $d \in D_D \implies \text{norm}\ (\text{inv}_L\ (Q\ d)\ o_L\ (R\ d)) \leq \text{QR-disc}$   
 $\langle \text{proof} \rangle$

**lemma** *a-nonneg*:  $0 \leq \text{QR-disc}$   
 $\langle \text{proof} \rangle$

### 6.4 Bellman-Operator

**abbreviation** *L-split*  $d\ v \equiv \text{inv}_L\ (Q\ d)\ (r\text{-dec}_b\ (\text{mk-dec-det}\ d) + R\ d\ v)$

**definition** *L-split*  $v\ s = (\bigsqcup d \in D_D. L\text{-split}\ d\ v\ s)$

**lemma** *L-split-bfun-aux*:  
**assumes**  $d \in D_D$   
**shows**  $\text{norm}\ (L\text{-split}\ d\ v) \leq (\bigsqcup d \in D_D. \text{norm}\ (\text{inv}_L\ (Q\ d))) * r_M + \text{norm}\ v$   
 $\langle \text{proof} \rangle$

**lift-definition** *L<sub>b</sub>-split*  $:: ('s \Rightarrow_b \text{real}) \Rightarrow ('s \Rightarrow_b \text{real})$  **is** *L-split*  
 $\langle \text{proof} \rangle$

**lemma** *L<sub>b</sub>-split-def'*:  $\mathcal{L}_b\text{-split}\ v\ s = (\bigsqcup d \in D_D. L\text{-split}\ d\ v\ s)$   
 $\langle \text{proof} \rangle$



**lemma**  $\mathcal{L}_b$ -split-contraction:  $\text{dist } (\mathcal{L}_b\text{-split } v) (\mathcal{L}_b\text{-split } u) \leq QR\text{-disc} * \text{dist } v u$   
 $\langle \text{proof} \rangle$

**lemma**  $\mathcal{L}_b$ -lim:  
 $\exists ! v. \mathcal{L}_b\text{-split } v = v$   
 $(\lambda n. (\mathcal{L}_b\text{-split } \sim^n n) v) \longrightarrow (THE\ v. \mathcal{L}_b\text{-split } v = v)$   
 $\langle \text{proof} \rangle$

**lemma**  $\mathcal{L}_b$ -split-tendsto-opt:  $(\lambda n. (\mathcal{L}_b\text{-split } \sim^n n) v) \longrightarrow \nu_b\text{-opt}$   
 $\langle \text{proof} \rangle$

**lemma**  $\mathcal{L}_b$ -split-fix[simp]:  $\mathcal{L}_b\text{-split } \nu_b\text{-opt} = \nu_b\text{-opt}$   
 $\langle \text{proof} \rangle$

**lemma**  $\text{dist-}\mathcal{L}_b\text{-split-opt-eps}$ :  
**assumes**  $\text{eps} > 0 \ 2 * QR\text{-disc} * \text{dist } v (\mathcal{L}_b\text{-split } v) < \text{eps} * (1 - QR\text{-disc})$   
**shows**  $\text{dist } (\mathcal{L}_b\text{-split } v) \nu_b\text{-opt} < \text{eps} / 2$   
 $\langle \text{proof} \rangle$

**lemma**  $L$ -split-fix:  
**assumes**  $d \in D_D$   
**shows**  $L\text{-split } d (\nu_b (mk\text{-stationary-det } d)) = \nu_b (mk\text{-stationary-det } d)$   
 $\langle \text{proof} \rangle$

**lemma**  $L$ -split-contraction:  
**assumes**  $d \in D_D$   
**shows**  $\text{dist } (L\text{-split } d v) (L\text{-split } d u) \leq QR\text{-disc} * \text{dist } v u$   
 $\langle \text{proof} \rangle$

**lemma**  $\text{find-policy-QR-error-bound}$ :  
**assumes**  $\text{eps} > 0 \ 2 * QR\text{-disc} * \text{dist } v (\mathcal{L}_b\text{-split } v) < \text{eps} * (1 - QR\text{-disc})$   
**assumes**  $am: \bigwedge s. \text{is-arg-max } (\lambda d. L\text{-split } d (\mathcal{L}_b\text{-split } v) s) (\lambda d. d \in D_D) d$   
**shows**  $\text{dist } (\nu_b (mk\text{-stationary-det } d)) \nu_b\text{-opt} < \text{eps}$   
 $\langle \text{proof} \rangle$   
**end**

**context**  $MDP\text{-ord}$  **begin**

**lemma**  $\text{inv-one-sub-Q'}$ :  
**fixes**  $Q :: 'c :: \text{banach} \Rightarrow_L 'c$   
**assumes**  $\text{onorm-le: norm } (id\text{-blinfun} - Q) < 1$   
**shows**  $\text{inv}_L Q = (\sum i. (id\text{-blinfun} - Q) \sim^i)$   
 $\langle \text{proof} \rangle$

An important theorem: allows to compare the rate of convergence

for different splittings

**lemma** *norm-splitting-le*:

**assumes** *is-splitting-blin* (*id-blinfun* - *l* \*<sub>R</sub>  $\mathcal{P}_1$  *d*) *Q1 R1*  
**and** *is-splitting-blin* (*id-blinfun* - *l* \*<sub>R</sub>  $\mathcal{P}_1$  *d*) *Q2 R2*  
**and** (*blinfun-to-matrix* *R2*) ≤ (*blinfun-to-matrix* *R1*)  
**and** (*blinfun-to-matrix* *R1*) ≤ (*blinfun-to-matrix* (*l* \*<sub>R</sub>  $\mathcal{P}_1$  *d*))  
**shows** *norm* (*inv*<sub>L</sub> *Q2* *o*<sub>L</sub> *R2*) ≤ *norm* (*inv*<sub>L</sub> *Q1* *o*<sub>L</sub> *R1*)

⟨*proof*⟩

## 6.5 Gauss Seidel Splitting

### 6.5.1 Definition of Upper and Lower Triangular Matrices

**definition** *P-dec* *d* ≡ *blinfun-to-matrix* ( $\mathcal{P}_1$  (*mk-dec-det* *d*))

**definition** *P-upper* *d* ≡ ( $\chi$  *i j*. if *i* ≤ *j* then *P-dec* *d* \$ *i* \$ *j* else 0)

**definition** *P-lower* *d* ≡ ( $\chi$  *i j*. if *j* < *i* then *P-dec* *d* \$ *i* \$ *j* else 0)

**definition**  $\mathcal{P}_U$  *d* = *matrix-to-blinfun* (*P-upper* *d*)

**definition**  $\mathcal{P}_L$  *d* = *matrix-to-blinfun* (*P-lower* *d*)

**lemma** *P-dec-elem*: *P-dec* *d* \$ *i* \$ *j* = *pmf* (*K* (*i*, *d i*)) *j*

⟨*proof*⟩

**lemma** *nonneg-P<sub>U</sub>*: *nonneg-blinfun* ( $\mathcal{P}_U$  *d*)

⟨*proof*⟩

**lemma** *nonneg-P-dec*: 0 ≤ *P-dec* *d*

⟨*proof*⟩

**lemma** *nonneg-P-upper*: 0 ≤ *P-upper* *d*

⟨*proof*⟩

**lemma** *nonneg-P-lower*: 0 ≤ *P-lower* *d*

⟨*proof*⟩

**lemma** *nonneg-P<sub>L</sub>*: *nonneg-blinfun* ( $\mathcal{P}_L$  *d*)

⟨*proof*⟩

**lemma** *nonneg-P<sub>1</sub>*: *nonneg-blinfun* ( $\mathcal{P}_1$  *d*)

⟨*proof*⟩

**lemma** *norm-P<sub>L</sub>-le*: *norm* ( $\mathcal{P}_L$  *d*) ≤ *norm* ( $\mathcal{P}_1$  (*mk-dec-det* *d*))

⟨*proof*⟩

**lemma** *norm-P<sub>L</sub>-le-one*: *norm* ( $\mathcal{P}_L$  *d*) ≤ 1

⟨*proof*⟩

**lemma** *norm-P<sub>L</sub>-less-one*: *norm* (*l* \*<sub>R</sub>  $\mathcal{P}_L$  *d*) < 1

$\langle proof \rangle$

**lemma**  $\mathcal{P}_L\text{-le-}\mathcal{P}_1$ :  $0 \leq v \implies \mathcal{P}_L \ d \ v \leq \mathcal{P}_1 \ (mk\text{-dec-det } d) \ v$   
 $\langle proof \rangle$

**lemma**  $\mathcal{P}_U\text{-le-}\mathcal{P}_1$ :  $0 \leq v \implies \mathcal{P}_U \ d \ v \leq \mathcal{P}_1 \ (mk\text{-dec-det } d) \ v$   
 $\langle proof \rangle$

**lemma**  $row\text{-}P\text{-upper-indep}$ :  $d \ s = d' \ s \implies row \ s \ (P\text{-upper } d) = row \ s \ (P\text{-upper } d')$   
 $\langle proof \rangle$

**lemma**  $row\text{-}P\text{-lower-indep}$ :  $d \ s = d' \ s \implies row \ s \ (P\text{-lower } d) = row \ s \ (P\text{-lower } d')$   
 $\langle proof \rangle$

**lemma**  $triangular\text{-mat-}P\text{-upper}$ :  $upper\text{-triangular-mat } (P\text{-upper } d)$   
 $\langle proof \rangle$

**lemma**  $slt\text{-}P\text{-lower}$ :  $strict\text{-lower-triangular-mat } (P\text{-lower } d)$   
 $\langle proof \rangle$

**lemma**  $lt\text{-}P\text{-lower}$ :  $lower\text{-triangular-mat } (P\text{-lower } d)$   
 $\langle proof \rangle$

### 6.5.2 Gauss Seidel is a Regular Splitting

**definition**  $Q\text{-GS } d = id\text{-blnfun} - l *_R \mathcal{P}_L \ d$

**definition**  $R\text{-GS } d = l *_R \mathcal{P}_U \ d$

**lemma**  $splitting\text{-gauss}$ :  $is\text{-splitting-blin } (id\text{-blnfun} - l *_R \mathcal{P}_1 \ (mk\text{-dec-det } d)) \ (Q\text{-GS } d) \ (R\text{-GS } d)$   
 $\langle proof \rangle$

**abbreviation**  $r\text{-det}_b \ d \equiv r\text{-dec}_b \ (mk\text{-dec-det } d)$

**abbreviation**  $r\text{-vec } d \equiv \chi \ i. \ r\text{-dec}_b \ (mk\text{-dec-det } d) \ i$

**abbreviation**  $Q\text{-mat } d \equiv blnfun\text{-to-matrix } (Q\text{-GS } d)$

**abbreviation**  $R\text{-mat } d \equiv blnfun\text{-to-matrix } (R\text{-GS } d)$

**lemma**  $Q\text{-mat-def}$ :  $Q\text{-mat } d = mat \ 1 - l *_R \ P\text{-lower } d$   
 $\langle proof \rangle$

**lemma**  $R\text{-mat-def}$ :  $R\text{-mat } d = l *_R \ P\text{-upper } d$   
 $\langle proof \rangle$

**lemma**  $triangular\text{-mat-}R$ :  $upper\text{-triangular-mat } (R\text{-mat } d)$   
 $\langle proof \rangle$

**definition**  $GS\text{-}inv\ d\ v \equiv matrix\text{-}inv\ (Q\text{-}mat\ d) *v\ (r\text{-}vec\ d + R\text{-}mat\ d *v\ v)$

$Q\text{-}mat$  can be expressed as an infinite sum of  $P\text{-}lower$ . It is therefore lower triangular.

**lemma**  $inv\text{-}Q\text{-}mat\text{-}suminf$ :  $matrix\text{-}inv\ (Q\text{-}mat\ d) = (\sum k. (matpow\ (l *R\ (P\text{-}lower\ d))\ k))$   
 $\langle proof \rangle$

**lemma**  $lt\text{-}Q\text{-}inv$ :  $lower\text{-}triangular\text{-}mat\ (matrix\text{-}inv\ (Q\text{-}mat\ d))$   
 $\langle proof \rangle$

Each row of the matrix  $Q\text{-}mat\ d$  only depends on  $d$ 's actions in lower states.

**lemma**  $inv\text{-}Q\text{-}mat\text{-}indep$ :  
**assumes**  $\bigwedge i. i \leq s \implies d\ i = d'\ i\ i \leq s$   
**shows**  $row\ i\ (matrix\text{-}inv\ (Q\text{-}mat\ d)) = row\ i\ (matrix\text{-}inv\ (Q\text{-}mat\ d'))$   
 $\langle proof \rangle$

As a result, also  $GS\text{-}inv$  is independent of lower actions.

**lemma**  $GS\text{-}indep\text{-}high\text{-}states$ :  
**assumes**  $\bigwedge s'. s' \leq s \implies d\ s' = d'\ s'$   
**shows**  $GS\text{-}inv\ d\ v\ \$\ s = GS\text{-}inv\ d'\ v\ \$\ s$   
 $\langle proof \rangle$

This recursive definition mimics the computation of the GS iteration.

**lemma**  $GS\text{-}inv\text{-}rec$ :  $GS\text{-}inv\ d\ v = r\text{-}vec\ d + l *R\ (P\text{-}upper\ d *v\ v + P\text{-}lower\ d *v\ (GS\text{-}inv\ d\ v))$   
 $\langle proof \rangle$

**lemma**  $is\text{-}am\text{-}GS\text{-}inv\text{-}extend$ :  
**assumes**  $\bigwedge s. s < k \implies is\text{-}arg\text{-}max\ (\lambda d. GS\text{-}inv\ d\ v\ \$\ s)\ (\lambda d. d \in D_D)\ d$   
**and**  $is\text{-}arg\text{-}max\ (\lambda a. GS\text{-}inv\ (d\ (k := a))\ v\ \$\ k)\ (\lambda a. a \in A\ k)\ a$   
**and**  $s \leq k$   
**and**  $d \in D_D$   
**shows**  $is\text{-}arg\text{-}max\ (\lambda d. GS\text{-}inv\ d\ v\ \$\ s)\ (\lambda d. d \in D_D)\ (d\ (k := a))$   
 $\langle proof \rangle$

**lemma**  $is\text{-}arg\text{-}max\text{-}GS\text{-}le$ :  
 $\exists d. \forall s \leq k. is\text{-}arg\text{-}max\ (\lambda d. GS\text{-}inv\ d\ v\ \$\ s)\ (\lambda d. d \in D_D)\ d$   
 $\langle proof \rangle$

**lemma**  $ex\text{-}is\text{-}arg\text{-}max\text{-}GS$ :

$\exists d. \forall s. \text{is-arg-max } (\lambda d. \text{GS-inv } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
 $\langle \text{proof} \rangle$

**function** *GS-rec-fun* **where**

$\text{GS-rec-fun } v \ s = (\bigsqcup a \in A \ s. r \ (s, a) + l * ($   
 $(\sum s' < s. \text{pmf } (K \ (s, a)) \ s' * (\text{GS-rec-fun } v \ s')) +$   
 $(\sum s' \in \{s'. \ s \leq s'\}. \text{pmf } (K \ (s, a)) \ s' * v \ s'))$   
 $\langle \text{proof} \rangle$

**termination**

$\langle \text{proof} \rangle$

**declare** *GS-rec-fun.simps*[*simp del*]

**definition** *GS-rec-elem*  $v \ s \ a = r \ (s, a) + l * ($   
 $(\sum s' < s. \text{pmf } (K \ (s, a)) \ s' * (\text{GS-rec-fun } v \ s')) +$   
 $(\sum s' \in \{s'. \ s \leq s'\}. \text{pmf } (K \ (s, a)) \ s' * v \ s'))$

**lemma** *GS-rec-fun-elem*:  $\text{GS-rec-fun } v \ s = (\bigsqcup a \in A \ s. \text{GS-rec-elem } v$   
 $s \ a)$   
 $\langle \text{proof} \rangle$

**definition** *GS-rec*  $v = (\chi \ s. \text{GS-rec-fun } (\text{vec-nth } v) \ s)$

**lemma** *GS-rec-def'*:  $\text{GS-rec } v \ \$ \ s = (\bigsqcup a \in A \ s. r \ (s, a) + l * ($   
 $(\sum s' < s. \text{pmf } (K \ (s, a)) \ s' * (\text{GS-rec } v \ \$ \ s')) +$   
 $(\sum s' \in \{s'. \ s \leq s'\}. \text{pmf } (K \ (s, a)) \ s' * v \ \$ \ s'))$   
 $\langle \text{proof} \rangle$

**lemma** *GS-rec-eq*:  $\text{GS-rec } v \ \$ \ s = (\bigsqcup a \in A \ s. r \ (s, a) + l * ($   
 $(P\text{-lower } (d(s := a)) * v \ (\text{GS-rec } v)) \ \$ \ s + (P\text{-upper } (d(s := a)) * v$   
 $v) \ \$ \ s))$   
 $\langle \text{proof} \rangle$

**definition** *GS-rec-step*  $d \ v \equiv r\text{-vec } d + l *_R (P\text{-lower } d * v \ \text{GS-rec } v$   
 $+ P\text{-upper } d * v \ v)$

**lemma** *GS-rec-eq'*:  $\text{GS-rec } v \ \$ \ s = (\bigsqcup a \in A \ s. \text{GS-rec-step } (d(s := a))$   
 $v \ \$ \ s)$   
 $\langle \text{proof} \rangle$

**lemma** *GS-rec-eq-vec*:

$\text{GS-rec } v \ \$ \ s = (\bigsqcup d \in D_D. \text{GS-rec-step } d \ v \ \$ \ s)$   
 $\langle \text{proof} \rangle$

**lift-definition** *GS-rec-fun<sub>b</sub>*  $:: ('s \Rightarrow_b \text{real}) \Rightarrow ('s \Rightarrow_b \text{real}) \text{ is } \text{GS-rec-fun}$   
 $\langle \text{proof} \rangle$

**definition** *GS-rec-fun-inner*  $(v :: 's \Rightarrow_b \text{real}) \ s \ a \equiv r \ (s, a) + l * ($   
 $(\sum s' < s. \text{pmf } (K \ (s, a)) \ s' * (\text{GS-rec-fun}_b \ v \ s')) +$

$$(\sum s' \in \{s'. s \leq s'\}. \text{pmf } (K(s, a)) s' * v s')$$

**definition** *GS-rec-iter* **where**

$$\begin{aligned} \text{GS-rec-iter } v s &= (\bigsqcup a \in A. s. r(s, a) + l * \\ &(\sum s' \in \text{UNIV}. \text{pmf } (K(s, a)) s' * v s')) \end{aligned}$$

**lemma** *GS-rec-fun-eq-GS-iter*:

**assumes**  $\forall s' < s. v\text{-next } s' = \text{GS-rec-fun } v s' \forall s' \in \{s'. s \leq s'\}.$   
 $v\text{-next } s' = v s'$

**shows**  $\text{GS-rec-fun } v s = \text{GS-rec-iter } v\text{-next } s$

$\langle \text{proof} \rangle$

**lemma** *foldl-upd-notin*:  $x \notin \text{set } X \implies \text{foldl } (\lambda f y. f(y := g f y)) c X$   
 $x = c x$

$\langle \text{proof} \rangle$

**lemma** *foldl-upd-notin'*:  $x \notin \text{set } Y \implies \text{foldl } (\lambda f y. f(y := g f y)) c$   
 $(X @ Y) x = \text{foldl } (\lambda f y. f(y := g f y)) c X x$

$\langle \text{proof} \rangle$

**lemma** *sorted-list-of-set-split*:

**assumes** *finite*  $X$

**shows**  $\text{sorted-list-of-set } X = \text{sorted-list-of-set } \{x \in X. x < y\} @$   
 $\text{sorted-list-of-set } \{x \in X. y \leq x\}$

$\langle \text{proof} \rangle$

**lemma** *sorted-list-of-set-split'*:

**assumes** *finite*  $X$

**shows**  $\text{sorted-list-of-set } X = \text{sorted-list-of-set } \{x \in X. x \leq y\} @$   
 $\text{sorted-list-of-set } \{x \in X. y < x\}$

$\langle \text{proof} \rangle$

**lemma** *GS-rec-fun-code*:  $\text{GS-rec-fun } v s = \text{foldl } (\lambda v s. v(s := \text{GS-rec-iter}$   
 $v s)) v (\text{sorted-list-of-set } \{..s\}) s$

$\langle \text{proof} \rangle$

**lemma** *GS-rec-fun-code'*:  $\text{GS-rec-fun } v s = \text{foldl } (\lambda v s. v(s := \text{GS-rec-iter}$   
 $v s)) v (\text{sorted-list-of-set } \text{UNIV}) s$

$\langle \text{proof} \rangle$

**lemma** *GS-rec-fun-code''*:  $\text{GS-rec-fun } v = \text{foldl } (\lambda v s. v(s := \text{GS-rec-iter}$   
 $v s)) v (\text{sorted-list-of-set } \text{UNIV})$

$\langle \text{proof} \rangle$

**lemma** *GS-rec-eq-elem*:  $\text{GS-rec } v \$ s = \text{GS-rec-fun } (\text{vec-nth } v) s$

$\langle \text{proof} \rangle$

**lemma** *GS-rec-step-elem*:  $GS\text{-rec-step } d \ v \ \$ \ s = r \ (s, d \ s) + l * ((\sum s' < s. \text{pmf } (K \ (s, d \ s)) \ s' * GS\text{-rec } v \ \$ \ s') + (\sum s' \in \{s'. \ s \leq s'\}. \text{pmf } (K \ (s, d \ s)) \ s' * v \ \$ \ s'))$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-rec-step-act*:  
**assumes**  $d \in D_D$  *is-arg-max*  $(\lambda a. GS\text{-rec-step } (d'(s := a)) \ v \ \$ \ s) \ (\lambda a. a \in A \ s) \ a$   
**shows** *is-arg-max*  $(\lambda d. GS\text{-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ (d(s := a))$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-rec-step-act'*:  
**assumes**  $d \in D_D$  *is-arg-max*  $(\lambda a. GS\text{-rec-step } (d'(s := a)) \ v \ \$ \ s) \ (\lambda a. a \in A \ s) \ (d \ s)$   
**shows** *is-arg-max*  $(\lambda d. GS\text{-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-rec*:  
**assumes**  $\bigwedge s. \text{is-arg-max } (\lambda d. GS\text{-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**shows**  $GS\text{-rec } v = GS\text{-rec-step } d \ v$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-rec'*:  
**assumes** *is-arg-max*  $(\lambda d. GS\text{-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**shows**  $GS\text{-rec } v \ \$ \ s = GS\text{-rec-step } d \ v \ \$ \ s$   
 $\langle \text{proof} \rangle$

**lemma** *GS-rec-eq-GS-inv*:  
**assumes**  $\bigwedge s. \text{is-arg-max } (\lambda d. GS\text{-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**shows**  $GS\text{-rec } v = GS\text{-inv } d \ v$   
 $\langle \text{proof} \rangle$

**lemma** *GS-rec-step-eq-GS-inv*:  
**assumes**  $\bigwedge s. \text{is-arg-max } (\lambda d. GS\text{-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**shows**  $GS\text{-rec-step } d \ v = GS\text{-inv } d \ v$   
 $\langle \text{proof} \rangle$

**lemma** *strict-lower-triangular-mat-mult*:  
**assumes** *strict-lower-triangular-mat*  $M \ \bigwedge i. i < j \implies v \ \$ \ i = v' \ \$ \ i$   
**shows**  $(M * v \ v) \ \$ \ j = (M * v \ v') \ \$ \ j$   
 $\langle \text{proof} \rangle$

**lemma** *Q-mat-invertible*: *invertible*  $(Q\text{-mat } d)$   
 $\langle \text{proof} \rangle$

**lemma** *GS-eq-GS-inv*:

**assumes**  $\bigwedge s. s \leq k \implies \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**assumes**  $s \leq k$   
**shows**  $\text{GS-rec-step } d \ v \ \$ \ s = \text{GS-inv } d \ v \ \$ \ s$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-imp-splitting'*:

**assumes**  $\bigwedge s. s \leq k \implies \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**assumes**  $s \leq k$   
**shows**  $\text{is-arg-max } (\lambda d. \text{GS-inv } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
 $\langle \text{proof} \rangle$

**lemma** *is-am-GS-rec-step-indep*:

**assumes**  $d \ s = d' \ s$   
**assumes**  $\text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**shows**  $\text{GS-rec } v \ \$ \ s = \text{GS-rec-step } d' \ v \ \$ \ s$   
 $\langle \text{proof} \rangle$

**lemma** *is-am-GS-rec-step-indep'*:

**assumes**  $d \ s = d' \ s$   
**assumes**  $\text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**shows**  $\text{GS-rec } v \ \$ \ s = \text{GS-rec-step } d' \ v \ \$ \ s$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-imp-splitting''*:

**assumes**  $\bigwedge s. s \leq k \implies \text{is-arg-max } (\lambda d. \text{GS-inv } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**assumes**  $s \leq k$   
**shows**  $\text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d \wedge \text{GS-inv } d \ v \ \$ \ s = \text{GS-rec } v \ \$ \ s$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-imp-splitting'''*:

**assumes**  $\bigwedge s. s \leq k \implies \text{is-arg-max } (\lambda d. \text{GS-inv } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**assumes**  $s \leq k$   
**shows**  $\text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-GS-imp-splitting*:

**assumes**  $\bigwedge s. \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
**shows**  $\text{is-arg-max } (\lambda d. \text{GS-inv } d \ v \ \$ \ k) \ (\lambda d. d \in D_D) \ d$   
 $\langle \text{proof} \rangle$

**lemma** *is-arg-max-gs-iff*:

**assumes**  $d \in D_D$



**shows**  $(\forall s \leq k. \text{is-arg-max } (\lambda d. \text{GS-inv } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d)$   
 $\longleftrightarrow$   
 $(\forall s \leq k. \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d)$   
 $\langle \text{proof} \rangle$

**lemma** *GS-opt-indep-high*:

**assumes**  $(\bigwedge s'. s' < s \implies \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s') \text{ is-dec-det } d) \ s' < s \ a \in A \ s$   
**shows**  $\text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s') \text{ is-dec-det } (d(s := a))$   
 $\langle \text{proof} \rangle$

**lemma** *mult-mat-vec-nth*:  $(X * v \ x) \ \$ \ i = \text{scalar-product } (\text{row } i \ X) \ x$   
 $\langle \text{proof} \rangle$

**lemma** *ext-GS-opt-le*:

**assumes**  $(\bigwedge s'. s' < s \implies \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s') \ (\lambda d. d \in D_D) \ d)$   
**and**  $\text{is-arg-max } (\lambda a. \text{GS-rec-step } (d(s := a)) \ v \ \$ \ s) \ (\lambda a. a \in A \ s)$   
 $a \ s' \leq s$   
**and**  $d \in D_D$   
**shows**  $\text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s') \ (\lambda d. d \in D_D) \ (d(s := a))$   
 $\langle \text{proof} \rangle$

**lemma** *ex-GS-opt-le*:

**shows**  $\exists d. (\forall s' \leq s. \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s') \ (\lambda d. d \in D_D) \ d)$   
 $\langle \text{proof} \rangle$

**lemma** *ex-GS-opt*:

**shows**  $\exists d. \forall s. \text{is-arg-max } (\lambda d. \text{GS-rec-step } d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d$   
 $\langle \text{proof} \rangle$

**lemma** *GS-rec-eq-GS-inv'*:  $\text{GS-rec } v \ \$ \ s = (\bigsqcup d \in D_D. \text{GS-inv } d \ v \ \$ \ s)$   
 $\langle \text{proof} \rangle$

**lemma** *GS-rec-fun-eq-GS-inv*:  $\text{GS-rec-fun } v \ s = (\bigsqcup d \in D_D. \text{GS-inv } d \ (\text{vec-lambda } v) \ \$ \ s)$   
 $\langle \text{proof} \rangle$

**lemma** *invertible-Q-GS*:  $\text{invertible}_L \ (Q\text{-GS } d)$  **for**  $d$   
 $\langle \text{proof} \rangle$

**lemma** *ex-opt-blinfo*:  $\exists d. \forall s. \text{is-arg-max } (\lambda d. ((\text{inv}_L \ (Q\text{-GS } d)) \ (r\text{-det}_b \ d + (R\text{-GS } d) \ v)) \ s) \text{ is-dec-det } d$   
 $\langle \text{proof} \rangle$

**lemma** *GS-inv-blinfun-to-matrix*:  $((inv_L (Q-GS\ d)) (r-det_b\ d + R-GS\ d\ v)) = Bfun\ (vec-nth\ (GS-inv\ d\ (vec-lambda\ v)))$   
 $\langle proof \rangle$

**lemma** *norm-GS-QR-le-disc*:  $norm\ (inv_L (Q-GS\ d)\ o_L\ R-GS\ d) \leq l$   
 $\langle proof \rangle$

**sublocale** *GS*: *MDP-QR* *A* *K* *r* *l* *Q-GS* *R-GS*  
**rewrites** *GS.L<sub>b</sub>-split* = *GS-rec-fun<sub>b</sub>*  
 $\langle proof \rangle$

**abbreviation** *gs-measure*  $\equiv (\lambda(eps, v).$   
 $\text{if } v = \nu_{b-opt} \vee l = 0$   
 $\text{then } 0$   
 $\text{else } nat\ (ceiling\ (\log\ (1/l)\ (dist\ v\ \nu_{b-opt}) - \log\ (1/l)\ (eps * (1-l)$   
 $/\ (8 * l))))$

**lemma** *dist-L<sub>b</sub>-split-lt-dist-opt*:  $dist\ v\ (GS-rec-fun_b\ v) \leq 2 * dist\ v\ \nu_{b-opt}$   
 $\langle proof \rangle$

**lemma** *GS-QR-disc-le-disc*:  $GS.QR-disc \leq l$   
 $\langle proof \rangle$

**lemma** *gs-rel-dec*:  
**assumes**  $l \neq 0$  *GS-rec-fun<sub>b</sub>*  $v \neq \nu_{b-opt}$   
**shows**  $\lceil \log\ (1 / l)\ (dist\ (GS-rec-fun_b\ v)\ \nu_{b-opt}) - c \rceil < \lceil \log\ (1 / l)\ (dist\ v\ \nu_{b-opt}) - c \rceil$   
 $\langle proof \rangle$

**function** *gs-iteration* :: *real*  $\Rightarrow$  (*s*  $\Rightarrow_b$  *real*)  $\Rightarrow$  (*s*  $\Rightarrow_b$  *real*) **where**  
 $gs-iteration\ eps\ v =$   
 $(if\ 2 * l * dist\ v\ (GS-rec-fun_b\ v) < eps * (1-l) \vee eps \leq 0\ then$   
 $GS-rec-fun_b\ v\ else\ gs-iteration\ eps\ (GS-rec-fun_b\ v))$   
 $\langle proof \rangle$   
**termination**  
 $\langle proof \rangle$

**lemma** *THE-fix-GS-rec-fun<sub>b</sub>*:  $(THE\ v.\ GS-rec-fun_b\ v = v) = \nu_{b-opt}$   
 $\langle proof \rangle$

The distance between an estimate for the value and the optimal value can be bounded with respect to the distance between the estimate and the result of applying it to  $\mathcal{L}_b$

**lemma** *contraction-L-split-dist*:  $(1 - l) * dist\ v\ \nu_{b-opt} \leq dist\ v\ (GS-rec-fun_b\ v)$   
 $\langle proof \rangle$

**lemma** *dist- $\mathcal{L}_b$ -split-opt-eps*:

**assumes**  $eps > 0 \ 2 * l * dist \ v \ (GS-rec-fun_b \ v) < eps * (1-l)$

**shows**  $dist \ (GS-rec-fun_b \ v) \ \nu_b-opt < eps / 2$

$\langle proof \rangle$

**end**

**context** *MDP-ord*

**begin**

**lemma** *is-am-GS-inv-extend'*:

**assumes**  $(\bigwedge s. s < x \implies is-arg-max \ (\lambda d. GS-inv \ d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ d)$

**assumes**  $is-arg-max \ (\lambda d. GS-rec-step \ d \ v \ \$ \ x) \ (\lambda d. d \in D_D) \ (d(x := a))$

**assumes**  $s \leq x \ d \in D_D$

**shows**  $is-arg-max \ (\lambda d. GS-inv \ d \ v \ \$ \ s) \ (\lambda d. d \in D_D) \ (d(x := a))$

$\langle proof \rangle$

**definition** *opt-policy-gs'*  $d \ v \ s = (LEAST \ a. is-arg-max \ (\lambda a. GS-rec-step \ (d(s := a)) \ v \ \$ \ s) \ (\lambda a. a \in A \ s) \ a)$

**definition** *GS-iter*  $a \ v \ s = r \ (s, a) + l * (\sum s' \in UNIV. pmf \ (K(s, a)) \ s' * v \ \$ \ s')$

**definition** *GS-iter-max*  $v \ s = (\bigsqcup a \in A \ s. GS-iter \ a \ v \ s)$

**lemma** *GS-rec-eq-iter*:

**assumes**  $\bigwedge s. s < k \implies v' \ \$ \ s = GS-rec \ v \ \$ \ s \ \bigwedge s. k \leq s \implies v' \ \$ \ s = v \ \$ \ s$

**shows**  $GS-rec-step \ (d(k := a)) \ v \ \$ \ k = GS-iter \ a \ v' \ k$

$\langle proof \rangle$

**lemma** *GS-rec-eq-iter-max*:

**assumes**  $\bigwedge s. s < k \implies v' \ \$ \ s = GS-rec \ v \ \$ \ s \ \bigwedge s. k \leq s \implies v' \ \$ \ s = v \ \$ \ s$

**shows**  $GS-rec \ v \ \$ \ k = GS-iter-max \ v' \ k$

$\langle proof \rangle$

**definition** *GS-iter-arg-max*  $v \ s = (LEAST \ a. is-arg-max \ (\lambda a. GS-iter \ a \ v \ s) \ (\lambda a. a \in A \ s) \ a)$

**definition** *GS-rec-am-code*  $v \ d \ s = foldl \ (\lambda v d s. vd(s := (GS-iter-max \ (\chi \ s. fst \ (vd \ s)) \ s, GS-iter-arg-max \ (\chi \ s. fst \ (vd \ s)) \ s))) \ (\lambda s. (v \ \$ \ s, d \ s)) \ (sorted-list-of-set \ \{..s\}) \ s$

**definition** *GS-rec-am-code'*  $v \ d \ s = foldl \ (\lambda v d s. vd(s := (GS-iter-max \ (\chi \ s. fst \ (vd \ s)) \ s, GS-iter-arg-max \ (\chi \ s. fst \ (vd \ s)) \ s))) \ (\lambda s. (v \ \$ \ s, d \ s)) \ (sorted-list-of-set \ UNIV) \ s$

**lemma** *GS-rec-am-code'*:  $GS\text{-rec-am-code} = GS\text{-rec-am-code}'$   
 $\langle proof \rangle$

**lemma** *opt-policy-gs'-eq-GS-iter*:  
**assumes**  $\bigwedge s. s < k \implies v' \$ s = GS\text{-rec } v \$ s \wedge s. k \leq s \implies v' \$ s = v \$ s$   
**shows**  $opt\text{-policy-gs}' d v k = GS\text{-iter-arg-max } v' k$   
 $\langle proof \rangle$

**lemma** *opt-policy-gs'-eq-GS-iter'*:  
 $opt\text{-policy-gs}' d v k = GS\text{-iter-arg-max } (\chi s. \text{if } s < k \text{ then } GS\text{-rec } v \$ s \text{ else } v \$ s) k$   
 $\langle proof \rangle$

**lemma** *opt-policy-gs'-is-dec-det*:  $opt\text{-policy-gs}' d v \in D_D$   
 $\langle proof \rangle$

**lemma** *opt-policy-gs'-is-arg-max*:  $is\text{-arg-max } (\lambda d. GS\text{-inv } d v \$ s) (\lambda d. d \in D_D) (opt\text{-policy-gs}' d v)$   
 $\langle proof \rangle$

**lemma** *GS-rec-am-code*  $v d s = (GS\text{-rec } v \$ s, opt\text{-policy-gs}' d v s)$   
 $\langle proof \rangle$

**lemma** *GS-rec-am-code-eq*:  $GS\text{-rec-am-code } v d s = (GS\text{-rec } v \$ s, opt\text{-policy-gs}' d v s)$   
 $\langle proof \rangle$

**definition** *GS-rec-iter-arg-max* **where**

$GS\text{-rec-iter-arg-max } v s = (LEAST a. is\text{-arg-max } (\lambda a. r(s, a) + l * (\sum s' \in UNIV. pmf(K(s, a)) s' * v s')) (\lambda a. a \in A s) a)$   
**definition** *opt-policy-gs*  $v s = (LEAST a. is\text{-arg-max } (\lambda a. GS\text{-rec-fun-inner } v s a) (\lambda a. a \in A s) a)$

**lemma** *opt-policy-gs-eq'*:  $opt\text{-policy-gs } v = opt\text{-policy-gs}' d (vec\text{-lambda } v)$   
 $\langle proof \rangle$

**declare** *gs-iteration.simps*[*simp del*]

**lemma** *gs-iteration-error*:  
**assumes**  $eps > 0$   
**shows**  $dist(gs\text{-iteration } eps v) \nu_{b\text{-opt}} < eps / 2$   
 $\langle proof \rangle$

**lemma** *GS-rec-fun-inner-vec*:  $GS\text{-rec-fun-inner } v s a = GS\text{-rec-step } (d(s := a)) (vec\text{-lambda } v) \$ s$   
 $\langle proof \rangle$

```

lemma find-policy-error-bound-gs:
  assumes  $\text{eps} > 0 \ 2 * l * \text{dist } v \ (GS\text{-rec-fun}_b \ v) < \text{eps} * (1-l)$ 
  shows  $\text{dist } (\nu_b \ (mk\text{-stationary-det } (opt\text{-policy-gs } (GS\text{-rec-fun}_b \ v))))$ 
 $\nu_b\text{-opt} < \text{eps}$ 
   $\langle proof \rangle$ 

definition vi-gs-policy  $\text{eps } v = opt\text{-policy-gs } (gs\text{-iteration } \text{eps } v)$ 

lemma vi-gs-policy-opt:
  assumes  $0 < \text{eps}$ 
  shows  $\text{dist } (\nu_b \ (mk\text{-stationary-det } (vi\text{-gs-policy } \text{eps } v))) \ \nu_b\text{-opt} < \text{eps}$ 
   $\langle proof \rangle$ 

lemma GS-rec-iter-eq-iter-max:  $GS\text{-rec-iter } v = GS\text{-iter-max } (vec\text{-lambda}$ 
 $v)$ 
   $\langle proof \rangle$ 
end

end

theory Algorithms
imports
  Value-Iteration
  Policy-Iteration
  Modified-Policy-Iteration
  Splitting-Methods
begin
end

theory Code-DP
imports
  Value-Iteration
  Policy-Iteration
  Modified-Policy-Iteration
  Splitting-Methods

HOL-Library.Code-Target-Numeral
Gauss-Jordan.Code-Generation-IArrays
begin

```

## 7 Code Generation for MDP Algorithms

### 7.1 Least Argmax

```

lemma least-list:
  assumes  $\text{sorted } xs \ \exists x \in \text{set } xs. \ P \ x$ 

```

**shows**  $(LEAST\ x \in\ set\ xs.\ P\ x) = the\ (find\ P\ xs)$   
 $\langle proof \rangle$

**definition**  $least-enum\ P = the\ (find\ P\ (sorted-list-of-set\ (UNIV :: ('b:: \{finite, linorder\})\ set)))$

**lemma**  $least-enum-eq: \exists x.\ P\ x \implies least-enum\ P = (LEAST\ x.\ P\ x)$   
 $\langle proof \rangle$

**definition**  $least-max-arg-max-list\ f\ init\ xs = foldl\ (\lambda(am, m)\ x.\ if\ f\ x > m\ then\ (x, f\ x)\ else\ (am, m))\ init\ xs$

**lemma**  $snd\ least-max-arg-max-list:$   
 $snd\ (least-max-arg-max-list\ f\ (n, f\ n)\ xs) = (MAX\ x \in\ insert\ n\ (set\ xs).\ f\ x)$   
 $\langle proof \rangle$

**lemma**  $least-max-arg-max-list-snd-fst: snd\ (least-max-arg-max-list\ f\ (x, f\ x)\ xs) = f\ (fst\ (least-max-arg-max-list\ f\ (x, f\ x)\ xs))$   
 $\langle proof \rangle$

**lemma**  $fst\ least-max-arg-max-list:$   
**fixes**  $f :: - \Rightarrow - :: linorder$   
**assumes**  $sorted\ (n\#xs)$   
**shows**  $fst\ (least-max-arg-max-list\ f\ (n, f\ n)\ xs) = (LEAST\ x.\ is-arg-max\ f\ (\lambda x.\ x \in\ insert\ n\ (set\ xs))\ x)$   
 $\langle proof \rangle$

**definition**  $least-arg-max-enum\ f\ X = (let\ xs = sorted-list-of-set\ (X :: (- :: \{finite, linorder\})\ set)\ in\ fst\ (least-max-arg-max-list\ f\ (hd\ xs, f\ (hd\ xs))\ (tl\ xs)))$

**definition**  $least-max-arg-max-enum\ f\ X = (let\ xs = sorted-list-of-set\ (X :: (- :: \{finite, linorder\})\ set)\ in\ (least-max-arg-max-list\ f\ (hd\ xs, f\ (hd\ xs))\ (tl\ xs)))$

**lemma**  $least-arg-max-enum-correct:$   
**assumes**  $X \neq \{\}$   
**shows**  
 $(least-arg-max-enum\ (f :: - \Rightarrow (- :: linorder))\ X) = (LEAST\ x.\ is-arg-max\ f\ (\lambda x.\ x \in\ X)\ x)$   
 $\langle proof \rangle$

**lemma**  $least-max-arg-max-enum-correct1:$   
**assumes**  $X \neq \{\}$   
**shows**  $fst\ (least-max-arg-max-enum\ (f :: - \Rightarrow (- :: linorder))\ X) = (LEAST\ x.\ is-arg-max\ f\ (\lambda x.\ x \in\ X)\ x)$   
 $\langle proof \rangle$

```

lemma least-max-arg-max-enum-correct2:
  assumes  $X \neq \{\}$ 
  shows  $\text{snd } (\text{least-max-arg-max-enum } (f :: - \Rightarrow (- :: \text{linorder})) X) =$ 
 $(\text{MAX } x \in X. f x)$ 
 $\langle \text{proof} \rangle$ 

```

## 7.2 Functions as Vectors

```

typedef ( $'a, 'b$ ) Fun = UNIV :: ( $'a \Rightarrow 'b$ ) set
 $\langle \text{proof} \rangle$ 

```

```

setup-lifting type-definition-Fun

```

```

lift-definition to-Fun :: ( $'a \Rightarrow 'b$ )  $\Rightarrow$  ( $'a, 'b$ ) Fun is id  $\langle \text{proof} \rangle$ 

```

```

definition fun-to-vec ( $v :: ('a::\text{finite}, 'b) \text{Fun}$ ) = vec-lambda (Rep-Fun  $v$ )

```

```

lift-definition vec-to-fun ::  $'b^{'a} \Rightarrow ('a, 'b) \text{Fun}$  is vec-nth  $\langle \text{proof} \rangle$ 

```

```

lemma Fun-inverse[simp]: Rep-Fun (Abs-Fun  $f$ ) =  $f$ 
 $\langle \text{proof} \rangle$ 

```

```

lift-definition zero-Fun :: ( $'a, 'b::\text{zero}$ ) Fun is 0  $\langle \text{proof} \rangle$ 

```

```

code-datatype vec-to-fun

```

```

lemmas vec-to-fun.rep-eq[code]

```

```

instantiation Fun :: (enum, equal) equal

```

```

begin

```

```

definition equal-Fun ( $f :: ('a::\text{enum}, 'b::\text{equal}) \text{Fun}$ )  $g = (\text{Rep-Fun } f$ 
 $= \text{Rep-Fun } g)$ 

```

```

instance

```

```

 $\langle \text{proof} \rangle$ 

```

```

end

```

## 7.3 Bounded Functions as Vectors

```

lemma Bfun-inverse-fin[simp]: apply-bfun (Bfun ( $f :: 'c :: \text{finite} \Rightarrow -$ ))
=  $f$ 
 $\langle \text{proof} \rangle$ 

```

```

definition bfun-to-vec ( $v :: ('a::\text{finite}) \Rightarrow_b ('b::\text{metric-space})) = \text{vec-lambda}$ 
 $v$ 

```

```

definition vec-to-bfun  $v = \text{Bfun } (\text{vec-nth } v)$ 

```

```

code-datatype vec-to-bfun

```

**lemma** *apply-bfun-vec-to-bfun*[code]: *apply-bfun (vec-to-bfun f) x = f*  
 $\$ x$   
 $\langle proof \rangle$

**lemma** [code]:  $0 = \text{vec-to-bfun } 0$   
 $\langle proof \rangle$

## 7.4 IArrays with Lengths in the Type

**typedef** ( $'s :: \text{mod-type}, 'a$ ) *iarray-type* =  $\{\text{arr} :: 'a \text{ iarray}. \text{IArray.length arr} = \text{CARD}('s)\}$   
 $\langle proof \rangle$

**setup-lifting** *type-definition-iarray-type*

**lift-definition** *fun-to-iarray-t* ::  $('s :: \{\text{mod-type}\} \Rightarrow 'a) \Rightarrow ('s, 'a) \text{ iarray-type}$  **is**  $\lambda f. \text{IArray.of-fun } (\lambda s. f (\text{from-nat } s)) (\text{CARD}('s))$   
 $\langle proof \rangle$

**lift-definition** *iarray-t-sub* ::  $('s :: \text{mod-type}, 'a) \text{ iarray-type} \Rightarrow 's \Rightarrow 'a$   
**is**  $\lambda v x. \text{IArray.sub } v (\text{to-nat } x) \langle proof \rangle$

**lift-definition** *iarray-to-vec* ::  $('s, 'a) \text{ iarray-type} \Rightarrow 'a^{s :: \{\text{mod-type}, \text{finite}\}}$   
**is**  $\lambda v. (\chi s. \text{IArray.sub } v (\text{to-nat } s)) \langle proof \rangle$

**lift-definition** *vec-to-iarray* ::  $'a^{s :: \{\text{mod-type}, \text{finite}\}} \Rightarrow ('s, 'a) \text{ iarray-type}$   
**is**  $\lambda v. \text{IArray.of-fun } (\lambda s. v \$ ((\text{from-nat } s) :: 's)) (\text{CARD}('s))$   
 $\langle proof \rangle$

**lemma** *length-iarray-type* [simp]:  $\text{length } (\text{IArray.list-of } (\text{Rep-iarray-type } (v :: ('s :: \{\text{mod-type}\}, 'a) \text{ iarray-type}))) = \text{CARD}('s)$   
 $\langle proof \rangle$

**lemma** *iarray-t-eq-iff*:  $(v = w) = (\forall x. \text{iarray-t-sub } v x = \text{iarray-t-sub } w x)$   
 $\langle proof \rangle$

**lemma** *iarray-to-vec-inv*:  $\text{iarray-to-vec } (\text{vec-to-iarray } v) = v$   
 $\langle proof \rangle$

**lemma** *vec-to-iarray-inv*:  $\text{vec-to-iarray } (\text{iarray-to-vec } v) = v$   
 $\langle proof \rangle$

**code-datatype** *iarray-to-vec*

**lemma** *vec-nth-iarray-to-vec*[code]:  $\text{vec-nth } (\text{iarray-to-vec } v) x = \text{iarray-t-sub } v x$



$\langle \text{proof} \rangle$

**lemma** *vec-lambda-iarray-t*[code]: *vec-lambda* *v* = *iarray-to-vec* (*fun-to-iarray-t* *v*)  
 $\langle \text{proof} \rangle$

**lemma** *zero-iarray*[code]: 0 = *iarray-to-vec* (*fun-to-iarray-t* 0)  
 $\langle \text{proof} \rangle$

## 7.5 Value Iteration

**locale** *vi-code* =  
 MDP-ord *A K r l* **for** *A* :: '*s*::*mod-type*  $\Rightarrow$  ('*a*::{*finite*, *wellorder*})  
 set  
**and** *K* :: ('*s*::{*finite*, *mod-type*}  $\times$  '*a*::{*finite*, *wellorder*})  $\Rightarrow$  '*s* *pmf*  
**and** *r l*  
**begin**  
**definition** *vi-test* (*v*::'*s* $\Rightarrow_b$  *real*) *v'* *eps* = 2 \* *l* \* *dist* *v v'*

**partial-function** (*tailrec*) *value-iteration-partial* **where** [code]: *value-iteration-partial* *eps v* =  
 (let *v'* =  $\mathcal{L}_b$  *v* in  
 (if 2 \* *l* \* *dist* *v v'* < *eps* \* (1 - *l*) then *v'* else (*value-iteration-partial* *eps v'*)))

**lemma** *vi-eq-partial*: *eps* > 0  $\implies$  *value-iteration-partial* *eps v* =  
*value-iteration* *eps v*  
 $\langle \text{proof} \rangle$

**definition** *L-det* *d* = *L* (*mk-dec-det* *d*)

**lemma** *code-L-det* [code]: *L-det* *d* (*vec-to-bfun* *v*) = *vec-to-bfun* ( $\chi$  *s*.  
 $L_a$  (*d s*) (*vec-nth* *v*) *s*)  
 $\langle \text{proof} \rangle$

**lemma** *code-L<sub>b</sub>* [code]:  $\mathcal{L}_b$  (*vec-to-bfun* *v*) = *vec-to-bfun* ( $\chi$  *s*. (*MAX* *a*  
 $\in A$  *s*. *r* (*s*, *a*) + *l* \* *measure-pmf.expectation* (*K* (*s*, *a*)) (*vec-nth* *v*)))  
 $\langle \text{proof} \rangle$

**lemma** *code-value-iteration*[code]: *value-iteration* *eps* (*vec-to-bfun* *v*)  
 =  
 (if *eps*  $\leq$  0 then  $\mathcal{L}_b$  (*vec-to-bfun* *v*) else *value-iteration-partial* *eps*  
 (*vec-to-bfun* *v*))  
 $\langle \text{proof} \rangle$

**lift-definition** *find-policy-impl* :: ('*s*  $\Rightarrow_b$  *real*)  $\Rightarrow$  ('*s*, '*a*) *Fun* **is**  $\lambda v$ .  
*find-policy'* *v*  $\langle \text{proof} \rangle$

**lemma** *code-find-policy-impl*: *find-policy-impl* *v* = *vec-to-fun* ( $\chi$  *s*.  
 (*LEAST* *x*. *x*  $\in$  *opt-acts* *v s*))

$\langle \text{proof} \rangle$

**lemma** *code-find-policy-impl-opt*[code]: *find-policy-impl*  $v = \text{vec-to-fun}$   
 $(\chi \ s. \text{least-arg-max-enum} (\lambda a. L_a \ a \ v \ s) (A \ s))$   
 $\langle \text{proof} \rangle$

**lemma** *code-vi-policy'*[code]: *vi-policy'*  $\text{eps } v = \text{Rep-Fun} (\text{find-policy-impl}$   
 $(\text{value-iteration } \text{eps } v))$   
 $\langle \text{proof} \rangle$

## 7.6 Policy Iteration

**partial-function** (*tailrec*) *policy-iteration-partial* **where** [code]: *policy-iteration-partial*  $d =$   
 $(\text{let } d' = \text{policy-step } d \text{ in if } d = d' \text{ then } d \text{ else } \text{policy-iteration-partial } d')$

**lemma** *pi-eq-partial*:  $d \in D_D \implies \text{policy-iteration-partial } d = \text{policy-iteration } d$   
 $\langle \text{proof} \rangle$

**definition** *P-mat*  $d = (\chi \ i \ j. \text{pmf} (K (i, \text{Rep-Fun } d \ i)) \ j)$

**definition** *r-vec'*  $d = (\chi \ i. r(i, \text{Rep-Fun } d \ i))$

**lift-definition** *policy-eval'* ::  $(s :: \{\text{mod-type}, \text{finite}\}, 'a) \text{Fun} \Rightarrow ('s \Rightarrow_b \text{real})$  **is** *policy-eval*  $\langle \text{proof} \rangle$

**lemma** *mat-eq-blinfun*:  $\text{mat } 1 - l *_R (P\text{-mat} (\text{vec-to-fun } d)) = \text{blinfun-to-matrix} (\text{id-blinfun} - l *_R \mathcal{P}_1 (\text{mk-dec-det} (\text{vec-nth } d)))$   
 $\langle \text{proof} \rangle$

**lemma**  $\nu_b\text{-vec}$ :  $\text{policy-eval}' (\text{vec-to-fun } d) = \text{vec-to-bfun} (\text{matrix-inv}$   
 $(\text{mat } 1 - l *_R (P\text{-mat} (\text{vec-to-fun } d))) * v (r\text{-vec}' (\text{vec-to-fun } d)))$   
 $\langle \text{proof} \rangle$

**lemma**  $\nu_b\text{-vec-opt}$ [code]:  $\text{policy-eval}' (\text{vec-to-fun } d) = \text{vec-to-bfun} (\text{Matrix-To-IArray.iarray-to-vec}$   
 $(\text{Matrix-To-IArray.vec-to-iarray} ((\text{fst} (\text{Gauss-Jordan-PA} ((\text{mat } 1 - l *_R (P\text{-mat} (\text{vec-to-fun } d)))))) * v (r\text{-vec}' (\text{vec-to-fun } d))))))$   
 $\langle \text{proof} \rangle$

**lift-definition** *policy-improvement'* ::  $(s, 'a) \text{Fun} \Rightarrow ('s \Rightarrow_b \text{real}) \Rightarrow ('s, 'a) \text{Fun}$   
**is** *policy-improvement*  $\langle \text{proof} \rangle$

**lemma** [code]:  $\text{policy-improvement}' (\text{vec-to-fun } d) \ v = \text{vec-to-fun} (\chi \ s. (\text{if is-arg-max} (\lambda a. L_a \ a \ v \ s) (\lambda a. a \in A \ s) (d \ \$ \ s) \text{ then } d \ \$ \ s \text{ else } \text{LEAST } x. \text{is-arg-max} (\lambda a. L_a \ a \ v \ s) (\lambda a. a \in A \ s) \ x)))$   
 $\langle \text{proof} \rangle$

**lift-definition** *policy-step'* :: ('s, 'a) Fun  $\Rightarrow$  ('s, 'a) Fun  
**is** *policy-step*⟨proof⟩

**lemma** [code]: *policy-step'* d = *policy-improvement'* d (*policy-eval'* d)  
 ⟨proof⟩

**lift-definition** *policy-iteration-partial'* :: ('s, 'a) Fun  $\Rightarrow$  ('s, 'a) Fun  
**is** *policy-iteration-partial*⟨proof⟩

**lemma** [code]: *policy-iteration-partial'* d = (let d' = *policy-step'* d in  
 if d = d' then d else *policy-iteration-partial'* d')  
 ⟨proof⟩

**lift-definition** *policy-iteration'* :: ('s, 'a) Fun  $\Rightarrow$  ('s, 'a) Fun **is** *policy-iteration*⟨proof⟩

**lemma** *code-policy-iteration'*[code]: *policy-iteration'* d =  
 (if Rep-Fun d  $\notin$  D<sub>D</sub> then d else (*policy-iteration-partial'* d))  
 ⟨proof⟩

**lemma** *code-policy-iteration*[code]: *policy-iteration* d = Rep-Fun (*policy-iteration'*  
 (vec-to-fun (vec-lambda d)))  
 ⟨proof⟩

## 7.7 Gauss-Seidel Iteration

**partial-function** (*tailrec*) *gs-iteration-partial* **where**  
 [code]: *gs-iteration-partial* eps v = (  
 let v' = (*GS-rec-fun<sub>b</sub>* v) in  
 (if 2 \* l \* dist v v' < eps \* (1 - l) then v' else *gs-iteration-partial*  
 eps v'))

**lemma** *gs-iteration-partial-eq*: eps > 0  $\implies$  *gs-iteration-partial* eps v  
 = *gs-iteration* eps v  
 ⟨proof⟩

**lemma** *gs-iteration-code-opt*[code]: *gs-iteration* eps v = (if eps  $\leq$  0  
 then *GS-rec-fun<sub>b</sub>* v else *gs-iteration-partial* eps v)  
 ⟨proof⟩

**definition** *vec-upd* v i x = ( $\chi$  j. if i = j then x else v \$ j)

**lemma** *GS-rec-eq-fold*: *GS-rec* v = foldl ( $\lambda$  v s. (*vec-upd* v s (*GS-iter-max*  
 v s))) v (*sorted-list-of-set* UNIV)  
 ⟨proof⟩

**lemma** *GS-rec-fun-code''''*[code]: *GS-rec-fun<sub>b</sub>* (vec-to-bfun v) = vec-to-bfun  
 (foldl ( $\lambda$  v s. (*vec-upd* v s (*GS-iter-max* v s))) v (*sorted-list-of-set*

$UNIV))$   
 $\langle proof \rangle$

**lemma**  $GS\text{-}iter\text{-}max\text{-}code$  [code]:  $GS\text{-}iter\text{-}max\ v\ s = (MAX\ a \in A\ s.$   
 $GS\text{-}iter\ a\ v\ s)$   
 $\langle proof \rangle$

**lift-definition**  $opt\text{-}policy\text{-}gs'' :: ('s \Rightarrow_b real) \Rightarrow ('s, 'a)\ Fun\ is\ opt\text{-}policy\text{-}gs \langle proof \rangle$

**declare**  $opt\text{-}policy\text{-}gs''.rep\text{-}eq[symmetric, code]$

**lemma**  $GS\text{-}rec\text{-}am\text{-}code'\text{-}prod$ :  $GS\text{-}rec\text{-}am\text{-}code'\ v\ d =$   
 $(\lambda s'. ($   
 $\quad let\ (v',\ d') = foldl\ (\lambda(v,d)\ s.\ (v(s := (GS\text{-}iter\text{-}max\ (vec\text{-}lambda$   
 $v)\ s)),\ d(s := GS\text{-}iter\text{-}arg\text{-}max\ (vec\text{-}lambda\ v)\ s)))\ (vec\text{-}nth\ v,\ d)$   
 $\quad (sorted\text{-}list\text{-}of\text{-}set\ UNIV)$   
 $\quad in\ (v'\ s',\ d'\ s')))$   
 $\langle proof \rangle$

**lemma**  $code\text{-}GS\text{-}rec\text{-}am\text{-}arr\text{-}opt$ [code]:  $opt\text{-}policy\text{-}gs''\ (vec\text{-}to\text{-}bfun\ v) =$   
 $vec\text{-}to\text{-}fun\ ((snd\ (foldl\ (\lambda(v,d)\ s.$   
 $\quad let\ (am,\ m) = least\text{-}max\text{-}arg\text{-}max\text{-}enum\ (\lambda a.\ r\ (s,\ a) + l * (\sum s' \in$   
 $UNIV.\ pmf\ (K\ (s,a))\ s' * v\ \$\ s'))\ (A\ s)\ in$   
 $\quad (vec\text{-}upd\ v\ s\ m,\ vec\text{-}upd\ d\ s\ am))$   
 $\quad (v,\ (\chi\ s.\ (least\text{-}enum\ (\lambda a.\ a \in A\ s))))\ (sorted\text{-}list\text{-}of\text{-}set\ UNIV))))$   
 $\langle proof \rangle$

## 7.8 Modified Policy Iteration

**sublocale**  $MDP\text{-}MPI\ A\ K\ r\ l\ \lambda X.$   $Least\ (\lambda x.\ x \in X)$   
 $\langle proof \rangle$

**definition**  $d0\ s = (LEAST\ a.\ a \in A\ s)$   
**lift-definition**  $d0' :: ('s, 'a)\ Fun\ is\ d0 \langle proof \rangle$

**lemma**  $d0\text{-}dec\text{-}det$ :  $is\text{-}dec\text{-}det\ d0$   
 $\langle proof \rangle$

**lemma**  $v0\text{-}code$ [code]:  $v0\text{-}mpi_b = vec\text{-}to\text{-}bfun\ (\chi\ s.\ r\text{-}min / (1 - l))$   
 $\langle proof \rangle$

**lemma**  $d0'\text{-}code$ [code]:  $d0' = vec\text{-}to\text{-}fun\ (\chi\ s.\ (LEAST\ a.\ a \in A\ s))$   
 $\langle proof \rangle$

**lemma**  $step\text{-}value\text{-}code$ [code]:  $L\text{-}pow\ v\ d\ m = (L\text{-}det\ d \rightsquigarrow Suc\ m)\ v$   
 $\langle proof \rangle$

**partial-function** (*tailrec*) *mpi-partial* **where** [*code*]: *mpi-partial eps*  
 $d \ v \ m =$   
 (let  $d' = \text{policy-improvement } d \ v$  in (  
 if  $2 * l * \text{dist } v \ (\mathcal{L}_b \ v) < \text{eps} * (1 - l)$   
 then  $(d', v)$   
 else *mpi-partial eps*  $d' \ (L\text{-pow } v \ d' \ (m \ 0 \ v)) \ (\lambda n. m \ (\text{Suc } n)))$ )

**lemma** *mpi-partial-eq-algo*:  
**assumes**  $\text{eps} > 0 \ d \in D_D \ v \leq \mathcal{L}_b \ v$   
**shows** *mpi-partial eps*  $d \ v \ m = \text{mpi-algo } \text{eps} \ d \ v \ m$   
 $\langle \text{proof} \rangle$

**lift-definition** *mpi-partial'* ::  $\text{real} \Rightarrow ('s, 'a) \text{Fun} \Rightarrow ('s \Rightarrow_b \text{real}) \Rightarrow$   
 $(\text{nat} \Rightarrow ('s \Rightarrow_b \text{real}) \Rightarrow \text{nat})$   
 $\Rightarrow ('s, 'a) \text{Fun} \times ('s \Rightarrow_b \text{real})$  **is** *mpi-partial*  $\langle \text{proof} \rangle$

**lemma** *mpi-partial'-code*[*code*]: *mpi-partial' eps*  $d \ v \ m =$   
 (let  $d' = \text{policy-improvement}' \ d \ v$  in (  
 if  $2 * l * \text{dist } v \ (\mathcal{L}_b \ v) < \text{eps} * (1 - l)$   
 then  $(d', v)$   
 else *mpi-partial' eps*  $d' \ (L\text{-pow } v \ (\text{Rep-Fun } d') \ (m \ 0 \ v)) \ (\lambda n. m \ (\text{Suc } n)))$ )  
 $\langle \text{proof} \rangle$

**lemma** *r-min-code*[*code-unfold*]: *r-min* =  $(\text{MIN } s. \text{MIN } a. r(s, a))$   
 $\langle \text{proof} \rangle$

**lemma** *mpi-user-code*[*code*]: *mpi-user eps*  $m =$   
 (if  $\text{eps} \leq 0$  then undefined else  
 let  $(d, v) = \text{mpi-partial}' \ \text{eps} \ d0' \ v0\text{-mpi}_b \ m$  in  $(\text{Rep-Fun } d, v)$ )  
 $\langle \text{proof} \rangle$   
**end**

## 7.9 Auxiliary Equations

**lemma** [*code-unfold*]:  $\text{dist } (f :: 'a :: \text{finite} \Rightarrow_b 'b :: \text{metric-space}) \ g = (\text{MAX}$   
 $a. \text{dist } (\text{apply-bfun } f \ a) \ (g \ a))$   
 $\langle \text{proof} \rangle$

**lemma** *member-code*[*code del*]:  $x \in \text{List.coset } xs \longleftrightarrow \neg \text{List.member}$   
 $xs \ x$   
 $\langle \text{proof} \rangle$

**lemma** [*code*]:  $\text{iarray-to-vec } v + \text{iarray-to-vec } u = (\text{Matrix-To-IArray.iarray-to-vec}$   
 $(\text{Rep-iarray-type } v + \text{Rep-iarray-type } u))$   
 $\langle \text{proof} \rangle$

**lemma** [*code*]:  $\text{iarray-to-vec } v - \text{iarray-to-vec } u = (\text{Matrix-To-IArray.iarray-to-vec}$   
 $(\text{Rep-iarray-type } v - \text{Rep-iarray-type } u))$

$\langle proof \rangle$

**lemma** *matrix-to-iarray-minus*[code-unfold]: *matrix-to-iarray* ( $A - B$ )  
 $=$  *matrix-to-iarray*  $A -$  *matrix-to-iarray*  $B$   
 $\langle proof \rangle$

**declare** *matrix-to-iarray-fst-Gauss-Jordan-PA*[code-unfold]

**end**  
**theory** *Code-Mod*  
**imports** *Code-DP*  
**begin**

## 8 Code Generation for Concrete Finite MDPs

**locale** *mod-MDP* =  
**fixes** *transition* :: '*s*::{enum, mod-type}  $\times$  '*a*::{enum, mod-type}  $\Rightarrow$   
'*s* pmf  
**and** *A* :: '*s*  $\Rightarrow$  '*a* set  
**and** *reward* :: '*s*  $\times$  '*a*  $\Rightarrow$  real  
**and** *discount* :: real  
**begin**  
  
**sublocale** *mdp*: *vi-code*  
 $\lambda s.$  (if *Set.is-empty* (*A s*) then UNIV else *A s*)  
*transition*  
*reward*  
(if  $1 \leq \text{discount} \vee \text{discount} < 0$  then 0 else *discount*)  
**defines**  $\mathcal{L}_b = \text{mdp}.\mathcal{L}_b$   
**and** *L-det* = *mdp.L-det*  
**and** *value-iteration* = *mdp.value-iteration*  
**and** *vi-policy'* = *mdp.vi-policy'*  
**and** *find-policy'* = *mdp.find-policy'*  
**and** *find-policy-impl* = *mdp.find-policy-impl*  
**and** *is-opt-act* = *mdp.is-opt-act*  
**and** *value-iteration-partial* = *mdp.value-iteration-partial*  
**and** *policy-iteration* = *mdp.policy-iteration*  
**and** *is-dec-det* = *mdp.is-dec-det*  
**and** *policy-step* = *mdp.policy-step*  
**and** *policy-improvement* = *mdp.policy-improvement*  
**and** *policy-eval* = *mdp.policy-eval*  
**and** *mk-markovian* = *mdp.mk-markovian*  
**and** *policy-eval'* = *mdp.policy-eval'*  
**and** *policy-iteration-partial'* = *mdp.policy-iteration-partial'*  
**and** *policy-iteration'* = *mdp.policy-iteration'*  
**and** *policy-iteration-policy-step'* = *mdp.policy-step'*  
**and** *policy-iteration-policy-eval'* = *mdp.policy-eval'*  
**and** *policy-iteration-policy-improvement'* = *mdp.policy-improvement'*  
**and** *gs-iteration* = *mdp.gs-iteration*

```

and gs-iteration-partial = mdp.gs-iteration-partial
and vi-gs-policy = mdp.vi-gs-policy
and opt-policy-gs = mdp.opt-policy-gs
and opt-policy-gs'' = mdp.opt-policy-gs''
and P-mat = mdp.P-mat
and r-vec' = mdp.r-vec'
and GS-rec-funb = mdp.GS-rec-funb
and GS-iter-max = mdp.GS-iter-max
and GS-iter = mdp.GS-iter
and mpi-user = mdp.mpi-user
and v0-mpib = mdp.v0-mpib
and mpi-partial' = mdp.mpi-partial'
and L-pow = mdp.L-pow
and v0-mpi = mdp.v0-mpi
and r-min = mdp.r-min
and d0 = mdp.d0
and d0' = mdp.d0'
and νb = mdp.νb
and vi-test = mdp.vi-test
⟨proof⟩
end

```

```

global-interpretation mod-MDP transition A reward discount
for transition A reward discount
defines mod-MDP- $\mathcal{L}_b$  = mdp. $\mathcal{L}_b$ 
and mod-MDP- $\mathcal{L}_b$ -L-det = mdp.L-det
and mod-MDP-value-iteration = mdp.value-iteration
and mod-MDP-vi-policy' = mdp.vi-policy'
and mod-MDP-find-policy' = mdp.find-policy'
and mod-MDP-find-policy-impl = mdp.find-policy-impl
and mod-MDP-is-opt-act = mdp.is-opt-act
and mod-MDP-value-iteration-partial = mdp.value-iteration-partial
and mod-MDP-policy-iteration = mdp.policy-iteration
and mod-MDP-is-dec-det = mdp.is-dec-det
and mod-MDP-policy-step = mdp.policy-step
and mod-MDP-policy-improvement = mdp.policy-improvement
and mod-MDP-policy-eval = mdp.policy-eval
and mod-MDP-mk-markovian = mdp.mk-markovian
and mod-MDP-policy-eval' = mdp.policy-eval'
and mod-MDP-policy-iteration-partial' = mdp.policy-iteration-partial'
and mod-MDP-policy-iteration' = mdp.policy-iteration'
and mod-MDP-policy-iteration-policy-step' = mdp.policy-step'
and mod-MDP-policy-iteration-policy-eval' = mdp.policy-eval'
and mod-MDP-policy-iteration-policy-improvement' = mdp.policy-improvement'
and mod-MDP-gs-iteration = mdp.gs-iteration
and mod-MDP-gs-iteration-partial = mdp.gs-iteration-partial
and mod-MDP-vi-gs-policy = mdp.vi-gs-policy
and mod-MDP-opt-policy-gs = mdp.opt-policy-gs
and mod-MDP-opt-policy-gs'' = mdp.opt-policy-gs''

```

```

and mod-MDP-P-mat = mdp.P-mat
and mod-MDP-r-vec' = mdp.r-vec'
and mod-MDP-GS-rec-funb = mdp.GS-rec-funb
and mod-MDP-GS-iter-max = mdp.GS-iter-max
and mod-MDP-GS-iter = mdp.GS-iter
and mod-MDP-mpi-user = mdp.mpi-user
and mod-MDP-v0-mpib = mdp.v0-mpib
and mod-MDP-mpi-partial' = mdp.mpi-partial'
and mod-MDP-L-pow = mdp.L-pow
and mod-MDP-v0-mpi = mdp.v0-mpi
and mod-MDP-r-min = mdp.r-min
and mod-MDP-d0 = mdp.d0
and mod-MDP-d0' = mdp.d0'
and mod-MDP-νb = mdp.νb
and mod-MDP-vi-test = mdp.vi-test
⟨proof⟩

```

```

end
theory Code-Real-Approx-By-Float-Fix
imports
  HOL-Library.Code-Real-Approx-By-Float
  Gauss-Jordan.Code-Real-Approx-By-Float-Haskell
beginend

```

```

theory Code-Inventory
imports
  Code-Mod

  Code-Real-Approx-By-Float-Fix
begin

```

## 9 Inventory Management Example

```

lemma [code abstype]: embed-pmf (pmf P) = P
  ⟨proof⟩

lemmas [code-abbrev del] = pmf-integral-code-unfold

lemma [code-unfold]:
  measure-pmf.expectation P (f :: 'a :: enum ⇒ real) = (∑ x ∈ UNIV.
pmf P x * f x)
  ⟨proof⟩

lemma [code]: pmf (return-pmf x) = (λy. indicat-real {y} x)
  ⟨proof⟩

```



**lemma** *[code]*:  
 $\text{pmf } (\text{bind-pmf } N \ f) = (\lambda i :: 'a. \text{measure-pmf.expectation } N \ (\lambda(x :: 'b :: \text{enum}). \text{pmf } (f \ x) \ i))$   
 $\langle \text{proof} \rangle$

**lemma** *pmf-finite-le*:  $\text{finite } (X :: ('a :: \text{finite}) \ \text{set}) \implies \text{sum } (\text{pmf } p) \ X \leq 1$   
 $\langle \text{proof} \rangle$

**lemma** *mod-less-diff*:  
**assumes**  $0 < (x :: 's :: \{\text{mod-type}\}) \ x \leq y$   
**shows**  $y - x < y$   
 $\langle \text{proof} \rangle$

**locale** *inventory* =  
**fixes** *fixed-cost* :: *real*  
**and** *var-cost* :: *'s*:: $\{\text{mod-type}, \text{finite}\} \Rightarrow \text{real}$   
**and** *inv-cost* :: *'s*  $\Rightarrow \text{real}$   
**and** *demand-prob* :: *'s* *pmf*  
**and** *revenue* :: *'s*  $\Rightarrow \text{real}$   
**and** *discount* :: *real*  
**begin**  
**definition** *order-cost* *u* = (if *u* = 0 then 0 else *fixed-cost* + *var-cost* *u*)  
**definition** *prob-ge-inv* *u* =  $1 - (\sum j < u. \text{pmf } \text{demand-prob } j)$   
**definition** *exp-rev* *u* =  $(\sum j < u. \text{revenue } j * \text{pmf } \text{demand-prob } j) + \text{revenue } u * \text{prob-ge-inv } u$   
**definition** *reward* *sa* = (case *sa* of (*s*,*a*)  $\Rightarrow \text{exp-rev } (s + a) - \text{order-cost } a - \text{inv-cost } (s + a)$ )  
**lift-definition** *transition* :: *'s*  $\times$  *'s*  $\Rightarrow$  *'s* *pmf* **is**  $\lambda(s, a) \ s'. \text{if } \text{CARD}('s) \leq \text{Rep } s + \text{Rep } a \text{ then } (\text{if } s' = 0 \text{ then } 1 \text{ else } 0) \text{ else } (\text{if } s + a < s' \text{ then } 0 \text{ else } (\text{if } s' = 0 \text{ then } \text{prob-ge-inv } (s+a) \text{ else } \text{pmf } \text{demand-prob } (s + a - s'))))$   
 $\langle \text{proof} \rangle$

**definition** *A-inv* (*s*::*'s*) =  $\{a :: 's. \text{Rep } s + \text{Rep } a < \text{CARD}('s)\}$

**end**

**definition** *var-cost-lin* (*c*::*real*) *n* =  $c * \text{Rep } n$

**definition** *inv-cost-lin* (*c*::*real*) *n* =  $c * \text{Rep } n$

**definition** *revenue-lin* (*c*::*real*) *n* =  $c * \text{Rep } n$

**lift-definition** *demand-unif* :: *'a*::*finite* *pmf* **is**  $\lambda-. 1 / \text{card } (\text{UNIV} :: 'a \ \text{set})$   
 $\langle \text{proof} \rangle$

**lift-definition** *demand-three* :: 3 pmf is  $\lambda i.$  if  $i = 1$  then  $1/4$  else if  $i = 2$  then  $1/2$  else  $1/4$   
 <proof>

**abbreviation** *fixed-cost*  $\equiv 4$   
**abbreviation** *var-cost*  $\equiv \text{var-cost-lin } 2$   
**abbreviation** *inv-cost*  $\equiv \text{inv-cost-lin } 1$   
**abbreviation** *revenue*  $\equiv \text{revenue-lin } 8$   
**abbreviation** *discount*  $\equiv 0.99$   
**type-synonym** *capacity* = 30

**lemma** *card-ge-2-imp-ne*:  $\text{CARD}('a) \geq 2 \implies \exists (x::'a::\text{finite})\ y::'a. x \neq y$   
 <proof>

**global-interpretation** *inventory-ex*: *inventory fixed-cost var-cost:: capacity*  $\Rightarrow$  *real inv-cost demand-unif revenue discount*  
**defines** *A-inv* = *inventory-ex.A-inv*  
**and** *transition* = *inventory-ex.transition*  
**and** *reward* = *inventory-ex.reward*  
**and** *prob-ge-inv* = *inventory-ex.prob-ge-inv*  
**and** *order-cost* = *inventory-ex.order-cost*  
**and** *exp-rev* = *inventory-ex.exp-rev*<proof>

**abbreviation** *K*  $\equiv \text{inventory-ex.transition}$   
**abbreviation** *A*  $\equiv \text{inventory-ex.A-inv}$   
**abbreviation** *r*  $\equiv \text{inventory-ex.reward}$   
**abbreviation** *l*  $\equiv 0.95$   
**definition** *eps* = 0.1

**definition** *fun-to-list*  $f = \text{map } f (\text{sorted-list-of-set UNIV})$   
**definition** *benchmark-gs*  $(- :: \text{unit}) = \text{map Rep } (\text{fun-to-list } (\text{vi-policy}' K A r l \text{eps } 0))$   
**definition** *benchmark-vi*  $(- :: \text{unit}) = \text{map Rep } (\text{fun-to-list } (\text{vi-gs-policy}' K A r l \text{eps } 0))$   
**definition** *benchmark-mpi*  $(- :: \text{unit}) = \text{map Rep } (\text{fun-to-list } (\text{fst } (\text{mpi-user } K A r l \text{eps } (\lambda - . 3))))$   
**definition** *benchmark-pi*  $(- :: \text{unit}) = \text{map Rep } (\text{fun-to-list } (\text{policy-iteration } K A r l 0))$

**fun** *vs-n* **where**  
*vs-n* 0  $v = v$   
 | *vs-n* (Suc *n*)  $v = \text{vs-n } n (\text{mod-MDP-}\mathcal{L}_b K A r l v)$

**definition** *vs-n'*  $n = \text{vs-n } n 0$

**definition** *benchmark-vi-n*  $n = (\text{fun-to-list } (\text{vs-n } n 0))$   
**definition** *benchmark-vi-nopol* =  $(\text{fun-to-list } (\text{mod-MDP-value-iteration } K A r l 0))$

*K A r l (1/10) 0))*

**export-code** *dist vs-n' benchmark-vi-nopol benchmark-vi-n nat-of-integer  
integer-of-int benchmark-gs benchmark-vi benchmark-mpi benchmark-pi*  
**in Haskell module-name DP**

**export-code** *integer-of-int benchmark-gs benchmark-vi benchmark-mpi  
benchmark-pi* **in SML module-name DP**

**end**

**theory** *Code-Gridworld*  
**imports**  
    *Code-Mod*  
**begin**

## 10 Gridworld Example

**lemma** [*code abstype*]: *embed-pmf (pmf P) = P*  
    *⟨proof⟩*

**lemmas** [*code-abbrev del*] = *pmf-integral-code-unfold*

**lemma** [*code-unfold*]:  
    *measure-pmf.expectation P (f :: 'a :: enum ⇒ real) = (∑ x ∈ UNIV.*  
    *pmf P x \* f x)*  
    *⟨proof⟩*

**lemma** [*code*]: *pmf (return-pmf x) = (λy. indicat-real {y} x)*  
    *⟨proof⟩*

**lemma** [*code*]:  
    *pmf (bind-pmf N f) = (λi :: 'a. measure-pmf.expectation N (λ(x ::*  
    *'b :: enum). pmf (f x) i))*  
    *⟨proof⟩*

**type-synonym** *state-robot = 13*

**definition** *from-state x = (Rep x div 4, Rep x mod 4)*

**definition** *to-state x = (Abs (fst x \* 4 + snd x) :: state-robot)*

**type-synonym** *action-robot = 4*

**fun** *A-robot* :: *state-robot*  $\Rightarrow$  *action-robot set* **where**  
*A-robot pos* = *UNIV*

**abbreviation** *noise*  $\equiv$  (*0.2* :: *real*)

**lift-definition** *add-noise* :: *action-robot*  $\Rightarrow$  *action-robot pmf* **is**  $\lambda det$   
*rnd.* (  
  if *det* = *rnd* then *1 - noise* else if *det* = *rnd - 1*  $\vee$  *det* = *rnd + 1*  
  then *noise / 2* else *0*)  
*<proof>*

**fun** *r-robot* :: (*state-robot*  $\times$  *action-robot*)  $\Rightarrow$  *real* **where**  
*r-robot* (*s,a*) = (  
  if from-state *s* = (*2,3*) then *1* else  
  if from-state *s* = (*1,3*) then *-1* else  
  if from-state *s* = (*3,0*) then *0* else  
  *0*)

**fun** *K-robot* :: (*state-robot*  $\times$  *action-robot*)  $\Rightarrow$  *state-robot pmf* **where**  
*K-robot* (*loc, a*) =  
  do {  
    *a*  $\leftarrow$  *add-noise a*;  
    let (*y, x*) = from-state *loc*;  
    let (*y', x'*) =  
      (if *a* = *0* then (*y + 1, x*)  
      else if *a* = *1* then (*y, x+1*)  
      else if *a* = *2* then (*y-1, x*)  
      else if *a* = *3* then (*y, x-1*)  
      else undefined);  
    return-pmf (  
      if (*y,x*) = (*2,3*)  $\vee$  (*y,x*) = (*1,3*)  $\vee$  (*y,x*) = (*3,0*)  
      then to-state (*3,0*)  
      else if *y' < 0*  $\vee$  *y' > 2*  $\vee$  *x' < 0*  $\vee$  *x' > 3*  $\vee$  (*y',x'*) = (*1,1*)  
      then to-state (*y, x*)  
      else to-state (*y', x'*)  
    )  
  }

**definition** *l-robot* = *0.9*

**lemma** *vi-code A-robot r-robot l-robot*  
*<proof>*

**abbreviation** *to-gridworld f*  $\equiv$  *f K-robot r-robot l-robot*

**abbreviation** *to-gridworld' f*  $\equiv$  *f K-robot A-robot r-robot l-robot*

**abbreviation** *gridworld-policy-eval'*  $\equiv$  *to-gridworld mod-MDP-policy-eval'*

**abbreviation** *gridworld-policy-step'*  $\equiv$  *to-gridworld' mod-MDP-policy-iteration-policy-step'*

**abbreviation** *gridworld-mpi-user*  $\equiv$  *to-gridworld' mod-MDP-mpi-user*

**abbreviation** *gridworld-opt-policy-gs*  $\equiv$  *to-gridworld' mod-MDP-opt-policy-gs*  
**abbreviation** *gridworld- $\mathcal{L}_b$*   $\equiv$  *to-gridworld' mod-MDP- $\mathcal{L}_b$*   
**abbreviation** *gridworld-find-policy'*  $\equiv$  *to-gridworld' mod-MDP-find-policy'*  
**abbreviation** *gridworld-GS-rec-fun<sub>b</sub>*  $\equiv$  *to-gridworld' mod-MDP-GS-rec-fun<sub>b</sub>*  
**abbreviation** *gridworld-vi-policy'*  $\equiv$  *to-gridworld' mod-MDP-vi-policy'*  
**abbreviation** *gridworld-vi-gs-policy*  $\equiv$  *to-gridworld' mod-MDP-vi-gs-policy*  
**abbreviation** *gridworld-policy-iteration*  $\equiv$  *to-gridworld' mod-MDP-policy-iteration*

**fun** *pi-robot-n* **where**

*pi-robot-n* 0 *d* = (*d*, *gridworld-policy-eval' d*) |  
*pi-robot-n* (Suc *n*) *d* = *pi-robot-n n* (*gridworld-policy-step' d*)

**definition** *mpi-robot eps* = *gridworld-mpi-user eps* ( $\lambda\cdot. 3$ )

**fun** *gs-robot-n* **where**

*gs-robot-n* (0 :: nat) *v* = (*gridworld-opt-policy-gs v*, *v*) |  
*gs-robot-n* (Suc *n* :: nat) *v* = *gs-robot-n n* (*gridworld-GS-rec-fun<sub>b</sub> v*)

**fun** *vi-robot-n* **where**

*vi-robot-n* (0 :: nat) *v* = (*gridworld-find-policy' v*, *v*) |  
*vi-robot-n* (Suc *n* :: nat) *v* = *vi-robot-n n* (*gridworld- $\mathcal{L}_b$  v*)

**definition** *mpi-result eps* =

(let (*d*, *v*) = *mpi-robot eps* in (*d*, *v*))

**definition** *gs-result n* =

(let (*d*, *v*) = *gs-robot-n n* 0 in (*d*, *v*))

**definition** *vi-result-n n* =

(let (*d*, *v*) = *vi-robot-n n* 0 in (*d*, *v*))

**definition** *pi-result-n n* =

(let (*d*, *v*) = *pi-robot-n n* (*vec-to-fun* 0) in (*d*, *v*))

**definition** *fun-to-list f* = *map f* (*sorted-list-of-set UNIV*)

**definition** *benchmark-gs* = *fun-to-list* (*gridworld-vi-policy' 0.1* 0)

**definition** *benchmark-vi* = *fun-to-list* (*gridworld-vi-gs-policy 0.1* 0)

**definition** *benchmark-mpi* = *fun-to-list* (*fst* (*gridworld-mpi-user 0.1* ( $\lambda\cdot. 3$ )))

**definition** *benchmark-pi* = *fun-to-list* (*gridworld-policy-iteration* 0)

**export-code** *benchmark-gs benchmark-vi benchmark-mpi benchmark-pi*

**in** *Haskell module-name DP*

**export-code** *benchmark-gs benchmark-vi benchmark-mpi benchmark-pi*

**in** *SML module-name DP*

**end**

**theory** *Examples*  
**imports**  
    *Code-Inventory*  
    *Code-Gridworld*  
**begin**  
**end**

## References

- [1] M. L. Puterman. *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. Wiley Series in Probability and Statistics. Wiley, 1994.