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Abstract

We consider concurrent mean-payoff games, a very well-studied class of two-player (player 1 vs player 2) zero-sum games on finite-state graphs where every transition is assigned a reward between 0 and 1, and the payoff function is the long-run average of the rewards. The value is the maximal expected payoff that player 1 can guarantee against all strategies of player 2. We consider the computation of the set of states with value 1 under finite-memory strategies for player 1, and our main results for the problem are as follows: (1) we present a polynomial-time algorithm; (2) we show that whenever there is a finite-memory strategy, there is a stationary strategy that does not need memory at all; and (3) we present an optimal bound (which is double exponential) on the patience of stationary strategies (where patience of a distribution is the inverse of the smallest positive probability and represents a complexity measure of a stationary strategy).
1 Introduction

Concurrent mean-payoff games. Concurrent mean-payoff games are played on finite-state graphs by two players (player 1 and player 2) for infinitely many rounds. In each round, the players simultaneously choose moves (or actions), and the current state along with the two chosen moves determine a probability distribution over the successor states. The outcome of the game (or a play) is an infinite sequence of states and action pairs. Every transition is associated with a reward between 0 and 1, and the mean-payoff (or limit-average payoff) of a play is the limit-inferior (or limit-superior) average of the rewards of the play. Concurrent games were introduced in a seminal work of Shapley [21], where discounted sum objectives (or games that halt with probability 1) were considered. The generalization to concurrent games with mean-payoff objectives (or games that have zero stop probabilities) was presented by Gillette in [14]. The player-1 value \( \text{val}(s) \) of the game at a state \( s \) is the supremum value of the expectation that player 1 can guarantee for the mean-payoff objective against all strategies of player 2. The games are zero-sum where the objective of player 2 is the opposite.

Important previous results. Many celebrated results have been established for concurrent mean-payoff games and its sub-classes: (1) the existence of values (or determinacy or equivalence of switching of strategy quantifiers for the players as in von-Neumann’s min-max theorem) for concurrent discounted games was established in [21]; (2) the result of Blackwell and Ferguson established existence of values for the celebrated game of Big-Match [2] (the celebrated Big-Match example is from [14])\(^1\); and (3) developing on the results of [2] and of Bewley and Kohlberg on Puisieux series [1] the existence of values for concurrent mean-payoff games was established in [20]. The decision problem of whether the value \( \text{val}(s) \) is at least a rational constant \( \lambda \) can be decided in PSPACE [6, 16]; and is square-root sum hard even for concurrent reachability games [10], where reachability objectives are the very special case of mean-payoff objectives where reward zero is assigned to all transitions other than a set of sink terminal states which are assigned reward 1.

Value 1 problem. While the decision problem for value computation is notoriously hard for concurrent mean-payoff games, an important special case of the problem is to compute the set of states with value 1. We refer to this problem as the value 1 set computation problem which has been extensively studied in many different contexts; such as, concurrent games with reachability objectives [9] as well as with \( \omega \)-regular and prefix independent objectives [5, 4], probabilistic automata [7, 12], and probabilistic systems with counters [3].

Strategies. A strategy in a concurrent game, considers the past history of the game (the finite sequence of states and actions played so far), and specifies a probability distribution over the next moves. Thus a strategy requires memory to remember the past history of the game. A strategy is stationary if it is independent of the past history and only depends on the current state. The complexity of a stationary strategy is described by its patience which is the inverse of the minimum non-zero probability assigned to a move. The notion of patience was introduced in [11] and also studied in the context of concurrent reachability games [17, 15]. A strategy is finite-memory if the memory set used by the strategy is finite. Note that for implementability of a strategy (such as by an automata), we need a finite-memory strategy.

Examples. We now illustrate concurrent mean-payoff games with a few examples. Consider the four games \((G_1, G_2, G_3, \text{and } G_4)\) shown in Figure 1: the transition functions are deterministic and shown as arrows; and transition with rewards 1 are annotated, and all other rewards are 0. Each game has four states, namely, 1, 2, \( \top \) and \( \bot \); and since \( \top \) and \( \bot \) remain the same, in the figures \( G_1 \) and \( G_2 \) (also \( G_3 \) and \( G_4 \)) are drawn such that they share \( \top \) and \( \bot \). The state \( \top \) has value 1 and state \( \bot \) has value 0. In the first game \( G_1 \), both state 1

\(^1\)note that even showing existence of a value for the specific Big-Match game was open for years, which shows the hardness of analysis of such games
and state 2 have value $1/2$ (because of symmetry). The other three example games, $G_2$, $G_3$ and $G_4$, are minor variants of $G_1$ (only one successor is changed).

1. In $G_2$, the edge from state 2 to ⊥ is changed to a self-loop. In $G_2$, there exists an infinite-memory strategy to ensure that the mean-payoff is 1, and for every $\epsilon > 0$ there is a stationary strategy to ensure mean-payoff $1 - \epsilon$. The witness stationary strategy is as follows: in state 1 play the action pairs with probability $(\epsilon/4, 1 - \epsilon/4)$ and in state 2 with probability $(1/2, 1/2)$.

2. In $G_3$, the top edge from state 1 to state 2 is changed to a self-loop. In $G_3$, there is no strategy to ensure that the mean-payoff is 1, but for every $\epsilon > 0$ there is a stationary strategy to ensure mean-payoff $1 - \epsilon$. The witness stationary strategy is as follows: in state 1 play the action pairs with probability $(\epsilon/2, 1 - \epsilon/2)$ and in state 2 with probability $(1 - \epsilon^2/2, \epsilon^2/2)$.

3. In $G_4$, the bottom edge from state 1 to state 2 is changed to a self-loop. In $G_4$, there exists no stationary strategy that can ensure positive mean-payoff value; however, for every $\epsilon > 0$ there exists an infinite-memory strategy to ensure mean-payoff $1 - \epsilon$.

Details regarding the analysis of the values of the above games and in depth discussion on the strategy constructions for them are available in [18, Section 1.6.2].

**Our contributions.** Our main contributions are related to the computation of the value 1 problem for concurrent mean-payoff games where player 1 is restricted to finite-memory strategies\(^2\). Our main results are as follows: (1) We present a polynomial-time algorithm to compute the value 1 set. (2) We show that stationary strategies are sufficient, i.e., whenever finite-memory strategies exist, then there is a stationary strategy. (3) We establish an optimal double exponential patience bound for the witness stationary strategies.

\(^2\)note that once a finite-memory strategy for player 1 is fixed, then there always exists a finite-memory optimal counter-strategy for player 2, and thus the strategies for player 2 are not restricted.
(our contribution for patience is the upper bound, and the matching lower bound follows from [15, 17] for the special case of reachability objectives). In addition we also establish a robustness result, which shows that for concurrent games, if the support of the transition probabilities match (but the precise transition probabilities may differ), then the value 1 set remains unchanged.

2 Definitions

In this section we present the definitions of game structures, strategies, mean-payoff objectives, the value and value 1 problem, and other basic notions.

**Probability distributions.** For a finite set \( A \), a probability distribution on \( A \) is a function \( \delta : A \to [0, 1] \) such that \( \sum_{a \in A} \delta(a) = 1 \). We denote the set of probability distributions on \( A \) by \( \mathcal{D}(A) \). Given a distribution \( \delta \in \mathcal{D}(A) \), we denote by \( \text{Supp}(\delta) = \{ x \in A \mid \delta(x) > 0 \} \) the support of the distribution \( \delta \). For a distribution, the patience of the distribution is the inverse of the minimum non-zero probability assigned to an element: formally, the patience \( \text{pat}(\delta) \) is \( \max_{a \in A} \{ \frac{1}{\delta(a)} \mid \delta(a) > 0 \} \).

**Concurrent game structures.** A (two-player) concurrent stochastic game structure \( G = (S, A, \Gamma_1, \Gamma_2, \delta) \) consists of the following components.

- A finite state space \( S \) and a finite set \( A \) of actions (or moves).
- Two move assignments \( \Gamma_1, \Gamma_2 : S \to 2^A \setminus \emptyset \). For \( i \in \{1, 2\} \), assignment \( \Gamma_i \) associates with each state \( s \in S \) the non-empty set \( \Gamma_i(s) \subseteq A \) of moves available to player \( i \) at state \( s \). For technical convenience, we assume that \( \Gamma_i(s) \cap \Gamma_j(t) = \emptyset \) unless \( i = j \) and \( s = t \), for all \( i, j \in \{1, 2\} \) and \( s, t \in S \). If this assumption is not met, then the moves can be trivially renamed to satisfy the assumption.
- A probabilistic transition function \( \delta : S \times A \times A \to \mathcal{D}(S) \), which associates with every state \( s \in S \) and moves \( a_1 \in \Gamma_1(s) \) and \( a_2 \in \Gamma_2(s) \) a probability distribution \( \delta(s, a_1, a_2) \in \mathcal{D}(S) \) for the successor state.

For a set \( Q \subseteq S \) of states we will denote by \( \overline{Q} = S \setminus Q \) the complement of \( Q \). We will denote by \( \delta_{\text{min}} \) the minimum non-zero transition probability, i.e., \( \delta_{\text{min}} = \min_{s,t \in S} \min_{a_1 \in \Gamma_1(s), a_2 \in \Gamma_2(s)} \{ \delta(s, a_1, a_2)(t) \mid \delta(s, a_1, a_2)(t) > 0 \} \). We will denote by \( n \) the number of states (i.e., \( n = |S| \)), and by \( m \) the maximal number of actions available for a player at a state (i.e., \( m = \max_{s \in S} \max\{|\Gamma_1(s)|, |\Gamma_2(s)|\} \)). We will later define Markov chains as games where \( m = 1 \). Since finding the mean-payoff of Markov chains can be done in polynomial time, we will only consider the case where \( m \geq 2 \). For all states \( s \in S \), moves \( a_1 \in \Gamma_1(s) \) and \( a_2 \in \Gamma_2(s) \), we indicate by \( \text{Succ}(s, a_1, a_2) = \text{Supp}(\delta(s, a_1, a_2)) \) the set of possible successors of \( s \) when moves \( a_1 \) and \( a_2 \) are selected. The size of the transition relation of a game structure is defined as \( |\delta| = \sum_{s \in S} \sum_{a_1 \in \Gamma_1(s)} \sum_{a_2 \in \Gamma_2(s)} |\text{Succ}(s, a_1, a_2)| \).

**One step probabilities.** Given a concurrent game structure \( G \), a state \( s \), two distributions \( \xi_1 \in \mathcal{D}(\Gamma_1(s)) \) and \( \xi_2 \in \mathcal{D}(\Gamma_2(s)) \), the one step probability transition for a set \( U \) of states, denoted as \( \delta(s, \xi_1, \xi_2)(U) \) is \( \sum_{a_1 \in \Gamma_1(s), a_2 \in \Gamma_2(s), t \in U} \delta(s, a_1, a_2)(t) \cdot \xi_1(a_1) \cdot \xi_2(a_2) \). Often we will consider the distribution of player 2 to be a single action, i.e., \( \xi_2(a_2) = 1 \) for an action \( a_2 \), and then use the notation \( \delta(s, \xi_1, a_2) \). We will also write \( \text{Succ}(s, \xi_1, \xi_2) = \bigcup_{a_1 \in \text{Supp}(\xi_1), a_2 \in \text{Supp}(\xi_2)} \text{Succ}(s, a_1, a_2) \) for the set of possible successors under the distributions.
Turn-based stochastic games, turn-based deterministic games and MDPs. A game structure $G$ is turn-based stochastic if at every state at most one player can choose among multiple moves; that is, for every state $s \in S$ there exists at most one $i \in \{1, 2\}$ with $|\Gamma_i(s)| > 1$. A turn-based stochastic game with a deterministic transition function is a turn-based deterministic game. A game structure is a player-2 Markov decision process (MDP) if for all $s \in S$ we have $|\Gamma_1(s)| = 1$, i.e., only player 2 has choice of actions in the game, and player-1 MDPs are defined analogously.

**Plays.** At every state $s \in S$, player 1 chooses a move $a_1 \in \Gamma_1(s)$, and simultaneously and independently player 2 chooses a move $a_2 \in \Gamma_2(s)$. The game then proceeds to the successor state $t$ with probability $\delta(s, a_1, a_2)(t)$, for all $t \in S$. A path or a play of $G$ is an infinite sequence $\omega = ((s_0, a_1^0, a_2^0), (s_1, a_1^1, a_2^1), (s_2, a_1^2, a_2^2) \ldots)$ of states and action pairs such that for all $k \geq 0$ we have (1) $s_{k+1} \in \text{Succ}(s_k, a_1^k, a_2^k)$; and (2) $a_1^k \in \Gamma_1(s_k)$; and (3) $a_2^k \in \Gamma_2(s_k)$. We denote by $\Omega$ the set of all paths.

**Strategies.** A strategy for a player is a recipe that describes how to extend prefixes of a play. Formally, a strategy for player $i \in \{1, 2\}$ is a mapping $\sigma_i : (S \times A \times A)^* \times S \to D(A)$ that associates with every finite sequence $x \in (S \times A \times A)^*$ of state and action pairs, and the current state $s \in S$, representing the past history of the game, a probability distribution $\sigma_i(x \cdot s)$ used to select the next move. The strategy $\sigma_i$ can prescribe only moves that are available to player $i$; that is, for all sequences $x \in (S \times A \times A)^*$ and states $s \in S$, we require that $\text{Supp}(\sigma_i(x \cdot s)) \subseteq \Gamma_i(s)$. We denote by $\Sigma_i$ the set of all strategies for player $i \in \{1, 2\}$. Once the starting state $s$ and the strategies $\sigma_1$ and $\sigma_2$ for the two players have been chosen, the probabilities of events are uniquely defined [22], where an event $A \subseteq \Omega$ is a measurable set of paths. For an event $A \subseteq \Omega$, we denote by $P_{\Gamma_1^{\sigma_1} \Gamma_2^{\sigma_2}}(A)$ the probability that a path belongs to $A$ when the game starts from $s$ and the players use the strategies $\sigma_1$ and $\sigma_2$. We denote by $\mathbb{E}_{s}^{\sigma_1 \sigma_2}$ the associated expectation measure. We will consider the following special classes of strategies:

1. **Stationary (memoryless) and positional strategies.** A strategy $\sigma_i$ is stationary (or memoryless) if it is independent of the history but only depends on the current state, i.e., for all $x, x' \in (S \times A \times A)^*$ and all $s \in S$, we have $\sigma_i(x \cdot s) = \sigma_i(x' \cdot s)$, and thus can be expressed as a function $\sigma_i : S \to D(A)$. For stationary strategies, the complexity of the strategy is described by the patience of the strategy, which is the inverse of the minimum non-zero probability assigned to an action [11]. Formally, for a stationary strategy $\sigma_i : S \to D(A)$ for player $i$, the patience is $\text{pat}(\sigma_i(s))$, where $\text{pat}(\sigma_i(s))$ is the patience of the distribution $\sigma_i(s)$. A strategy is pure (deterministic) if it does not use randomization, i.e., for any history there is always some unique action $a$ that is played with probability 1. A pure stationary strategy $\sigma_i$ is also called a positional strategy, and represented as a function $\sigma_i : S \to A$. We denote by $\Sigma_i^S$ the set of stationary strategies for player $i$.

2. **Strategies with memory and finite-memory strategies.** A strategy $\sigma_i$ can be equivalently defined as a pair of functions $(\sigma_i^n, \sigma_i^u)$, along with a set $\text{Mem}$ of memory states, such that (i) the next move function $\sigma_i^n : S \times \text{Mem} \to D(A)$ given the current state of the game and the current memory state specifies the probability distribution over the actions; and (ii) the memory update function $\sigma_i^u : S \times A \times A \times \text{Mem} \to \text{Mem}$ given the current state of the game, the action pairs, and the current memory state updates the memory state. Any strategy can be expressed with an infinite set $\text{Mem}$ of memory states, and a strategy is a finite-memory strategy if the set $\text{Mem}$ of memory states is finite, otherwise it is an infinite-memory strategy. We denote by $\Sigma_i^F$ the set of finite-memory strategies for player $i$.

**Absorbing states.** A state $s$ is absorbing if for all actions $a_1 \in \Gamma_1(s)$ and all actions $a_2 \in \Gamma_2(s)$ we have
Succ\((s, a_1, a_2) = \{s\}. In the present paper we will also require that |\(\Gamma_1(s)\) = |\(\Gamma_2(s)\)| = 1 if s is absorbing.

**Objectives.** A quantitative objective \(\Phi : \Omega \to \mathbb{R}\) is a measurable function. In this work we will consider limit-average (or mean-payoff) objectives. We will consider concurrent games with a reward function \(r : S \times A \times A \to [0,1]\) that assigns a reward value \(r(s, a_1, a_2)\) for all \(s \in S\), \(a_1 \in \Gamma_1(s)\) and \(a_2 \in \Gamma_2(s)\). For a path \(\omega = ((s_0, a_0^0, a_0^1), (s_1, a_1^0, a_1^1), \ldots)\), the limit-infimum average (resp. limit-supremum average) is defined as follows: \(\text{LimInfAvg}(\omega) = \lim\inf_{n \to \infty} \frac{1}{n} \sum_{i=0}^{n-1} r(s_i, a_i^0, a_i^1)\) (resp. \(\text{LimSupAvg}(\omega) = \lim\sup_{n \to \infty} \frac{1}{n} \sum_{i=0}^{n-1} r(s_i, a_i^0, a_i^1)\)). For the analysis of concurrent games with Boolean limit-average objectives (with rewards 0 and 1 only) we will also need reachability and safety objectives. Given a target set \(U \subseteq S\), the reachability objective Reach\((U)\) requires some state in \(U\) be visited at least once, i.e., defines the set

\[
\text{Reach}(U) = \{\omega = ((s_0, a_0^0, a_0^1), (s_1, a_1^0, a_1^1), \ldots) | \exists i \geq 0. s_i \in U\}
\]

of paths. The dual safety objective for a set \(F \subseteq S\) of safe states requires that the set \(F\) is never left, i.e.,

\[
\text{Safe}(F) = \{\omega = ((s_0, a_0^0, a_0^1), (s_1, a_1^0, a_1^1), \ldots) | \forall i \geq 0. s_i \not\in F\}.
\]

We also consider the eventual safety objective, namely coBüchi objective, that requires for a given set \(F\) that ultimately only states in \(F\) are visited, i.e.,

\[
\text{coBuchi}(F) = \{\omega = ((s_0, a_0^0, a_0^1), (s_1, a_1^0, a_1^1), \ldots) | \exists j \geq 0. \forall i \geq j. s_i \in F\}.
\]

Observe that reachability objectives are a very special case of Boolean reward limit-average objectives where states in \(U\) are absorbing and are exactly the states with reward 1, and similarly for safety objectives.

**Markov chains.** A game structure \(G\) is a Markov chain if \(m = 1\). We will in that case write \(\delta(s)\) for the distribution \(\delta(s, a_1, a_2)\), where \(a_1\) is the unique action in \(\Gamma_1(s)\) and \(a_2\) is the unique action in \(\Gamma_2(s)\). Markov chains defines a weighted graph \((S, E, w)\), where \((s, s') \in E\) iff \(\delta(s)(s') > 0\) and for all \((s, s') \in E\) we have that \(w((s, s')) = \delta(s)(s')\). For an event \(A \subseteq \Omega\), we denote by \(\Pr_A(A)\) the probability \(\Pr^{\sigma_1, \sigma_2}(A)\), where \(\sigma_1\) and \(\sigma_2\) are the unique strategies for player 1 and player 2, respectively. A state \(s\) is reachable from another state \(s'\) iff \(s'\) is reachable from \(s\) in \((S, E, w)\). A set of states \(Z\) is reachable from a state \(s\) iff a state in \(Z\) is reachable from \(s\). For any set of states \(Z\) in a Markov chain, let \(R_S(Z)\), be the set of states from which \(Z\) is not reachable. Clearly, \(R_S(Z) \subseteq (S \setminus Z)\). A set of states \(L\) is called a recurrent class if for each pair of states \(s, s' \in L\) we have that \(s'\) is reachable from \(s\) and for each pair of states \(s \in L\) and \(s'' \in (S \setminus L)\) we have that \(s''\) is not reachable from \(s\). A recurrent class in a Markov chain is a bottom scc (strongly connected component) in the graph of the Markov chain, where a bottom scc \(L\) is an scc with no edges leaving the scc.

**Properties of Markov chains to be explicitly used in proofs.** We will use several basic properties of Markov chains in our proof and we explicitly state them here. Let us fix a Markov chain with state space \(S\).

1. Given a set \(Z \subseteq S\), for all \(s \in S\), with probability 1 either \(Z\) is visited infinitely often or \(R_S(Z)\) is reached.

2. Given \(Z \subseteq S\), for all \(s \in S\), with probability 1 \(R_S(Z)\) or \(Z\) is reached, i.e., \(\Pr(A(\text{Reach}(R_S(Z) \cup Z))) = 1\).

3. Given sets \(Z \subseteq S\) and \(Z' \subseteq S\), such that \(Z\) can only be left from \((Z' \cap Z)\), then for all \(s \in Z\) with probability 1 \((R_S(Z') \cap Z)\) or \((Z' \cap Z)\) is reached, i.e., \(\Pr(A(\text{Reach}((R_S(Z') \cap Z) \cup (Z' \cap Z)))) = 1\). Note the similarity with the previous property, only intersection with \(Z\) is taken.
4. Given sets $Z \subseteq S$ and $Z' \subseteq S$, such that $Z$ can only be left from $(Z' \cap Z)$ and from each state in $(Z' \cap Z)$ there is a positive probability to leave $Z$, then for all $s \in Z$ with probability 1 $(R_S(Z') \cap Z)$ or $(S \setminus Z)$ is reached, i.e., $\Pr_s(\text{Reach}((R_S(Z') \cap Z) \cup (S \setminus Z))) = 1$.

5. From every state $s \in S$, with probability 1 some recurrent class $L$ is reached; and given a recurrent class $L$ is reached, with probability 1 every state in $L$ is reached.

6. Consider $Z \subseteq S$ and $Z' \subseteq S$ such that for all $z \in Z$ the set $Z'$ is reachable. Then for all $s \in S$ with probability 1 either $R_S(Z)$ or $Z'$ is reached, i.e., $\Pr_s(\text{Reach}(R_S(Z) \cup Z')) = 1$.

7. Consider $Z \subseteq S$ and $Z' \subseteq S$ such that for all $s \in (S \setminus (Z \cup Z'))$, we have that $\delta(s)(Z) \cdot \epsilon \geq \delta(s)(Z')$, for $\epsilon > 0$. Then, for all $s \in (S \setminus (Z \cup Z'))$ the probability to reach $Z$ or $R_S(Z \cup Z')$ is at least $1 - \epsilon$, i.e., $\Pr_s(\text{Reach}(Z \cup R_S(Z \cup Z'))) \geq 1 - \epsilon$.

8. Consider $Z \subseteq S$ and $Z' \subseteq S$ such that for all $s \in Z$ the set $Z'$ is reachable. Then for all $s \in Z$ with probability 1 $(S \setminus Z)$ or $Z'$ is reached, i.e., $\Pr_s(\text{Reach}((S \setminus Z) \cup Z')) = 1$.

We will refer to these properties as Markov property 1 to Markov property 8, respectively.

**$\mu$-calculus.** Consider a $\mu$-calculus expression $\Psi = \mu X.\psi(X)$ over a finite set $S$, where $\psi : 2^S \mapsto 2^S$ is monotonic. The least fixpoint $\Psi = \mu X.\psi(X)$ is equal to the limit $\lim_{k \to \infty} X_k$, where $X_0 = \emptyset$, and $X_{k+1} = \psi(X_k)$. For every state $s \in \Psi$, we define the level $k \geq 0$ of $s$ to be the integer such that $s \not\in X_k$ and $s \in X_{k+1}$. The greatest fixpoint $\Psi = \nu X.\psi(X)$ is equal to the limit $\lim_{k \to \infty} X_k$, where $X_0 = S$, and $X_{k+1} = \psi(X_k)$. For every state $s \not\in \Psi$, we define the level $k \geq 0$ of $s$ to be the integer such that $s \in X_k$ and $s \not\in X_{k+1}$. The height of a $\mu$-calculus expression $\gamma X.\psi(X)$, where $\gamma \in \{\mu, \nu\}$, is the least integer $h$ such that $X_h = \lim_{k \to \infty} X_k$. An expression of height $h$ can be computed in $h + 1$ iterations. A $\mu$-calculus formula with nested $\mu$ and $\nu$ operators is a very succinct description of a nested iterative algorithm.

The value problem. Given an objective $\Phi$, and a class $C$ of strategies for player 1, the value for player 1 under the class $C$ of strategies is the maximal payoff that player 1 can guarantee with a strategy in class $C$. Formally, $\text{val}(\Phi, C)(s) = \sup_{\sigma_1 \in C} \inf_{\sigma_2 \in C} \Sigma_2^{s_1, s_2}[\Phi]$. In this work we will consider the computation of the value 1 set under finite-memory strategies, i.e., the computation of the set $\{s \in S \mid \text{val}(\text{LimInfAvg}(r), \Sigma_2^{s_1, s_2})(s) = 1\}$. Observe that to ensure value 1, player 1 must ensure that for all $\epsilon > 0$, the probability to visit reward 1 is at least $1 - \epsilon$, and hence it follows if all rewards less than 1 are decreased to 0 the value 1 set still remains the same, and hence for simplicity for the value 1 set computation we will consider Boolean reward functions.

3 The Value 1 Set Computation

In this section we will present a polynomial-time algorithm to compute the value 1 set, $\text{val}_1(\Phi, \Sigma_1^{s_1, s_2})$, for mean-payoff objectives $\Phi$. We start with a very basic and informal overview of the algorithm.

Basic overview of the algorithm. The algorithm will compute the value 1 set $W$ by iteratively adding chunks of states that are guaranteed to be in the value 1 set, and the iteration will finally converge to $W$. Let $U \subseteq W$ be the set of states that are already guaranteed to be in the value 1 set (already identified as subset of $W$ in some previous iteration). Then a new chunk $X$ of states are added such that $U \subseteq X \subseteq W$, and the new chunk of states are also added iteratively (the algorithm is a nested iterative algorithm). For the set $X$, let $U \subseteq Y \subseteq X$ be the subset that is already added, and then a new chunk $Y \subseteq Z \subseteq X$ is added such that player 1 can ensure that one of the following three conditions hold: (1) the probability to reach
$Pr = x$  
$Pr < x \cdot \epsilon$  

Figure 2: Pictorial illustration of Equation 1.

$Pr = x > 0$  
$y = Pr < 1$  
$x + y = 1$  

Figure 3: Pictorial illustration of Equation 2.

$U$ in one step can be made arbitrarily large as compared to the probability to leave $W$ in one step (then $U$ can be reached with probability arbitrarily close to 1); or (2) the probability to stay in $X$ in one step is 1 and the probability to reach $Y$ in one step is positive (then $Y$ can be reached with probability 1); or (3) the probability to stay in $X$ in one step is 1, the one step expected reward and the probability to stay in $Z$ in one step can be made arbitrarily close to 1. Figure 2, Figure 3, and Figure 4 illustrate the above three conditions, respectively, pictorially. Note that the above three conditions are local (one-step) conditions and we will first define an one-step predecessor operator to capture the above conditions. We will then show how to compute the one-step predecessor operator in polynomial time, and finally show how to use the one-step predecessor operator in a nested iterative algorithm to compute the value 1 set in polynomial time.

$Pr \geq 1 - \epsilon$  
$ExpRew \geq 1 - \epsilon$  
$Pr \leq \epsilon$  

Figure 4: Pictorial illustration of Equation 3.
3.1 One-step predecessor operator

We first formally define the one-step predecessor operator that was described informally in the basic overview of the algorithm. Given a state \( s \) and two distributions \( \xi_1 \in \mathcal{D}(\Gamma_1(s)) \) and \( \xi_2 \in \mathcal{D}(\Gamma_2(s)) \), the expected one-step reward \( \text{ExpRew}(s, \xi_1, \xi_2) \) is defined as follows: \( \sum_{a_1 \in \Gamma_1(s), a_2 \in \Gamma_2(s)} \xi_1(a_1) \cdot \xi_2(a_2) \cdot r(s, a_1, a_2) \). We often use distributions for player 2 that plays a single action \( a_2 \) with probability 1, and use \( a_2 \) to denote such a distribution. For sets \( U \subseteq Y \subseteq Z \subseteq X \subseteq W \), the one-step predecessor operator for limit-average (mean-payoff) objectives, denoted as \( \text{LimAvgPre}(W, U, X, Y, Z) \), is the set of states \( s \) such that for all \( 0 < \epsilon < \frac{1}{\mathcal{P}} \), there exists a distribution \( \xi_1^\epsilon \) over \( \Gamma_1(s) \) such that for all actions \( a_2 \) in \( \Gamma_2(s) \), we have that

\[
(\epsilon \cdot \delta(s, \xi_1^\epsilon, a_2)(U) > \delta(s, \xi_1^\epsilon, a_2)(\overline{W}))
\]

\[
\lor (\delta(s, \xi_1, a_2)(X) = 1 \land \delta(s, \xi_1, a_2)(Y) > 0)
\]

\[
\lor (\delta(s, \xi_1, a_2)(X) = 1 \land \text{ExpRew}(s, \xi_1^\epsilon, a_2) \geq 1 - \epsilon \land \delta(s, \xi_1^\epsilon, a_2)(Z) \geq 1 - \epsilon).
\]

We denote the above conditions as Equation 1, Equation 2, and Equation 3, respectively. Also our nested \( \text{LimAvgPre} \) operator and witness parametrized distribution. Before presenting the algorithm for the computation of the \( \text{LimAvgPre} \) set, we first discuss the special case when we only have the first condition Equation 1, then describe some key properties of witness distributions, and finally present an iterative algorithm to compute \( \text{LimAvgPre} \).

The LPre operator and witness parametrized distribution. An algorithm for the computation of the predecessor operator (called the LPre operator) for reachability games was presented in [9] where only Equation 1 is required to be satisfied. We extend the results of [9, 8] to obtain the following properties (details presented in technical appendix):

- **(Input and output).** The algorithm takes as input a state \( s \), two sets \( U \subseteq W \) of states, two sets of action sets \( A_1 \subseteq \Gamma_1(s) \) and \( A_2 \subseteq \Gamma_2(s) \), and either rejects the input or returns the largest set \( A_3 \subseteq A_2 \) such that the following conditions hold: for every \( 0 < \epsilon < \frac{1}{\mathcal{P}} \) there exists a witness distribution \( \xi_1^\epsilon \in \mathcal{D}(A_1) \), with patience at most \( \left( \frac{\epsilon \cdot \mathcal{P}}{2} \right)^{-((|A_1|-1)}} \), such that (i) for all actions \( a_2 \in A_2 \) Equation 1 is satisfied; and (ii) for all actions \( a_2' \in (A_2 \setminus A_3) \) we have \( \text{Succ}(s, \xi_1^\epsilon, a_2') \subseteq W \). The set \( A_3 \) is largest in the sense that if \( A_4 \subseteq A_2 \) and \( A_4 \) satisfies the above conditions, then \( A_4 \subseteq A_3 \). Notice that this indicates that for all \( a_2 \in (A_2 \setminus A_3) \) we have \( \text{Succ}(s, \xi_1^\epsilon, a_2) \cap U = \emptyset \), because otherwise \( a_2 \) would be in \( A_3 \). Moreover, the distribution \( \xi_1^\epsilon \) has the largest possible support, i.e., for all actions \( a_1 \in (A_1 \setminus \text{Supp}(\xi_1^\epsilon)) \), there exists an action \( a_2 \) in \( (A_2 \setminus A_3) \) such that \( \text{Succ}(s, a_1, a_2) \cap \overline{W} \neq \emptyset \). An input would only be rejected if for each action \( a_1 \in A_1 \) there exists an action \( a_2 \in A_2 \) such that \( \text{Succ}(s, a_1, a_2) \cap \overline{W} \neq \emptyset \).

- **(Parametrized distribution).** Finally, the witness family of distributions \( \xi_1^\epsilon \), for \( 0 < \epsilon < \frac{1}{\mathcal{P}} \), is presented in a parametrized fashion as follows: the support \( \text{Supp}(\xi_1^\epsilon) \) for all \( 0 < \epsilon < \frac{1}{\mathcal{P}} \) is the same (denoted as \( A^* \)), and the algorithm gives the support set \( A^* \), and a ranking function that assigns a number from 0 to at most \( |A^*| \) to every action in \( A^* \), and for any \( 0 < \epsilon < \frac{1}{\mathcal{P}} \), the witness distribution \( \xi_1^\epsilon \) plays actions with rank \( i \) with probability proportional to \( \epsilon^i \). In other words, the support set \( A^* \) and the ranking number of the actions in \( A^* \) is a polynomial witness for the parametrized family of witness distributions \( \xi_1^\epsilon \), for all \( 0 < \epsilon < \frac{1}{\mathcal{P}} \).
We summarize the important properties which we explicitly use later: \( \text{LPre}(s, W, U, A_1, A_2) \) for \( U \subseteq W \) returns the following (see Technical Appendix for correctness proof):

1. **(Reject property of LPre).** Reject and then for all \( a_1 \in A_1 \) there exists \( a_2 \in A_2 \) such that \( \text{Succ}(s, a_1, a_2) \cap \overline{W} \neq \emptyset \)

2. **(Accept properties of LPre).** Accepts and returns the set \( A_3 \subseteq A_2 \) and a parametrized distribution \( \xi_1^* \), for \( 0 < \epsilon < \frac{1}{2} \), with support \( \text{Supp}(\xi_1^*) \subseteq A_1 \), such that the following properties hold:
   
   - (Accept property a). For all \( a_2 \in A_3 \), the distribution \( \xi_1^* \) satisfies Equation 1 for \( a_2 \).
   - (Accept property b). For all \( a_2 \in (A_2 \setminus A_3) \), we have \( \text{Succ}(s, \xi_1^*, a_2) \cap \overline{W} = \emptyset \) and \( \text{Succ}(s, \xi_1^*, a_2) \cap U = \emptyset \).
   - (Accept property c). For all \( a_1 \in (A_1 \setminus \text{Supp}(\xi_1^*)) \), there exists an action \( a_2 \) in \( (A_2 \setminus A_3) \) such that \( \text{Succ}(s, a_1, a_2) \cap \overline{W} \neq \emptyset \).
   - (Accept property d). The set \( A_3 \) is largest in the sense that for all \( a_2 \in (A_2 \setminus A_3) \) and for all parametrized distributions \( \xi_1^* \) over \( A_1 \), the Equation 1 cannot be satisfied, while satisfying actions in \( A_2 \) using Equation 1, or Equation 2, or Equation 3, for any \( X, Y, Z \) such that \( U \subseteq Y \subseteq Z \subseteq X \subseteq W \).

**One action with large probability property.** We will now show that if a state belongs to \( \text{LimAvgPre} \), then there is a family of witness distributions where one action \( a \) is played with very large probability.

**Lemma 1.** Given \( U \subseteq Y \subseteq Z \subseteq X \subseteq W \), if \( s \in \text{LimAvgPre}(W, U, X, Y, Z) \), then for all \( 0 < \epsilon \leq \frac{\delta_{\text{min}}}{m} \) there is a witness distribution to satisfy at least one of the three conditions (Equation 1, Equation 2, or Equation 3) of \( \text{LimAvgPre} \) where an action \( a \in \Gamma_1(s) \) is played with probability at least \( 1 - \epsilon \cdot \delta_{\text{min}} \).

**Proof.** Given \( 0 < \epsilon \leq \frac{\delta_{\text{min}}}{m} \), let \( \xi_1^* \) be a witness distribution such that for all actions in \( \Gamma_2(s) \) at least one of the three conditions for \( \text{LimAvgPre} \) is satisfied. Let \( C_1 \) be the set of actions \( a_2 \) in \( \Gamma_2(s) \) such that \( \xi_1^* \) and \( a_2 \) satisfy Equation 1; respectively, \( C_2 \) for Equation 2, and \( C_3 \) for Equation 3. Let \( a \) be some action such that \( \xi_1^*(a) \geq \frac{1}{m} \) (note that such an action must exist). If \( \xi_1^*(a) \geq 1 - \epsilon \cdot \delta_{\text{min}} \), then we already have the desired action \( a \); and we are done. Otherwise, we consider the distribution \( \xi_1^* \) defined as follows:

\[
\xi_1^*(a) = \begin{cases} 
1 - \epsilon \cdot \delta_{\text{min}} & \text{if } a = a_1 \\
\epsilon \cdot \delta_{\text{min}} \cdot \frac{\Gamma_2(a)}{\Gamma_1(a)} & \text{otherwise}.
\end{cases}
\]

We now consider three cases to show \( \xi_1^* \) is also a witness distribution to satisfy at least one of the three conditions of \( \text{LimAvgPre} \) for \( \epsilon \).

1. Consider an action \( a_2 \) in \( C_1 \). Since \( a_2 \) in \( C_1 \) and \( \epsilon < \frac{\delta_{\text{min}}}{m} \), we must have that \( \text{Succ}(s, a, a_2) \cap \overline{W} \neq \emptyset \), because otherwise given \( \xi_1^* \) and \( a_2 \) the set \( \overline{W} \) is reached with probability at least \( \frac{\delta_{\text{min}}}{m} \) (as \( a \) is played with probability at least \( \frac{1}{m} \) by \( \xi_1^* \)), i.e., \( \delta(s, \xi_1^*, a_2)(\overline{W}) \geq \frac{\delta_{\text{min}}}{m} > \epsilon \). This contradicts that \( a_2 \) satisfies Equation 1 for \( \xi_1^* \) for the given \( \epsilon < \frac{\delta_{\text{min}}}{m} \). Hence given \( a \) and \( a_2 \), the probability to leave the set \( W \) is 0; and since all the other actions are only scaled in \( \xi_1^* \) as compared to \( \xi_1^* \) we have

\[
\frac{\delta(s, \xi_1^*, a_2)(U)}{\delta(s, \xi_1^*, a_2)(\overline{W})} \leq \frac{\delta(s, \xi_1^*, a_2)(U)}{\delta(s, \xi_1^*, a_2)(\overline{W})}
\]

Hence, given \( \xi_1^* \) the action \( a_2 \) must also satisfy Equation 1 for \( \epsilon \).
2. Consider an action $a_2$ in $C_2$. Since $a_2$ in $C_2$ (i.e., satisfies Equation 2) we must have $\text{Succ}(s, \xi_1', a_2) \subseteq X$ (stay in $X$ with probability 1) and $\text{Succ}(s, \xi_1', a_2) \cap Y \neq \emptyset$ (next state in $Y$ with positive probability). Since $\xi_1'$ assigns positive probability to precisely the same set of actions as $\xi_1$, i.e., $\text{Supp}(\xi_1') = \text{Supp}(\xi_1)$, we have that $\text{Succ}(s, \xi_1', a_2) = \text{Succ}(s, \xi_1, a_2) \subseteq X$ (stay in $X$ with probability 1) and $\text{Succ}(s, \xi_1', a_2) \cap Y = \text{Succ}(s, \xi_1, a_2) \cap Y \neq \emptyset$ (next state in $Y$ with positive probability). Hence we have that $\xi_1'$ and $a_2$ must also satisfy Equation 2.

3. Finally consider an action $a_2$ in $C_3$. We must have that (i) $\text{Succ}(s, a, a_2) \subseteq Z$ and (ii) $\tau(s, a, a_2) = 1$; because otherwise we would either not end up in $Z$ or not get reward 1 with probability at least $\delta_{\text{min}}$ when $a_2$ is played against $\xi_1'$ (contradicting that $a_2$ satisfies Equation 3). Since $\xi_1'$ plays a with larger probability than $\xi_1$, and all other actions are scaled with probabilities of $\xi_1'$, it follows that for every $a_2$ in $C_3$ we must have that $\xi_1'$ and $a_2$ satisfy Equation 3.

The desired result follows.

The action with large probability. In Lemma 1 we showed that some action is played with large probability. In the lemma the action was chosen depending on $\epsilon$, but since there are only finitely many actions and if an action satisfies for some $0 < \epsilon < \frac{1}{2}$, then it also satisfies for all $\epsilon'$ such that $\epsilon \leq \epsilon' < \frac{1}{2}$, and thus it follows that there is an action that is played with large probability. We will call a parametrized distribution $\xi_1'$, for $0 < \epsilon < \frac{1}{2}$, an $a$-large distribution if the distribution plays action $a$ with probability at least $1 - \epsilon \cdot \delta_{\text{min}}$. Thus the existence of witness $a$-large distributions, if such distributions exist, follows from Lemma 1. The main crux of the algorithm would be to find an action $a$ and a parametrized distribution that is $a$-large as a witness distribution for $\text{LimAvgPre}$. Our algorithm will use the $\text{LPre}$ operator iteratively. The key information we need is encoded as a matrix as follows.

The matrix for action sets. Given a state $s$, and the sets $W \subseteq Y \subseteq Z \subseteq X \subseteq W$, we define an $|\Gamma_1(s)| \times |\Gamma_2(s)|$-matrix $M$, such that $M_{a_1, a_2} \in \{W, W, W, U, X, Y, Z^0, Z^1\}$, that corresponds to the type of successor encountered if player 1 plays action $a_1$ and player 2 plays action $a_2$. Let

$$M_{a_1, a_2} = \begin{cases} W & \text{if } \text{Succ}(s, a_1, a_2) \cap W \neq \emptyset \\ U & \text{if } \text{Succ}(s, a_1, a_2) \cap U \neq \emptyset \text{ and } \text{Succ}(s, a_1, a_2) \cap \overline{W} = \emptyset \\ W & \text{if } \text{Succ}(s, a_1, a_2) \cap (W \setminus X) \neq \emptyset \text{ and } \text{Succ}(s, a_1, a_2) \cap (\overline{W} \cup U) = \emptyset \\ Y & \text{if } \text{Succ}(s, a_1, a_2) \cap (Y \setminus U) \neq \emptyset \text{ and } \text{Succ}(s, a_1, a_2) \cap (\overline{W} \cup U \cup (W \setminus X)) = \emptyset \\ X & \text{if } \text{Succ}(s, a_1, a_2) \cap (X \setminus Z) \neq \emptyset \\ & \text{ and } \text{Succ}(s, a_1, a_2) \cap (\overline{W} \cup U \cup (W \setminus X) \cup (Y \setminus U)) = \emptyset \\ Z^\ell & \text{if } \text{Succ}(s, a_1, a_2) \cap (Z \setminus Y) \neq \emptyset \\ & \text{ and } \text{Succ}(s, a_1, a_2) \cap (\overline{W} \cup U \cup (W \setminus X) \cup (Y \setminus U) \cup (X \setminus Z)) = \emptyset \\ & \text{ and } \tau(s, a_1, a_2) = \ell, \text{ for } \ell \in \{0, 1\} . \end{cases}$$

The matrix uses that $U \subseteq Y \subseteq Z \subseteq X \subseteq W$, to ensure that the matrix is well-defined. Notice that $M$ encodes all the information needed by $\text{LPre}$ (the entries equal to $W, Y, X, Z^1, Z^0$ all ensures both $\overline{W}$ and $U$ are not reached, $U$ ensures that $U$ is reached with probability at least $\delta_{\text{min}}$ and $\overline{W}$ is not reached. The entries $\overline{W}$ ensures that $\overline{W}$ is reached with probability between $\delta_{\text{min}}$ and 1). Hence, we could alternatively give $M$ as input to $\text{LPre}$.

Intuitive description of the algorithm. We first present an intuitive description of our algorithm and then present it formally. The basic idea of the algorithm is to use $\text{LPre}$ iteratively and the existence of $a$-large
witness distributions. Given a candidate action \( a \), we reject \( a \) or accept \( a \) using the following procedure. First, given the action \( a \), if there is an action \( a_2 \) such that \( W \) is left with positive probability given \( a \) and \( a_2 \) (i.e., \( M_{a,a_2} = \overline{W} \)), then we reject \( a \). Second, we check if playing \( a \) with probability 1 satisfies all actions (by either of the three conditions), and if so we accept. If neither of the first two conditions hold, then we use an iterative procedure. Let \( C \) be the set of actions which are guaranteed to be satisfied (by Equation 1) by playing an \( a \)-large distribution (\( C \) consists of each action \( a_2 \) such that \( M_{a,a_2} = U \)). We run \text{LPre} \text{, and start with } (\Gamma_1(s) \setminus \{a\}) \text{ as available actions for player } 1 \text{ (we are only interested in } a \text{-large distributions and we do not consider } a \text{ for \text{LPre}}) \text{ and } (\Gamma_2(s) \setminus C) \text{ as available actions for player } 2 \text{. If \text{LPre} rejects, we also reject: this is because no matter which action } a_1 \neq a \text{ is played with the largest probability (and we could not play } a \text{ alone) there is an action } a_2, \text{ such that } M_{a_1,a_2} = \overline{W} \text{ and } M_{a,a_2} \neq U, \text{ which ensures that all three equations are violated. If \text{LPre} accepts, then we obtain a witness distribution } \xi_1 \text{ and a set } A_3 \text{ of actions of player } 2 \text{ such that } \xi_1 \text{ satisfies Equation 1 for all actions in } A_3 \text{. We then create } \xi_1', \text{ which is } \xi_1 \text{ scaled so that it plays an } \alpha \text{-large distribution (note that } \xi_1 \text{ plays } a \text{ with probability 0). Afterwards we check if all actions for player } 2 \text{ are satisfied by } \xi_1'. \text{ If so, we accept. Otherwise, we check that whether for each action } a_2 \text{ outside } (A_3 \cup C) \text{ we can satisfy either Equation 2 or Equation 3: for } a_2 \text{ to be satisfied using Equation 3, we must have that } M_{a,a_2} = Z^1; \text{ and for } a_2 \text{ to be satisfied using Equation 2, the distribution } \xi_1' \text{ must play some action } a_1 \text{ with positive probability such that } M_{a_1,a_2} = Y. \text{ If for some } a_2 \text{ outside } (A_3 \cup C), \text{ neither } M_{a,a_2} = Z^1, \text{ nor } M_{a_1,a_2} = Y, \text{ for some } a_1 \text{ played with positive probability, we reject. Otherwise, if we did not reject, we remove each action } a_1 \text{ for player } 1 \text{ from available actions, for which there exists an } a_2 \in (A_3 \cup C), \text{ such that } M_{a_1,a_2} = W. \text{ Note that if } M_{a_1,a_2} = W, \text{ then we cannot satisfy } a_2 \text{ using either Equation 2 or Equation 3, if we play } a_1 \text{ with positive probability. If the set of available actions does not contain } a, \text{ then we cannot play } a \text{ with positive probability in an } \alpha \text{-large distribution, which clearly means that no } \alpha \text{-large distribution exists and thus we reject. If this new, smaller set of actions for player } 1 \text{ contains } a, \text{ we iterate on with the new set as the set of available actions for player } 1, \text{ and the available set for player } 2 \text{ always remains as } (\Gamma_2(s) \setminus C). \text{ Since, in every iteration, we get a smaller set of actions for player } 1, \text{ we terminate at some point.}

**The algorithm** \text{ALGOpred}. We now describe the steps of the algorithm which we refer as \text{ALGOpred} (algorithm for predecessor computation). For a state \( s \), we consider every action \( a \in \Gamma_1(s) \) as a candidate for the existence of an \( \alpha \)-large witness distribution. For each action \( a \) we execute the following steps:

1. (Reject 1). Reject the choice of \( a \) if there exists \( a_2 \in \Gamma_2(s) \) such that \( M_{a,a_2} = \overline{W} \).

2. (Accept 1). Accept \( a \) if for all \( a_2 \in \Gamma_2(s) \) we have \( M_{a,a_2} \in \{U, Y, Z^1\} \), and then return the distribution that plays \( a \) with probability 1, and return “Accept” for state \( s \).

3. Let \( C \) be the set of actions \( a_2 \) in \( \Gamma_2(s) \) such that \( M_{a,a_2} \neq U \). Initialize \( B_1^0 \) and \( A_1^0 \) as \( (\Gamma_1(s) \setminus \{a\}) \). The remainder of the algorithm will be done in iterations.

4. (Iteration). In iteration \( i \geq 1 \), run \text{LPre}(s, W, U, (A_1^{i-1} \setminus B_1^{i-1}) \setminus \{a\}, C). (Reject 2): if \text{LPre}(s, W, U, (A_1^{i-1} \setminus B_1^{i-1}) \setminus \{a\}, C) rejects the input, then reject this choice of \( a \). Otherwise let \( A_2^i \) be the returned set; and let \( \xi_1^{i,1} \) be a witness parametrized distribution (parametrized by \( 0 < \epsilon < \frac{1}{2} \) which is obtained by the support of \( \xi_1^{i,1} \) and the ranking of the actions in the support). We will now define some sets of actions.

   (a) Let \( A_1^i = \text{Supp}(\xi_1^{i,1}) \cup \{a\} \).

   (b) Let \( B_1^i \) be all actions \( a_1 \) in \( \Gamma_1(s) \) such that for all \( a_2 \in (C \setminus A_2^i) \) we have \( M_{a_1,a_2} \neq W \).

   (c) Let \( B_2^i \) be all actions \( a_2 \) in \( (C \setminus A_2^i) \) such that either (i) \( M_{a,a_2} = Z^1 \); or (ii) there exists an action \( a_1 \in A_1^i \) with \( M_{a_1,a_2} = Y \).
5. We reject in the following cases:
   - (Reject 3). If \((A_i^1 \cap B_i^1) \setminus \{a\} = \emptyset\), then reject this choice of \(a\).
   - (Reject 4). If \((C \setminus A_i^2) \neq B_i^2\), then reject this choice of \(a\).
   - (Reject 5). If \(a \not\in B_i^1\), then reject this choice of \(a\).

6. (Accept 2). Otherwise if \(A_i^1 \subseteq B_i^1\), then return accept \(a\), and return the parametrized distribution \(\xi_{\epsilon,i}^{1}\), for \(0 < \epsilon < \frac{1}{2}\), that plays \(a\) with probability \(1 - \epsilon \cdot \delta_{\min}\) and with probability \(\epsilon \cdot \delta_{\min}\) follows \(\xi_{\epsilon,i}^{1}\), and also “Accept” state \(s\).

7. If the action is neither accepted nor rejected, then go to iteration \(i + 1\) in step 4.

If all choices of action \(a \in \Gamma_1(s)\) get rejected, then “Reject” state \(s\).

The parametrized distribution for Accept 2 is returned as the special action \(a\) (to be played with probability \(1 - \epsilon \cdot \delta_{\min}\), for \(0 < \epsilon < \frac{1}{2}\)), the support set of \(\xi_{\epsilon,i}^{1}\) and the ranking function of the support as given by the LPre operator (which gives the parametrized distribution for \(\xi_{\epsilon,i}^{1}\) which is multiplied by \(\epsilon \cdot \delta_{\min}\) to get the parametrized \(a\)-large witness distribution \(\xi_{\epsilon,i}^{1}\) and \(a\) is played with the remaining probability).

Illustrations with examples. We illustrate our algorithm on four \(M\)-matrices shown in Figure 5. First observe that the only feasible candidate for an \(a\)-large distribution is the first row, because each other row contains an \(\overline{W}\) entry, and thus will be rejected at the start. The first matrix shown in Figure 5a will be accepted by the algorithm and the other three will be rejected by the algorithm.

1. Consider first the matrix in Figure 5a. Then the algorithm is run with the first row as \(a\), it will call LPre with the all rows but the first row for player 1 and all columns but the first column for player 2 (since given the first row, the first column satisfies Equation 1). The LPre algorithm will then return the distribution \(d\) of playing the second row with probability \(1 - \frac{\epsilon}{2}\) and the third row with probability \(\frac{\epsilon}{2}\). It also returns the set \(A_3\) containing the second and third column (they satisfy Equation 1). We then get accept in that iteration, because column 4 and column 5 can be satisfied by Equation 2 and column 6 can be satisfied by Equation 3.

2. Consider now the second matrix, the one in Figure 5b. It will get rejected at start, because in this case each row contains an \(\overline{W}\) entry.

3. The third matrix, the one in Figure 5c, will get rejected in the second iteration. In the first iteration, LPre will return the same distribution \(d\) as for the first matrix along with the same \(A_3\). This time, we cannot accept directly, because \(d\) no longer satisfies any of the three equations, for column 5. At that point, the algorithm considers that each column \(a_2 \in \{4, 5, 6\}\) such that \(M_{a_1,a_2} = Y\) for some \(a_1 \in \{1, 2, 3\}\) or \(M_{a,a_2} = Z_1\) (where \(a = 1\)). Thus, the algorithm removes row 2, from the set of possible rows, because column 5 is such that \(M_{2,5} = W\), and \(5 \not\in A_3\) and iterate. Then the algorithm calls LPre and gets back reject, because each of the rows left contains at least one instance of \(\overline{W}\). Hence the algorithm rejects.

4. For the last matrix, the one in Figure 5d, the algorithm calls LPre and gets \(d\) and \(A_3\), but this time the algorithm rejects at that point, because row 6 (which is not in \(A_3\)) does not contain an action \(a_1\) played with positive probability such that \(M_{a_1,6} = Y\) or is such that \(M_{a,6} = Z_1\).
with patience at most 

some action \( a \) namely, (Accept 1) and (Accept 2). For the case of Accept 1: the algorithm returns a distribution that plays some action \( s \in \{ U, Y \} \) with positive probability. We analyze both the cases below.

Equation 2, or Equation 3) for \( \text{LimAvgPre} \).

Given \( U \subseteq Y \subseteq Z \subseteq X \subseteq W \) and a state \( s \), if algorithm ALGO\text{RED} accepts \( s \), then \( s \in \text{LimAvgPre}(W, U, X, Y, Z) \). Furthermore, for every \( 0 < \epsilon < \frac{1}{2} \) there exists a witness distribution \( \xi_1 \) with patience at most \( \left( \frac{\epsilon}{2}\right)^{-|\Gamma_1(s)|-1} \) to satisfy at least one of the three required conditions (Equation 1, Equation 2, or Equation 3) for \( \text{LimAvgPre} \) for every action \( a_2 \in \Gamma_2(s) \).

Proof. We will next show that if ALGO\text{RED} returns a parametrized distribution \( \xi_1 \), then for all \( 0 < \epsilon < \frac{1}{2} \) and for all actions \( a_2 \in \Gamma_2(s) \), at least one of the three conditions of \( \text{LimAvgPre} \) is satisfied. This will show that \( s \in \text{LimAvgPre}(W, U, X, Y, Z) \). The algorithm accepts state \( s \) and returns a distribution at two places, namely, (Accept 1) and (Accept 2). For the case of Accept 1: the algorithms returns a distribution that plays some action \( a \) with probability 1; and for the case of Accept 2 it returns a distribution that plays some subset of actions (at least 2) with positive probability. We analyze both the cases below.

1. Case Accept 1. In the first case for all actions \( a_2 \) we have that \( M_{a_2} \in \{ U, Y, Z \} \). We analyze the three sub-cases.

   (a) If \( M_{a_2} = U \), then \( \text{Succ}(s, a, s_2) \cap U \neq \emptyset \) (i.e., the next state is in \( U \) with positive probability) and \( \text{Succ}(s, a, a_2) \cap \overline{U} = \emptyset \) (i.e., the next state is in \( \overline{U} \) with probability 0) and hence Equation 1 is satisfied.

   (b) If \( M_{a_2} = Y \), then (i) \( \text{Succ}(s, a, a_2) \cap (Y \setminus U) \neq \emptyset \) which implies that \( \text{Succ}(s, a, a_2) \cap Y \neq \emptyset \), since \( (Y \setminus U) \subseteq Y \); and (ii) \( \text{Succ}(s, a, a_2) \cap (\overline{W} \cup U) = \emptyset \) which implies that \( \text{Succ}(s, a, a_2) \cap (\overline{W} \cup U \cup (W \setminus X)) = \emptyset \) because as \( X \subseteq W \) we have \( (\overline{W} \cup U \cup (W \setminus X)) = \overline{X} \cup U \); and hence \( \text{Succ}(s, a, a_2) \subseteq X \). The first condition ensures that the next state is in \( Y \) with positive probability and the second condition ensures the next state is in \( X \) with probability 1, and thus Equation 2 is satisfied.
(c) If \( M_{a_1,a_2} = Z^1 \), then (i) \( \text{Succ}(s, a, a_2) \cap (Z \setminus Y) \neq \emptyset \) which implies that \( \text{Succ}(s, a, a_2) \cap Z \neq \emptyset \); and (ii) \( \text{Succ}(s, a, a_2) \cap (W \cup U \cup (W \setminus X) \cup (Y \setminus U) \cup (X \setminus Z)) = \emptyset \) which implies that \( \text{Succ}(s, a, a_2) \cap (Z \cup U \cup Y) = \emptyset \), because as \( Z \subseteq X \subseteq W \) we have \( (W \cup U \cup (W \setminus X) \cup Y \cup (X \setminus Z)) = (Z \cup U \cup Y) \), and hence \( \text{Succ}(s, a, a_2) \subseteq Z \) (i.e., next state in \( Z \) with probability 1); and (iii) \( r(s, a, a_2) = 1 \) (i.e., expected reward is 1). It follows that Equation 3 is satisfied.

2. Case Accept 2. In the second case, we consider the case when the algorithm returns a parameterized distribution \( \xi^*_i \), for \( 0 < \epsilon < \frac{1}{2} \), in iteration \( i \). Let the action played with probability \( 1 - \epsilon \cdot \delta_{\text{min}} \) be \( a \).

Such an action clearly exists, by construction. For any \( a_2 \in \Gamma_2(s) \) such that \( M_{a,a_2} = U \), then the next state is in \( U \) with probability at least \( (1 - \epsilon \cdot \delta_{\text{min}}) \cdot \delta_{\text{min}} \) and the next state is in \( W \) with probability at most \( \epsilon \cdot \delta_{\text{min}} \) and the ratio is at least \( 2 \cdot \epsilon \); thus the distribution \( \xi^*_i \) and \( a_2 \) satisfy Equation 1 for \( 2 \cdot \epsilon \). As \( 0 < \epsilon < \frac{1}{2} \) is arbitrary the result follows for all \( a_2 \) such that \( M_{a,a_2} = U \). We consider the set \( C \) of remaining actions in \( \Gamma_2(s) \), i.e., for all \( a_2 \in C \) we have \( M_{a,a_2} \neq U \).

Satisfying Equation 1 in \( A^1_2 \). We have that \( M_{a,a_2} \neq W \), for all \( a_2 \in \Gamma_2(s) \), because otherwise the guess of action \( a \) would have been rejected, in (Reject 1). We also have that \( \text{LPre}(s, W, U, B', C) \), for \( B' \subseteq \Gamma_1(s) \setminus \{a\} \) must return an distribution \( \xi^* \) over \( B' \) and a set \( A' \subseteq C \), such that for all \( a_2 \in A' \), the action \( a_2 \) and the distribution \( \xi^* \) satisfies Equation 1 (by Accept property a of \( \text{LPre} \)).

In the last iteration the set \( A^1_2 \) is the set returned by \( \text{LPre}(s, W, U, ((A^*_{1-1} \cap B^*_{1-1}) \setminus \{a\}), C) \), and the distribution \( \xi^* \) satisfies Equation 1 for all actions in \( A^1_2 \) (again by Accept property a of \( \text{LPre} \) since \( A^1_2 \) is the returned subset of \( C \)). Since \( \xi^* \) only plays \( a \) with high probability and only scales the distribution \( \xi^* \), it follows (similarly to Case 1 of Lemma 1) that \( \xi^* \) satisfies Equation 1 for all actions in \( A^1_2 \).

Satisfying Equation 2 or Equation 3 in \( (C \setminus A^1_2) \). By definition of \( B^1_2 \) and \( A^1_2 \) (Step 4 (a) and Step 4 (b) of the algorithm), and that \( A^1_2 \subseteq B^1_2 \) (from Accept 2 of the algorithm), it follows that the distribution \( \xi^* \) is such that for all \( a_2 \in (C \setminus A^1_2) \) and \( a_1 \in \text{Supp}(\xi^*) \cup \{a\} \), we have \( M_{a_1,a_2} \neq W \). Also for all \( a_2 \in (C \setminus A^1_2) \) and all \( a_1 \) such that \( \xi^*(a_1) > 0 \), we have from Accept property b of \( \text{LPre} \) that \( M_{a_1,a_2} \neq W \) and \( M_{a_1,a_2} \neq U \). Notice that therefore for all \( a_1 \in \text{Supp}(\xi^*) \) and \( a_2 \in (C \setminus A^1_2) \) we have \( M_{a_1,a_2} \in \{X, Y, Z^0, Z^1\} \), which implies that \( \text{Succ}(s, \xi^*, a_2)(X) = 1 \). For all \( a_2 \in (C \setminus A^1_2) \) we have that either (i) \( M_{a_1,a_2} = Z^1 \), or (ii) \( \xi^* \) assigned positive probability to some \( a_1 \) such that \( M_{a_1,a_2} = Y \), because otherwise \( (C \setminus A^1_2) \neq B^1_2 \) and we would have rejected this choice of \( a \) (by Reject 4 of the algorithm). Notice that \( M_{a_1,a_2} = Z^1 \) implies that \( \text{Succ}(s, a, a_2)(Z) = 1 \) and that \( r(s, a, a_2) = 1 \), thus, since the distribution the algorithm returned was \( a \)-large, we get that we reach \( Z \) in one step with probability at least \( 1 - \epsilon \cdot \delta_{\text{min}} \) and get reward 1 with probability at least \( 1 - \epsilon \cdot \delta_{\text{min}} \), hence Equation 3 is satisfied. If the second case holds (i.e., \( M_{a_1,a_2} = Y \)), we have \( \text{Succ}(s, \xi^*, a_2) \cap (Y \setminus U) \neq \emptyset \) (i.e., \( Y \) is reached with positive probability in one step), thus implying that Equation 2 is satisfied.

Therefore the distribution \( \xi^* \) is a witness distribution to satisfy the required conditions for \( 0 < \epsilon < \frac{1}{2} \) for \( \text{LimAvgPre} \). It follows that \( s \in \text{LimAvgPre}(W, U, X, Y, Z) \).

**Patience.** The distribution returned by \( \text{LPre} \) over \( |\Gamma_1(s)| - 1 \) actions has patience at most \( \left( \frac{\epsilon \cdot \delta_{\text{min}}}{2} \right)^{-|\Gamma_1(s)| - 2} \). Hence it is clear from the algorithm that the distribution returned by the algorithm has patience at most \( \left( \frac{\epsilon \cdot \delta_{\text{min}}}{2} \right)^{-|\Gamma_1(s)| - 1} \). \( \square \)

Our next goal is to present a lemma that complements the previous lemma. In other words, we would show that if \( \text{ALGOPRED} \) rejects an action \( a \), then there would be no \( a \)-large distributions as witnesses for
We consider the case of Reject 1. In this case, there exists an action \( a_2 \) such that \( M_{a,a_2} = \overline{W} \). Given an \( a \)-large distribution \( \xi_1 \), the one step probability to reach \( \overline{W} \) (i.e., \( \delta(s, \xi_1, a_2)(\overline{W}) \)) is at least \( x = (1 - \epsilon \cdot \delta_{\text{min}}) \cdot \delta_{\text{min}} > \epsilon \), since \( \epsilon < \frac{1}{2} \) and \( \delta_{\text{min}} \leq 1 \), and even if \( U \) is reached with the remaining probability (i.e., even if \( \delta(s, \xi_1, a_2)(U) = 1 - x \)), it follows that Equation 1 is violated, for all \( 0 < \epsilon < \frac{1}{2} \). The remaining two expressions cannot be satisfied because \( X \subseteq W \) and since we leave \( W \) with positive probability we as well leave \( X \) with positive probability. It follows that the rejection of action \( a \) is sound for Reject 1.

**Soundness of Reject 1.** We consider the case of Reject 1. In this case, there exists an action \( a_2 \) such that \( M_{a,a_2} = \overline{W} \). Given an \( a \)-large distribution \( \xi_1 \), the one step probability to reach \( \overline{W} \) (i.e., \( \delta(s, \xi_1, a_2)(\overline{W}) \)) is at least \( x = (1 - \epsilon \cdot \delta_{\text{min}}) \cdot \delta_{\text{min}} > \epsilon \), since \( \epsilon < \frac{1}{2} \) and \( \delta_{\text{min}} \leq 1 \), and even if \( U \) is reached with the remaining probability (i.e., even if \( \delta(s, \xi_1, a_2)(U) = 1 - x \)), it follows that Equation 1 is violated, for all \( 0 < \epsilon < \frac{1}{2} \). The remaining two expressions cannot be satisfied because \( X \subseteq W \) and since we leave \( W \) with positive probability we as well leave \( X \) with positive probability. It follows that the rejection of action \( a \) is sound for Reject 1.

**Rejects in iteration.** The other places the algorithm can reject action \( a \), i.e., (Reject 2), (Reject 3), (Reject 4), and (Reject 5), are part of the iterative procedure. To prove soundness of these rejects we will define a loop invariant and prove the loop invariant inductively. We will also show that with the loop invariant we can establish soundness of the rejects in the iterative procedure as well as the termination of the algorithm.

**The loop invariant.** The loop invariant is as follows:

- Any \( a \)-large witness distribution \( \xi_1 \) for \( \text{LimAvgPre} \) only plays actions in \( (A_1^i \cap B_1^i) \cup \{a\} \) with positive probabilities, for all \( i \geq 0 \), i.e., \( \text{Supp}(\xi_1) \subseteq (A_1^i \cap B_1^i) \cup \{a\} \).

We will also establish the monotonicity (strictly decreasing till a fixpoint is reached) property that \( (A_1^i \cap B_1^i) \cup \{a\} \subseteq (A_1^{i-1} \cap B_1^{i-1}) \cup \{a\} \), for all \( i > 0 \); and equality implies termination in iteration \( i \).

**Inductive proof of loop invariant.** We present the basic inductive argument for the loop invariant:

- **The base case, \( i = 0 \).** The base case, for \( i = 0 \) is trivial, since \( A_1^0 = B_1^0 = (\Gamma_1(s) \setminus \{a\}) \), thus implying that \( (A_1^i \cap B_1^i) \cup \{a\} = \Gamma_1(s) \).

- **The induction case, \( i > 0 \).** By inductive hypothesis, any \( a \)-large witness distribution \( \xi_1 \) only plays actions in \( (A_1^{i-1} \cap B_1^{i-1}) \cup \{a\} \) with positive probabilities, and we need to establish for \( i \). We will show that any \( a \)-large witness distribution can only play actions in \( A_1^i \cup \{a\} = A_1^i \), (see the following description of \( A_1^i \) which uses the inductive hypothesis). We refer to this as required property 1 for loop invariant. Similarly, we establish the same for \( B_1^i \) (see the following description of \( B_1^i \) which uses the inductive hypothesis). We refer to this as required property 2 for loop invariant. Hence any witness \( a \)-large distribution can only play actions in \( (A_1^i \cap B_1^i) \cup \{a\} \).

The above proof requires to establish the key properties of \( A_1^i \) and \( B_1^i \). Before establishing them we first show the monotonicity property.

**Monotonicity property.** We will show that we have \( (A_1^i \cap B_1^i) \cup \{a\} \subseteq (A_1^{i-1} \cap B_1^{i-1}) \cup \{a\} \), for all \( i > 0 \), and equality implies termination of the inner loop in iteration \( i \). Notice that this implies that for any choice of \( a \) the inner loop rejects \( a \) or finds a distribution after at most \( |\Gamma_1(s)| \) iterations. We have that \( A_1^i = \text{Supp}(\xi_1) \cup \{a\} \) (by Step 4 (a) of \text{ALGO}PRED), where \( \xi_1 \) is a witness distribution returned by \text{LPre}(s,W,U,(A_1^{i-1} \cap B_1^{i-1}) \setminus \{a\}, C) \). Since \( \text{Supp}(\xi_1) \subseteq ((A_1^{i-1} \cap B_1^{i-1}) \setminus \{a\}) \), if \text{LPre} accepts, we have that \( A_1^i \subseteq (A_1^{i-1} \cap B_1^{i-1}) \cup \{a\} \). Thus we get that \( (A_1^i \cap B_1^i) \cup \{a\} \subseteq A_1^i \cup \{a\} \subseteq (A_1^{i-1} \cap B_1^{i-1}) \cup \{a\} \). This establish monotonicity and now we show the termination. Assume that \( (A_1^i \cap B_1^i) \cup \{a\} = (A_1^{i-1} \cap B_1^{i-1}) \cup \{a\} \). Therefore we have that \( \xi_1 \) can only use actions in \( ((A_1^{i-1} \cap B_1^{i-1}) \setminus \{a\}) \), which is thus also \( (A_1^i \cap B_1^i) \setminus \{a\} \). But then either (i) \( a \notin B_1^i \) or (ii) \( \text{Supp}(\xi_1) \cup \{a\} = A_1^i \subseteq (A_1^i \cap B_1^i) \cup \{a\} \); which implies that \( A_1^i \subseteq B_1^i \). But in the first case we reject (in (Reject 5)) and in the second case we accept (in (Accept 2)). This establishes the termination property.
The properties of the sets for loop invariant. We now present the associated properties of the sets $A_1^i$, $A_2^i$, $B_1^i$, and $B_2^i$ to complete the inductive proof of the loop invariant.

1. The property of the set $A_2^i$. We first argue that $A_2^i$ has certain properties which will imply the key properties for $A_2^i$.

   (a) Since $\text{LPre}(s, W, U, ((A_1^{i-1} \cap B_1^{i-1}) \setminus \{a\}), C)$ accepts, we have that $A_2^i$ is a subset of $C$. There exists a witness parametrized distribution $\xi'_1$, over $((A_1^{i-1} \cap B_1^{i-1}) \setminus \{a\})$ such that for all $a_2 \in A_2^i$ we have that $\xi'_1$ and $a_2$ satisfies Equation 1 (by Accept property a of LPre).

   (b) Also for all $a_2 \in (C \setminus A_2^i)$ we have that $M_{a_1, a_2} \neq \overline{W}$ for all $a_1 \in \text{Supp}(\xi'_1)$ (Accept property b of LPre).

   (c) Notice also that for any action $a_2 \in C$, if a distribution over $A_1^{i-1} \cap B_1^{i-1}$ cannot satisfy $a_2$ using Equation 1, then no distribution over $(A_1^{i-1} \cap B_1^{i-1}) \cup \{a\}$ can either, since $M_{a, a_2} \neq U$ (from the definition of the set $C$) and hence $U$ cannot be reached as long as the distribution plays $a$. For an distribution $\xi'_1$ to be a witness distribution, all actions in $\Gamma_2(s)$ must satisfy either (i) Equation 1; or (ii) Equation 2; or (iii) Equation 3. But if an action $a_2$ must satisfy either Equation 2 or Equation 3, we must have that $\xi'_1$ ensures that $\overline{X}$ is reached with probability 0 (i.e., $\text{Succ}(s, \xi'_1, a_2) \subseteq X$). Hence, since $X \subseteq W$ we also must have that $\overline{W}$ is reached with probability 0.

   By Accept property d of LPre we have that, since $A_2^i$ is returned by LPre, no $a$-large witness distribution $\xi'_1$ can satisfy any action $a_2$ in $(C \setminus A_2^i)$ using Equation 1, while satisfying all actions in $C$ using Equation 1, or Equation 2, or Equation 3. Also, for all $a_2 \in (C \setminus A_2^i)$ and all $a_1 \in \text{Supp}(\xi'_1)$ we have that $M_{a_1, a_2} \neq U$ (by Accept property b of LPre). Furthermore, by definition of $C$ for all $a_2 \in C$ we have that $M_{a, a_2} \neq U$. Therefore we have established the following key properties for $A_2^i$:

   - Any $a$-large witness distribution $\xi'_1$ must satisfy all actions $a_2$ in $(C \setminus A_2^i)$ using either Equation 2 or Equation 3.
   - For all $a_2 \in (C \setminus A_2^i)$ and $a_1 \in \text{Supp}(\xi'_1) \cup \{a\} = A_1^i$ we have that $M_{a_1, a_2} \neq U$.

2. The property of the set $A_1^i$. By accept property c of LPre and since we did not reject in Reject 1, the set $A_1^i$ is the largest set, such that for all $a_1 \in A_1^i$ there exists no $a_2$ in $(C \setminus A_2^i)$ with $M_{a_1, a_2} = \overline{W}$. But this means that any distribution that satisfies for all actions in $(C \setminus A_2^i)$ either Equation 2 or Equation 3, must play only actions in $A_1^i$. But from our description of $A_2^i$ we obtain that all $a$-large witness distributions must ensure that all actions in $(C \setminus A_2^i)$ are satisfied using either Equation 2 or Equation 3. Therefore we have established the following key property for $A_1^i$: All $a$-large witness distributions must play only actions in $A_1^i$ with positive probability. This proves the required property 1 of the loop invariant.

3. The property of the set $B_2^i$. From the first key property of $A_2^i$ we have that any $a$-large witness distribution must ensure that all actions in $(C \setminus A_2^i)$ satisfy either Equation 2 or Equation 3. From the second key property of $A_2^i$, for all $a_1 \in A_1^i$ and all $a_2 \in (C \setminus A_2^i)$, we have that $M_{a_1, a_2} \neq U$. The key property of $A_1^i$ implies that any $a$-large witness distribution must play only actions in $A_1^i$.

   Hence, for an $a$-large witness distribution $\xi'_1$, for all $a_2$ in $(C \setminus A_2^i)$ we must have that either (i) $M_{a, a_2} = Z^1$ (to satisfy Equation 3); or (ii) there is an action $a_1$ in $A_1^i$ such that $M_{a_1, a_2} = Y$ (to satisfy Equation 2) — it would also be satisfied if $M_{a_1, a_2} = U$ but we know that $M_{a_1, a_2} \neq U$ by Accept
Lemma 3. This establishes the inductive proof of the loop invariant. We prove the soundness of the other rejects below.

Proof. In the algorithm there are five places where a choice of a might get rejected. We have already argued the soundness of Reject 1. We prove the soundness of the other rejects below.

1. (Reject 2). If LPre(s, W, U, ((A_{i-1}^{w-1} \cap B_i^{w-1}) \setminus \{a\}), C) is rejected, then for all actions a_1 in ((A_{i-1}^{w-1} \cap B_i^{w-1}) \setminus \{a\}), there exists an action a_2 in C such that M_{a_1,a_2} = \overline{W}, by the reject property of LPre. Hence any action a_2 such that M_{a_1,a_2} = \overline{W}, cannot be satisfied using neither (i) Equation 1; nor (ii) Equation 2; nor (iii) Equation 3. The latter two because \overline{W} is entered with positive probability in one step and hence X is left with positive probability in one step. The first is because we reach \overline{W} with probability at least x = \frac{\delta m}{m} and even if we reach U with probability 1 - x, we still do not satisfy Equation 1. Now consider some distribution \xi_1 over (A_{i-1}^{w-1} \cap B_i^{w-1}) \setminus \{a\}. Either it plays a with probability 1 or not. If it does, then it cannot be a witness distribution, since it otherwise would have been accepted in Accept 1. If it does not then the argument is similar to the previous argument (in the case of Equation 1, the argument also uses that M_{a_1,a_2} = \overline{W} from the definition of C). Hence no witness distribution exists that only uses actions in (A_{i-1}^{w-1} \cap B_i^{w-1}) \setminus \{a\}. Thus Reject 2 is a sound reject, by the loop invariant.

2. (Reject 3). If a is not accepted by Accept 1, then a could not be played with probability 1. For Reject 3, the condition ((A_{i}^{w} \cap B_i^{w}) \setminus \{a\}) = \emptyset is satisfied. Thus no a-large witness distribution can play anything but a by the loop invariant. Therefore no a-large witness distribution can exist in this case. Thus, Reject 3 is a sound reject.

3. (Reject 4). Consider an a-large witness distribution \xi_1. The key property of B_i^{w} implies that any action a_2 \in (C \setminus (A_{i}^{w} \cup B_i^{w})) cannot be satisfied using either of the equations. But since B_i^{w} \subseteq (C \setminus A_{i}^{w}) we must have that B_i^{w} = (C \setminus A_{i}^{w}) for any a-large witness distribution to exists. Therefore we can reject the choice of a if (C \setminus A_{i}^{w}) = B_i^{w}. Hence Reject 4 is a sound reject.

4. (Reject 5). From the key property of the set B_i^{w}, we have that if a \notin B_i^{w}, then no a-large witness distribution can play a with positive probability, which implies that no a-large witness distribution can exist. Hence Reject 5 is also a sound reject.
Termination. We have already established (in "monotonicity and termination for loop invariant") that 
\((A_i \cap B_i) \cup \{a\} \subseteq (A_{i-1} \cap B_{i-1}) \cup \{a\}\), for all \(i > 0\) and equality implies termination of the inner loop in iteration \(i\). Notice that this implies that for any choice of \(a\) the inner loop rejects \(a\) or finds a distribution after at most \(|\Gamma_{1}(s)|\) iterations. We will now show that \(A_i \subseteq A_{i-1}\), for all \(i > 0\) and equality implies termination in iteration \(i\). Notice that this implies that for any choice of \(a\) the inner loop rejects \(a\) or finds a distribution after at most \(|\Gamma_{2}(s)|\) iterations. We have that \(A_i \subseteq A_{i-1}\), because \(\xi_{i,i}^{s}\) could also be returned in iteration \(i-1\) and \(\text{LPre}\) maximizes the number of \(a_1\)'s for which \(\xi_{i,i}^{s}(a_1) > 0\) (Accept property c). Assume that \(A_i = A_{i-1}\). Then \((C \setminus A_i) = (C \setminus A_{i-1})\) and thus \(B_1 = B_{1-1}\). We also have that \(A_i \subseteq (A_{i-1} \cap B_{i-1}) \cup \{a\}\), thus implying that \(A_i \subseteq (A_{i-1} \cap B_{i-1}) \cup \{a\}\). Therefore \(A_i \subseteq B_1\), since if \(B_i\) does not contain \(a\), neither does \(B_{i-1}\) and thus we would have rejected the choice of \(a\) in iteration \(i - 1\), because of (Reject 5). The desired result follows.

Lemma 4. Given \(U \subseteq Y \subseteq Z \subseteq X \subseteq W\) and a state \(s\), \text{ALGO\textsc{Pred}} terminates in time \(O(|\Gamma_{1}(s)|^2 \cdot |\Gamma_{2}(s)|^2 + \sum_{a_1 \in \Gamma_{1}(s), a_2 \in \Gamma_{2}(s)} |\text{Supp}(s, a_1, a_2)|)\). Alternatively, if \(M\) is given as input, the running time is \(O(|\Gamma_{1}(s)|^2 \cdot |\Gamma_{2}(s)|^2)\).

Proof. The calculation of \(M\) can be done in time \(\sum_{a_1 \in \Gamma_{1}(s), a_2 \in \Gamma_{2}(s)} |\text{Supp}(s, a_1, a_2)|\). As mentioned in the definition of \(M\), we could alternatively use \(M\) as input to \(\text{LPre}\) since it encodes all information needed. There are \(|\Gamma_{1}(s)|\) different choices for which action \(a\) to play with high probability. Given \(a\), there are at most \(\min(|\Gamma_{1}(s)|, |\Gamma_{2}(s)|)\) iterations of the inner loop, see Lemma 3. Each iteration of the inner loop can be done in \(O(|\Gamma_{1}(s)| \cdot |\Gamma_{2}(s)|)\) time, and is dominated by the running time of \(\text{LPre}\), which runs in time \(O(|\Gamma_{1}(s)| \cdot |\Gamma_{2}(s)|)\) on \(M\), see [9]. Hence, if \(M\) is given as input we get a running time of \(O(|\Gamma_{1}(s)| \cdot \min(|\Gamma_{1}(s)|, |\Gamma_{2}(s)|) \cdot |\Gamma_{1}(s)| \cdot |\Gamma_{2}(s)|)\), which is less than \(O(|\Gamma_{1}(s)|^2 \cdot |\Gamma_{2}(s)|^2)\).

Combining Lemma 2, Lemma 3 and Lemma 4 we get the following lemma.

Lemma 5. The algorithm \text{ALGO\textsc{Pred}}, for a given state \(s\) and sets \(U \subseteq Y \subseteq Z \subseteq X \subseteq W\), correctly computes if \(s \in \text{LimAvgPre}(W, U, X, Y, Z)\) and runs in time \(O(|\Gamma_{1}(s)|^2 \cdot |\Gamma_{2}(s)|^2 + \sum_{a_1 \in \Gamma_{1}(s), a_2 \in \Gamma_{2}(s)} |\text{Supp}(s, a_1, a_2)|)\).

3.2 Iterative algorithm for value 1 set computation

In this section we will present the nested iterative algorithm for the value 1 set computation. The nested iterative algorithm is succinctly represented as the following nested fixpoint formula (\(\mu\)-calculus formula) that uses the \(\text{LimAvgPre}\) one-step predecessor operator. Let

\[ W^* = \nu W. \mu U. \mu v X, \mu Y. \mu Z. \text{LimAvgPre}(W, U, X, Y, Z) \] .

We will show that \(W^* = \text{val}_1(\text{LimInfAvg}, \Sigma^i_{\text{L}})\). First in the next subsection we show that \(W^* \subseteq \text{val}_1(\text{LimInfAvg}, \Sigma^i_{\text{L}}) \subseteq \text{val}_1(\text{LimInfAvg}, \Sigma^i_{\text{L}})\); and in the following subsection will establish the other inclusion.

3.2.1 First inclusion: \(W^* \subseteq \text{val}_1(\text{LimInfAvg}, \Sigma^i_{\text{L}})\)

Let \(\Theta_i\) denote the random variable for the reward at the \(i\)-th step of the game. We will show that for all states \(s\) in \(W^*\) for all \(\epsilon > 0\), there exists a stationary (hence finite-memory) strategy \(\sigma^1\) for player 1 such that for all positional strategies \(\sigma_2\) for player 2 we have that

\[ \lim_{t \to \infty} \frac{\sum_{i=0}^{t} e^{\sigma^1_i, \sigma^2_i}[\Theta_i]}{t} \geq 1 - \epsilon \] .
This will show that $W^* \subseteq \text{val}_1(\text{LimInfAvg}, \Sigma_1^f) \subseteq \text{val}_1(\text{LimInfAvg}, \Sigma_1^f)$. Notice that the statement is trivially satisfied if $W^* = \emptyset$, and hence we will assume that this is not so.

**Computation of $W^*$**. We first analyze the computation of $W^*$. Since $W^*$ is a fixpoint, we can replace $W$ by $W^*$ and get rid of the outer most $\nu$ operator, and the rest of the $\mu$-calculus formula also computes $W^*$. In other words, we have

$$W^* = \mu U.\nu X.\nu Y.\nu Z.\text{LimAvgPre}(W^*, U, X, Y, Z),$$

Thus the computation of $W^*$ is achieved as follows: $U_0$ is the empty set; and $U_i = \nu X.\nu Y.\nu Z.\text{LimAvgPre}(W^*, U_{i-1}, X, Y, Z)$, for $i \geq 1$. Let $\ell$ be the least index such that $U_\ell = W^*$. For any $i \geq 0$, we also have that $Y_{i,0}$ is the empty set and that $Y_{i,j} = \nu Z.\text{LimAvgPre}(W^*, U_{i-1}, U_i, Y_{i,j-1}, Z)$, for $j \geq 1$. Let $\ell \geq i \geq 1$. For a state $s \in W^*$, let the rank of state $s$ (denoted $\text{rk}(s) = (i, j)$) be the tuple of $(i, j)$ such that $i$ is the least index with $s \in U_i$ (i.e., $s \in U_i \setminus U_{i-1}$); and $j$ is the least index with $s \in Y_{i,j}$ (i.e., $s \in Y_{i,j} \setminus Y_{i,j-1}$). For $1 \leq i \leq \ell$, let $\text{rk}(i) = j$ be the least index when the fix point converges for $U_i$, i.e., the least such that $Y_{i,j} = Y_{i,j+1}$. By definition of $W^*$, for all states $s \in W^*$, if $\text{rk}(s) = (i, j)$, then we must have that for all $\epsilon > 0$ there is a distribution $\xi_1^\epsilon$ over $\Gamma_1(s)$ such that for all actions $a_2 \in \Gamma_2(s)$ for player 2 we have that

$$\left( \epsilon \cdot \delta(s, \xi_1^\epsilon, a_2)(U_{i-1}) > \delta(s, \xi_1^\epsilon, a_2)(\overline{U^*}) \right)$$

\(\forall\) $\delta(s, \xi_1^\epsilon, a_2)(U_i) = 1 \wedge \delta(s, \xi_1^\epsilon, a_2)(Y_{i,j-1}) > 0$$

\(\forall\) $\delta(s, \xi_1^\epsilon, a_2)(U_i) = 1 \wedge \text{ExpRew}(s, \xi_1^\epsilon, a_2) \geq 1 - \epsilon \wedge \delta(s, \xi_1^\epsilon, a_2)(Y_{i,j}) \geq 1 - \epsilon$ \quad ;

where $\overline{W^*} = S \setminus W^*$ is the complement of $W^*$. We refer to the above as Equation 4, Equation 5, and Equation 6, respectively.

**The construction of stationary witness strategy $\sigma_1^\epsilon$.** Fix $0 < \epsilon < \frac{1}{2}$. The desired witness stationary strategy $\sigma_1^\epsilon$ will be constructed from a finite sequence of stationary strategies,

$$\sigma_1^{\epsilon,1,0}, \sigma_1^{\epsilon,1,1}, \ldots, \sigma_1^{\epsilon,1,\text{rk}(1)}, \sigma_1^{\epsilon,2,0}, \ldots, \sigma_1^{\epsilon,2,\text{rk}(2)}, \ldots, \sigma_1^{\epsilon,\ell,0}, \ldots, \sigma_1^{\epsilon,\ell,\text{rk}(\ell)}.$$

The strategies will be constructed inductively. First we will construct it for states in $U_1$ and $(U_2 \setminus U_{\ell-1})$, and then we will present the inductive construction for $(U_i \setminus U_{i-1})$, for $2 \leq i \leq \ell - 1$.

- (Base case). We will first describe the construction of the strategy $\sigma_1^{\epsilon,1,0}$ (resp. $\sigma_1^{\epsilon,\ell,0}$).

  1. The stationary strategy $\sigma_1^{\epsilon,1,0}$ (resp. $\sigma_1^{\epsilon,\ell,0}$) is arbitrary except for states in $(Y_{1,\text{rk}(1)} \setminus Y_{1,\text{rk}(1)-1})$ (resp. $(Y_{\ell,\text{rk}(\ell)} \setminus Y_{\ell,\text{rk}(\ell)-1})$).

  2. For states $s$ in $(Y_{1,\text{rk}(1)} \setminus Y_{1,\text{rk}(1)-1})$ (resp. $(Y_{\ell,\text{rk}(\ell)} \setminus Y_{\ell,\text{rk}(\ell)-1})$) the strategy plays the distribution $\xi_1^\eta$ over $\Gamma_1(s)$, for $\eta = \frac{\epsilon}{2}$.

  3. We next describe the construction of the strategy $\sigma_1^{\epsilon,1,j}$ (resp. $\sigma_1^{\epsilon,\ell,j}$), for $j \geq 1$, using induction in $j$.

    a) The strategy $\sigma_1^{\epsilon,1,j}$ (resp. $\sigma_1^{\epsilon,\ell,j}$) plays as $\sigma_1^{\epsilon,1,j-1}$ (resp. $\sigma_1^{\epsilon,\ell,j-1}$) except for states in $(Y_{1,\text{rk}(1)-j} \setminus Y_{1,\text{rk}(1)-(j+1)})$ (resp. $(Y_{\ell,\text{rk}(\ell)-j} \setminus Y_{\ell,\text{rk}(\ell)-(j+1)})$).

    b) For states $s$ in $(Y_{1,\text{rk}(1)-j} \setminus Y_{1,\text{rk}(1)-(j+1)})$ (resp. $(Y_{\ell,\text{rk}(\ell)-j} \setminus Y_{\ell,\text{rk}(\ell)-(j+1)})$) the strategy plays the distribution $\xi_1^\eta$ over $\Gamma_1(s)$, for $\eta = \left(\frac{1}{2}\right)^{(2m)^j}$.
Lemma 7. Since (2) where the inequality is as follows:

Proof. By construction, the patience of

1. The strategy \( \sigma^{c_{i+1},0} \) plays as the strategy \( \sigma^{\eta_{i+1},rk(i+1)} \), for \( \eta = \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{\delta(i)}} \), except for states in \( (Y_{i,rk(i)} \setminus Y_{i,rk(i)-1}) \).

2. For states \( s \) in \( Y_{i,rk(i)} \setminus Y_{i,rk(i)-1} \) the strategy plays \( \xi^\eta \) over \( \Gamma_1(s) \), for \( \eta = \frac{\epsilon}{2} \).

3. We now finally construct \( \sigma^{c_{i},j} \) for \( 2 \leq i \leq \ell - 1 \), using induction in \( j \).

   (a) The strategy \( \sigma^{c_{i},j} \) plays as \( \sigma^{c_{i},j-1} \) except for states in \( (Y_{i,rk(i)-j} \setminus Y_{i,rk(i)-(j+1)}) \).

   (b) For states \( s \) in \( (Y_{i,rk(i)-j} \setminus Y_{i,rk(i)-(j+1)}) \) the strategy plays \( \xi^\eta \) over \( \Gamma_1(s) \), for \( \eta = \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^j} \).

(Inductive case). We will next construct the strategy for the remaining states, in two steps, first for \( \sigma^{c_{i+1},0} \) and then for \( \sigma^{c_{i},j} \), for \( 2 \leq i \leq \ell - 1 \) and \( j \geq 1 \). We will do so using induction backwards in \( i \).

That is the base case is \( i = \ell \) and we then proceed downward.

Let \( \eta = \frac{\epsilon}{2} \) be given. The patience of the witness stationary strategy \( \sigma^{c_{i}} \) is at most \( \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{\delta(i)}} \) for all \( i \) and \( \delta(i) = \delta(i-1) + 1 \) for all \( i > 0 \).

Lemma 6. The patience of \( \sigma^{c_{i}}(s) \) for states \( s \) of rank \( \ell \) is at most \( \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{\delta(i)}} \) for all \( i \) and \( \delta(i) = \delta(i-1) + 1 \) for all \( i > 0 \).

(Inductive case). We will next construct the strategy for the remaining states, in two steps, first for \( \sigma^{c_{i+1},0} \) and then for \( \sigma^{c_{i},j} \), for \( 2 \leq i \leq \ell - 1 \) and \( j \geq 1 \). We will do so using induction backwards in \( i \).

That is the base case is \( i = \ell \) and we then proceed downward.

1. The strategy \( \sigma^{c_{i+1},0} \) plays as the strategy \( \sigma^{\eta_{i+1},rk(i+1)} \), for \( \eta = \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{\delta(i)}} \), except for states in \( (Y_{i,rk(i)} \setminus Y_{i,rk(i)-1}) \).

2. For states \( s \) in \( Y_{i,rk(i)} \setminus Y_{i,rk(i)-1} \) the strategy plays \( \xi^\eta \) over \( \Gamma_1(s) \), for \( \eta = \frac{\epsilon}{2} \).

3. We now finally construct \( \sigma^{c_{i},j} \) for \( 2 \leq i \leq \ell - 1 \), using induction in \( j \).

   (a) The strategy \( \sigma^{c_{i},j} \) plays as \( \sigma^{c_{i},j-1} \) except for states in \( (Y_{i,rk(i)-j} \setminus Y_{i,rk(i)-(j+1)}) \).

   (b) For states \( s \) in \( (Y_{i,rk(i)-j} \setminus Y_{i,rk(i)-(j+1)}) \) the strategy plays \( \xi^\eta \) over \( \Gamma_1(s) \), for \( \eta = \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^j} \).

(The entire strategy). Let \( \sigma^{c_{i}} = \sigma^{c_{i},rk(i)} \) for all \( i \). Let \( \sigma^{1} \) play as \( \sigma^{1,1} \) in \( U_1 \) and \( \sigma^{1,2} \), for \( \beta = \frac{\epsilon}{2} \), in the remaining states.

Lemma 7. Let \( 0 < \epsilon < \frac{1}{2} \) be given. The patience of the witness stationary strategy \( \sigma^{c_{i}} \) is less than \( \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{\delta(i)}} \).

Proof. By construction, the patience of \( \sigma^{c_{i}}(s) \) for states \( s \) of rank \( \ell \) is at most \( \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{\delta(i)}} \) for all \( i \) and \( \delta(i) = \delta(i-1) + 1 \) for all \( i > 0 \).

Also for \( j \geq 1 \), the patience of \( \sigma^{c_{i}}(s) \) for states \( s \) of rank \( \ell \) is at most

\[
\left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^j} \cdot \delta_{\min}^{-(m-1)} = \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^j} \cdot \delta_{\min}^{-(m-1)}
\]

where the inequality is as follows: \( \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^j} \cdot \delta_{\min}^{-(m-1)} \leq \left( \frac{\epsilon}{2} \right)^{(2m)^j} \cdot \delta_{\min}^{-(m-1)} \leq \frac{\epsilon}{2} \)

since \( (2m)^j \geq m \geq 1 \) and \( \epsilon < 1 \). The desired result follows.

□
Proof. We first present the bound for \( U_1 \) (also \( U_2 \)) and then for other states.

The patience of \( \sigma^{\epsilon,1}_1 \) for states in \( U_1 \) (also similar for \( U_2 \)). For each state \( s \) in \( U_1 \), the corresponding distribution \( \sigma^{\epsilon,1}_1(s) \) has patience at most \( \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{k(1)}} \), since no states are in \( Y_{1,0} \). Similarly for \( s \) in \( U_2 \) and the corresponding distribution \( \sigma^{\epsilon,1}_1(s) \).

The \( \eta \) for which the strategy \( \sigma^{\epsilon,2}_1 \) follows \( \sigma^{\eta,i}_1 \): Inductive statement. We will argue using induction that for each state \( S \in (W^* \setminus U_{i-1}), \) for \( i \geq 3 \), we have that the strategy \( \sigma^{\epsilon,2}_1 \) follows the strategy \( \sigma^{\eta,i}_1 \), for

\[
\eta \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{k(2)}}
\]

by construction, which is the wanted expression.

**Base case.** For each state \( s \in (S \setminus U_2) \), the strategy \( \sigma^{\epsilon,2}_1 \) follows the strategy \( \sigma^{\eta,3}_1 \), for \( \eta \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{k(2)}} \), by construction.

**Induction case** \( i + 1 \). For \( i \geq 4 \), for each state \( s \in (S \setminus U_{i-1}) \), the strategy \( \sigma^{\epsilon,2}_1 \) follows the strategy \( \sigma^{\eta,i}_1 \), for \( \eta \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{k(i)}} \), by induction. In each state \( s \in (S \setminus U_i) \), the strategy \( \sigma^{\eta,i}_1 \) follows the strategy \( \sigma^{\eta,i+1}_1 \), for \( \eta' \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{k(i)}} \), by construction. Thus, the strategy \( \sigma^{\epsilon,2}_1 \) follows \( \sigma^{\eta,i+1}_1 \) for

\[
\eta' \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{k(i)}}
\]

The first inequality comes from our preceding explanation. The second inequality uses the inductive hypothesis. The third uses that \( \frac{\delta_{\min}}{4} > \frac{\epsilon \cdot \delta_{\min}}{4} \). The last equality is the inductive hypothesis for \( i + 1 \) and follows from

\[
(2m)^{k(i)} + (2m)^{k(i)} \cdot \sum_{k=2}^{i-1} \sum_{k'=k}^{i-1} (2m)^{k(k')} = (2m)^{k(i)} + \sum_{k=2}^{i-1} \sum_{k'=k}^{i} (2m)^{k(k')}
\]

\[
= \sum_{k=2}^{i} \prod_{k'=k}^{i} (2m)^{k(k')}
\]

**Patience of \( \sigma^{\epsilon,2}_1(s) \) for states in \( U_i \), for \( i \geq 3 \).** We see that for \( i \geq 3 \) and for each \( s \) in \( U_i \) we have that \( \sigma^{\eta,i}_1(s) \) follows \( \xi^{\eta'}_i \) for \( \eta' \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{(2m)^{k(i)-1}} \) (since \( Y_{i,0} \) is empty), by construction. Hence, we get that
\( \sigma_1^{\epsilon,2}(s) = \xi_{s}^{\eta} \) for \( \eta \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right) \frac{\sum_{i=2}^{n} \prod_{k' = k}^{k'} (2m)^{rk(k')} - 2m}{2m} \), using a similar argument as the one used in the inductive case. Since \( rk(i) \geq 1 \) and \( m \geq 1 \), we see that each term in the sum \( \sum_{k=2}^{n} \prod_{k' = k}^{k'} (2m)^{rk(k')} \) is at least twice as large as the following. Thus, we have that

\[
\sum_{k=2}^{n} \prod_{k' = k}^{k'} (2m)^{rk(k')} < 2 \cdot \prod_{k' = 2}^{n} (2m)^{rk(k')} = 2 \cdot (2m)^{n-1} \leq (2m)^{n}.
\]

The first inequality is because \( U_1 \) must contain at least 1 state. The second comes from \( m \geq 1 \). Hence, \( \eta' \geq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right) (2m)^{n-1} \). Using an argument similar to the one used to prove Lemma 6, we get that the patience for \( \xi_{1}^{\eta} \) is then at most \( \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{-(2m)^{n-1}} \).

**Patience of \( \sigma_1' \).** We now need to consider the strategy \( \sigma_1' \). It follows \( \sigma_1^{\beta,1} \) in \( U_1 \) and \( \sigma_1^{\beta,2} \) elsewhere, for \( \beta = \frac{\delta}{2} \). We see that

\[
\left( \frac{\beta \cdot \delta_{\min}}{4} \right)^{-(2m)^{n-1}} = \left( \frac{\epsilon \cdot \delta_{\min}}{8} \right)^{-(2m)^{n-1}} \leq \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{-(2m)^{n}}.
\]

The inequality is because \( 4^2 = 16 > 8 \) (and the last expression more than squares the preceding). This completes the proof.

**Basic overview of the proof.** We first present the basic overview of the proof. Let \( \sigma_1 \) be a stationary strategy that follows distribution \( \xi_{1}^{\eta} \) over \( \Gamma_1(s) \) in state \( s \in W^* \) for some \( \eta > 0 \) and let \( \sigma_2 \) be a positional counterstrategy for player 2. For state \( s \) in \( W^* \), \( \sigma_1(s) \) and \( \sigma_2(s) \) satisfies at least one of Equation 4, Equation 5, or Equation 6 in \( s \). Let \( C_1^{\sigma_1,\sigma_2} \subseteq W^* \) (resp. \( C_2^{\sigma_1,\sigma_2} \subseteq W^* \) and \( C_3^{\sigma_1,\sigma_2} \subseteq W^* \)) be the set of states in \( W^* \) that satisfies Equation 4 (resp. Equation 5 and Equation 6). We will prove that \( \sigma_1' \) ensures value at least \( 1 - \epsilon \) for each states \( s \) in \( W^* \). We will split the proof into four parts, first we will show some properties for states in \( U_1 \), then for states in \( U_1 \setminus U_{\ell-1} \), and finally for states in \( U_1 \setminus U_{\ell-1} \) for \( 2 \leq \ell \leq \ell' \). In the fourth part, we will then combine the three properties to establish the desired result. The three properties are as follows

- **(Property 1).** For all states \( s \) in \( U_1 \) we will show that \( \sigma_1^{\epsilon,1} \) ensures Safe(\( U_1 \)) with probability 1 and mean-payoff at least \( 1 - \epsilon \) (i.e., for all positional strategies \( \sigma_2 \) we have \( \lim_{t \to \infty} \frac{1}{t} \sum_{s \in U_1} \mathbb{1}_{\epsilon,1}^{\sigma_1,\sigma_2}[s] \geq 1 - \epsilon \)).
- **(Property 2).** For all states \( s \) in \( (U_{\ell} \setminus U_{\ell-1}) \) we will show that \( \sigma_1^{\epsilon,\ell} \) ensures that against all positional strategies \( \sigma_2 \) we have that
  1. given the event Safe(\( U_{\ell} \setminus U_{\ell-1} \)), the mean-payoff is at least \( 1 - \epsilon \);
  2. \( \Pr_{\sigma_1^{\epsilon,\ell}}(\text{Safe}(U_{\ell} \setminus U_{\ell-1}) \cup \text{Reach}(U_{\ell-1} \cup W^*)) = 1 \); and
  3. \( \Pr_{\sigma_1^{\epsilon,\ell}}(\text{Safe}(U_{\ell} \setminus U_{\ell-1}) \cup \text{Reach}(U_{\ell-1})) \geq 1 - \epsilon \).

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(Property 3). For all states \( s \) in \( (U_{\ell} \setminus U_{\ell-(i+1)}) \), for \( 1 \leq i \leq \ell - 2 \), we will show that \( \sigma^{i+1}_{\ell} \) ensures that against all positional strategies \( \sigma_2 \) we have that

1. given the event \( \bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)}) \), the mean-payoff is at least \( 1 - \epsilon \);
2. \( \Pr_{\sigma}\sigma^{i+1}_{\ell} \cdot \sigma_2 \left( \bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)}) \cup \text{Reach}(U_{\ell-(i+1)} \cup \overline{W'}) \right) = 1 \); and
3. \( \Pr_{\sigma}\sigma^{i+1}_{\ell} \cdot \sigma_2 \left( \bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)}) \cup \text{Reach}(U_{\ell-(i+1)}) \right) \geq 1 - \epsilon \).

In Lemma 8, Lemma 9, and Lemma 12 we establish Properties 1, 2, and 3, respectively. We first present the basic intuition of the proof of Lemma 8.

The basic intuition of Lemma 8. The key idea of the proof is as follows. Once we fix the strategies for both the players we have a Markov chain. Let \( C_2 \) and \( C_3 \) denote the set of states in \( U_1 \) that satisfy Equation 5 and Equation 6, respectively. Since \( U_0 \) is empty, no state in \( U_1 \) can satisfy Equation 4. For states \( s \) in \( C_2 \) of rank \((1, j)\), the fact that Equation 5 is satisfied ensures that a state of rank \((1, j')\), for \( j' < j \), is visited from \( s \) with positive probability. Let \( \text{pat}(j) \) denote the patience of the strategy \( \sigma^{i+1}_{\ell} \) for states of rank \((1, rk(1) - j)\).

We now consider the following case analysis.

1. First we consider the set of states in \((Y_{1,rk(1)})\setminus Y_{1,rk(1)-1}\) and show that if we stay in the set \((Y_{1,rk(1)}\setminus Y_{1,rk(1)-1})\), then the mean-payoff is at least \(1 - \epsilon\). The argument is as follows: By Markov property 5, we must reach a recurrent class with probability 1. A recurrent class contained in \((Y_{1,rk(1)})\setminus Y_{1,rk(1)-1}\) must consist of only states in \( C_3 \) (since from states in \( C_2 \) we reach lower rank states with positive probability), and since Equation 6 is satisfied for states in \( C_3 \) it follows that the mean-payoff value is at least \(1 - \epsilon\). Hence, if we have a recurrent class of the Markov chain contained in \((U_1\setminus Y_{1,rk(1)-1}) = (Y_{1,rk(1)}\setminus Y_{1,rk(1)-1})\), then the mean-payoff of the recurrent class is at least \(1 - \epsilon\). This completes the argument. Also, if the set \((Y_{1,rk(1)})\setminus Y_{1,rk(1)-1}\) is left, then we can bound the number of visits to states in \( C_2 \) (and in the worst case each such visit gives reward 0) in expectation encountered before leaving the set \((Y_{1,rk(1)})\setminus Y_{1,rk(1)-1}\). This bound on the number of visits in expectation to \( C_2 \) (which we say has not been accounted for by visits to \( C_3 \)) is \( \kappa(0) = (\delta_{\text{min}})^{-1} \cdot \text{pat}(0) \). There is an illustration of this base case in Figure 6.

2. Now we consider that we are at some intermediate part of the computation, i.e., in some state in \((Y_{1,rk(1)-j})\setminus Y_{1,rk(1)-j+1}\), for \( j \geq 1 \). Inductively we have an upper bound \( \kappa(j) \) on the number of times that states in \( C_2 \) were visited (in the worst case each such visit gives reward 0) in expectation that has not been accounted for by visits to states in \( C_3 \) till we reach the set \((Y_{1,rk(1)-j})\setminus Y_{1,rk(1)-(j+1)}) \) from any state in \( Y_{1,rk(1)-j+1} \). The one-step probability distribution \( \xi^i_0 \) is chosen such that \( \eta \cdot \kappa(j) \leq \epsilon \). In other words, \( \eta \) decreases rapidly as \( i \) increases, and the small \( \eta \) ensures that if the play stays in \((U_1 \setminus Y_{1,rk(1)-(j+1)})\), then the mean-payoff is at least \(1 - \epsilon\), i.e., if we have a recurrent class \( L \) contained in \((U_1 \setminus Y_{1,rk(1)-(j+1)})\) and \((L \cap Y_{1,rk(1)-j})\) is non-empty, then all states in \((L \cap Y_{1,rk(1)-j})\) belong to \( C_3 \), and the mean-payoff of the recurrent class is at least \(1 - \epsilon\). Moreover, we can also upper bound the number of visits to states in \( C_2 \) in expectation that has not been accounted for by visits to states in \( C_3 \) before reaching the set \( Y_{1,rk(1)-(j+1)} \) if we leave \((U_1 \setminus Y_{1,rk(1)-(j+1)})\) by \( \kappa(j+1) = (\kappa(j) + 1) \cdot (\delta_{\text{min}})^{-1} \cdot \text{pat}(j) \), and then proceed inductively. There is an illustration of this inductive case in Figure 7.

Lemma 8. (Property 1). Let \( 0 < \epsilon < \frac{1}{2} \). The strategy \( \sigma^{i+1}_{\ell} \) ensures that for all \( s \in U_1 \) and all positional strategies \( \sigma_2 \) for player 2 we have \( \Pr_{\sigma}\sigma^{i+1}_{\ell} \cdot \sigma_2 (\text{Safe}(U_1)) = 1 \) and \( \lim_{t \to \infty} \sum_{s \in U_1} \sigma^{i+1}_{\ell} \cdot \sigma_2 (\Theta; s) \geq 1 - \epsilon \).
Figure 6: Pictorial illustration of the intuitive explanation of the base case of Lemma 8.

Figure 7: Pictorial illustration of the intuitive explanation of the inductive case of Lemma 8.
Proof. Given $\sigma_1^{r,1}$, let $\sigma_2$ be an arbitrary positional counter-strategy for player 2. Let $C_i^{r,1,\sigma_2} \cap U_1 = C_i$, i.e., given $\sigma_1^{r,1}$ and $\sigma_2$, we have that $C_1, C_2, C_3$ are the set of states of $U_1$ that satisfy Equation 4, Equation 5, Equation 6, respectively. Notice that since $U_0$ is the empty set we have that $C_1$ is also empty. Therefore we cannot leave $U_1$ if player 1 follows $\sigma_1^{r,1}$ (because both Equation 5 and Equation 6 require that we stay in $U_1$). This ensures that Safe($U_1$) is satisfied with probability 1. We now focus on the mean-payoff.

Basic notations. Let us consider the Markov chain obtained given $\sigma_1^{r,1}$ and $\sigma_2$. For a state $s \in U_1$, let the rank of $s$ be $\text{rk}(s) = (1, j)$, and then we denote $j$ by $\text{rk}_2(s)$ (the second component of the rank). Given a play $P$ in the Markov chain, and a number $t \in \mathbb{N}$, let $\bar{r}(P, t)$ be the expected number of times we get reward 0 in the first $t$ steps of $P$. This implies that $\bar{r}(P, 0) = 0$. For each state $s \in U_1$, let $P^0_s$ be (a prefix of) a play in the Markov chain, which ends if a state in $Y_{1,j}$ is reached after the starting point $s$ (i.e., the play does not end at $s$ if $s \in Y_{1,j}$), and if $Y_{1,j}$ is not reached, then the walk does not end. We will also use the following notations: for $0 \leq j \leq \text{rk}(1) - 1$, let us denote by $\kappa(j + 1) = \frac{\epsilon}{4} \cdot \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{-(2m)^{j+1}}$; and let $\text{pat}(j) = \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{-(2m)^{j+1}}$, the patience of $\sigma_1^{r,1}$ for states in $U_1$ of rank $(1, \text{rk}(1) - j)$ (by Lemma 6).

Using recurrent class property. First, observe that since $Y_{1,0}$ is the empty set, the set $Y_{1,0}$ can never be reached, and hence $P^0_s$ represents the entire play from the start state $s$, for $s \in U_1$. By Markov property 5 in the Markov chain, the recurrent classes are reached in a finite number of steps with probability 1, and given a recurrent class $L$ is reached, every state in $L$ is reached with probability 1 in a finite number of steps. Given a recurrent class $L$ in $U_1$, and consider a state $s^* \in L$ that has the maximum rank among states in $L$ (i.e., $\text{rk}_2(s^*) = \max_{s' \in L} \text{rk}_2(s')$). Then all states visited after $s^*$ have rank at most the rank of $s^*$. Hence every play $P^0_s$ with probability 1, after finitely many steps reaches a state $s^*$ such that all states $s'$ visited after $s^*$ satisfy that $\text{rk}_2(s') \geq \text{rk}_2(s^*)$. Since the mean-payoff is invariant under finite prefixes, we only need to obtain bounds for the mean-payoff of $P^0_{s^*}(s^*)^{-1}$ (and this play has infinite length by definition as no state with smaller rank is reached in the Markov chain after $s^*$).

Inductive proof statement. We will show, inductively, that for all $0 \leq j \leq \text{rk}(1)$, all $t \geq 1$, and all states $s \in U_1$, if $\text{rk}_2(s) = \text{rk}(1) - j$, then

$$\bar{r}(P^0_s, t) \leq t \cdot \epsilon + \frac{\kappa(j + 1)}{2} = t \cdot \epsilon + \frac{\epsilon}{4} \cdot \left( \frac{\epsilon \cdot \delta_{\min}}{4} \right)^{-(2m)^{j+1}}$$

This will imply the desired result, since then the mean-payoff of $P^0_{s^*}(s^*)^{-1}$ is at least $1 - \epsilon$: the play $P^0_{s^*}(s^*)^{-1}$ has infinite length and therefore the expected number of reward 1’s must be $t - \bar{r}(P^0_{s^*}(s^*)^{-1}, t)$ in the first $t$ steps for all $t$, because all rewards are either 0 or 1, and hence the mean-payoff of $P^0_{s^*}(s^*)^{-1}$ is infinite.

Splitting the play. Consider a play $P^0_s$ for $s \in U_1$. We will split up the play $P^0_s$ into a (possible infinite) sequence of rank preserving plays $(P^0_{s^*}(s_{i+1}))_{i \geq 0}$, such that $s_0 = s$, and for $i \geq 0$, the play $P^0_{s^*}(s_i)$ ends in state $s_{i+1}$ (which is formally a random variable and must be such that $\text{rk}_2(s_i) = \text{rk}_2(s_{i+1})$ by definition of $P^0_{s^*}(s_i)$) and since if a state of lower rank than $\text{rk}_2(s)$ is reached, then the play $P^0_{s^*}(s_i)$ ends. In other words, the next play begins where the previous play ends, and all the starting points of the play has the same rank. Similarly, we will split up plays $P^0_s$, for $0 \leq j < \text{rk}_2(s)$, into a finite sequence of rank decreasing plays $(P^0_{s_i}(s_{i+1}))_{i \geq 0}$, such that $s_0 = s$, and for $i \geq 0$, the play $P^0_{s_i}(s_{i+1})$ ends in state $s_{i+1}$ (which must be such that $\text{rk}_2(s_{i+1}) > \text{rk}_2(s_{i+1}) > j$). Note that since the play sequence is decreasing, the
sequence of plays is finite and the length of the sequence is at most $r_k(s) - j$. Pictorial illustrations of rank preserving (both when the sequence is finite and infinite) and rank decreasing plays are given in Figure 8, Figure 9, and Figure 10, respectively.

(Base case). We first consider the base case, where $j = 0$, i.e., we consider $s$ such that $r_k(s) = r_k(1)$. Consider the rank preserving split up of the play $P_{r_k(s)}^{-1}$ into the sequence of plays $(P_{r_k(s)}^{i})_{i \geq 0}$, mentioned above. As already mentioned, safety in $U_1 = Y_{1,r_k(1)}$ is guaranteed, and hence each play $P_{r_k(s)}^{i}$ has length 1. We will consider $\tilde{r}(P_{r_k(s')}^{i}, t)$, for all $s'$ such that $r_k(s') = r_k(s)$. We will now split the proof into the following two cases: (1) $s' \in C_2$; and (2) $s' \in C_3$; (as already argued at the start of the proof of this lemma, the set $C_1$ is empty).

1. In each state $s'$ in $(C_2 \cap (Y_{1,r_k(1)} \setminus Y_{1,r_k(1)}(1-1)))$ we reach a state $s''$ of rank $r_k(s'') = r_k(s) - 1$ in the next step with probability at least $\left(\frac{\delta_{\min}}{\epsilon}\right)^{-m}$, where $\delta_{\min}$ is an upper bound on the patience of states of rank $(1, r_k(1))$ in $\sigma_{1,1}^{t}$ by Lemma 6), otherwise we reach a state of rank $r_k(s)$. Hence the expected number of visits to states in $C_2$ is at most $\frac{\epsilon}{4} \cdot \left(\frac{\delta_{\min}}{\epsilon}\right)^{-m}$ before we reach $Y_{1,r_k(1)}$.

2. In each step we are in state $s'$ in $(C_3 \cap (Y_{1,r_k(1)} \setminus Y_{1,r_k(1)}(1-1)))$ we get reward 1 with probability at least $1 - \epsilon$ (by Equation 6).

For the play $P_{s}^{r_k(s)-1} = (P_{s}^{r_k(s)})_{i \geq 0}$, the expected number of indices $i$ such that $s_i \in C_2$ is at most $\frac{\epsilon}{4} \cdot \left(\frac{\delta_{\min}}{\epsilon}\right)^{-m}$ (by the first item above). The remaining (in the worst case, at least $t - \frac{\epsilon}{4} \cdot \left(\frac{\delta_{\min}}{\epsilon}\right)^{-m}$ in
Figure 9: Pictorial illustration of a play $P_{s_0}^{rk(s)-1}$ split into an infinite sequence $\left( P_{s_i}^{rk(s_i)} \right)_{i \geq 0}$ of rank preserving plays. Note that the last play could be infinite (which is not pictorially illustrated). Straight line segments indicate that all states are shown on them, while non-straight segments indicate that there might be states which are not shown.

Figure 10: Pictorial illustration of a play $P_{s_0}^{\ell-j}$ split into a (always finite) sequence $\left( P_{s_i}^{rk(s_i)-1} \right)_{i \geq 0}$ of rank decreasing plays. Note that the last play could be infinite (which is not pictorially illustrated). Straight line segments indicate that all states are shown on them, while non-straight segments indicate that there might be states which are not shown.
expectation) indices \(i'\) are such that \(s_{i'} \in C_3\), for which the expected reward is at least \(1 - \epsilon\) (by the second item above). Thus we have
\[
\tilde{r}(P_s^{rk_1(s) - 1}, t) \leq t \cdot \epsilon + \frac{\epsilon}{4} \cdot \left( \frac{\delta_{\min}}{4} \right)^{-m} \leq t \cdot \epsilon + \frac{\epsilon}{4} \cdot \left( \frac{\delta_{\min}}{4} \right)^{-2m} = t \cdot \epsilon + \frac{\kappa(1)}{2},
\]
as desired.

**Inductive case.** We now consider the inductive case for \(j \geq 1\), i.e., we now consider \(s\) such that \(rk_2(s) = rk(1) - j\). Consider the rank preserving split of the play \(P_s^{rk_2(s) - 1}\) as \((P_{s'}^{rk_2(s')})_{i \geq 0}\) as explained before the base case. We will consider \(\tilde{r}(P_s^{rk_2(s')}, t)\), for all \(s'\) with \(rk(s') = rk(s)\). As in the base case, we will split the proof into the two cases: (1) \(s' \in C_2\); and (2) \(s' \in C_3\); (and recall \(C_1\) is empty). Before we consider the case analysis, we first present the use of the inductive hypothesis.

**Use of inductive hypothesis.** The inductive hypothesis will be used in the same way for both cases in the case analysis. Let \(t \in \mathbb{N}\) be given. For all states \(s''\) in \(U_1\) such that \(rk_2(s'') > rk_2(s) = rk(1) - j\), we will use the inductive hypothesis to upper bound \(\tilde{r}(P_s^{rk(1)-j}, t)\). Consider the rank decreasing split of \(P_s^{rk(1)-j}\) as \((P_{s''}^{rk(1)-j})_{i \geq 0}\). There are most \(j\) such plays in the sequence, one for each rank strictly higher than \(rk(1) - j\). We only argue about the worst case, and in the worst case, \(s_i'\) is such that \(rk_2(s_i') = rk(1) - i\). Let \(t_i\) be the random variable indicating the number of steps among the first \(t\) steps such that \(P_s^{rk(1)-j}\) is exactly \(P_{s_i'}^{rk(1)-j}\). We see that \(\tilde{r}(P_s^{rk(1)-j}, t) = \sum_{i=1}^{j-1} \tilde{r}(P_{s_i'}^{rk(1)-j}, t_i)\). By the inductive hypothesis we have that \(\tilde{r}(P_{s_i'}^{rk(1)-j}, t_i) \leq t_i \cdot \epsilon + \frac{\kappa(i+1)}{2}\) for each \(t_i' \geq 1\). Thus, we get that
\[
\tilde{r}(P_{s''}^{rk(1)-j}, t) = \sum_{i=1}^{j-1} \tilde{r}(P_{s_i'}^{rk(1)-j}, t_i) \leq \sum_{i=0}^{j-1} \left( t_i \cdot \epsilon + \frac{\kappa(i+1)}{2} \right) \leq t \cdot \epsilon + \kappa(j).
\]
The first inequality is the inductive hypothesis, and we now argue that \(\sum_{i=0}^{j-1} \frac{\kappa(i+1)}{i+1} \leq \kappa(j)\). We have
\[
\sum_{i=0}^{j-1} \frac{\kappa(i+1)}{2} = \frac{\epsilon}{4} \sum_{i=0}^{j-1} \left( \frac{\delta_{\min}}{4} \right)^{-2m} \leq \frac{\epsilon}{2} \left( \frac{\delta_{\min}}{4} \right)^{-2m} = \kappa(j),
\]
because each term of the sum is over 4 times as large as the preceding (because \((2m)^{i+1} \geq 1 + (2m)^{i}\), for \(m \geq 2\) and \(i \geq 0\) and the factor of 4) and thus, the last term is over 2 times larger than the sum of all the other terms (we just use that it is larger). We now consider the case analysis.

- **(States in \(C_2\)).** In this case we consider \(\tilde{r}(P_s^{rk_2(s')}, t)\), for \(s' \in C_2\), such that \(rk(s') = rk(s)\). We know that \(s_i'\) has patience \(\text{pat}(j)\) for states \(s'' \in U_1\) such that \(rk_2(s'') = rk_2(s) = rk(1) - j\) (from Lemma 6). In expectation the play \(P_s^{rk_2(s') - 1}\) is therefore in a state \(s''\) in \(C_2\) such that \(rk(s'') = rk(s)\) at most \(\text{pat}(j) \cdot (\delta_{\min})^{-1}\) times before reaching a state with lower rank (i.e., before the play ends). If the play does not end, whenever we have been in \(C_2\), we reach some state \(s''\) in \(U_1\) (as safety to \(U_1\) is guaranteed). Also, in the worst case we get a reward of 0 in the every step we are in a state of rank \(rk_2(s)\) in \(C_2\). There are two sub-cases. Either \(rk_2(s'') = rk_2(s)\) or \(rk_2(s'') > rk_2(s)\) (because if the rank is lower the walk ends). In the first sub-case the play \(P_s^{rk_2(s')}\) has length 1. In the other case, we have already given an upper bound on \(\tilde{r}(P_s^{rk(1)-j}, t')\), for all \(t' \geq 1\), using the inductive hypothesis. We therefore have that
\[
\tilde{r}(P_s^{rk(s')}, t) \leq 1 + \tilde{r}(P_s^{rk(1)-j}, t-1) \leq 1 + (t-1) \cdot \epsilon + \kappa(j) = t \cdot \epsilon + (1 - \epsilon) + \kappa(j) \leq t \cdot \epsilon + 2 \cdot \kappa(j).
\]
where we have just explained the first inequality. The second inequality is our use of the inductive hypothesis as previously explained. The last inequality uses that \( \kappa(j) = \frac{\epsilon}{2} \cdot \left( \frac{c \cdot \delta_{min}}{4} \right)^{(2m)^j} > 8 > 1 \) (since \( 4^{(2m)^j} \geq 16 \) and hence \( \left( \frac{c \cdot \delta_{min}}{4} \right)^{(2m)^j} \geq \frac{16}{c} \) for \( i, m \geq 1 \) and \( 1 - \epsilon < 1 \).

- **(States in \( C_3 \)).** In this case we consider \( \tilde{\tau}(P_{s'}^{rk2(s')}, t) \), for \( s' \in C_3 \), such that \( rk(s') = rk(s) \). By construction, the strategy \( \sigma_1^{s',1} \) plays the distribution \( \xi_t \) over \( \Gamma_1(s') \), for \( \eta = \left( \frac{c \cdot \delta_{min}}{4} \right)^{(2m)^j} = \frac{c}{\kappa(j)} \).

For the play \( P_{s'}^{rk2(s')} \), the next state \( s_1 \) after the start state \( s' \) is in \( U_1 \) with probability 1; the reward is 1 with probability at least \( 1 - \eta \), and as well \( s' \in Y_{1,rk(1)-i} \) with probability at least \( 1 - \eta \) (since Equation 6 is ensured). With the remaining probability of at most \( \eta \), the play \( P_{s'}^{rk2(s')} \) goes to a state \( s'' \) in \( U_1 \). As before the worst case (for the proof) is that with the remaining probability of at most \( \eta \) the state \( s'' \) is such that \( rk_2(s'') > rk_2(s) \), for which we have a upper bound by inductive hypothesis on \( \tilde{\tau}(P_{s''}^{rk(1)-i}, t') \), for all \( t' \geq 1 \). Thus we have that

\[
\tilde{\tau}(P_{s'}^{rk2(s')}, t) \leq \eta + \eta \cdot \tilde{\tau}(P_{s''}^{rk(1)-i}, t-1) \leq \eta + \eta \cdot ((t-1) \cdot \epsilon + \kappa(j))
\]

\[
= \eta + (t-1) \cdot \eta \cdot \epsilon + \frac{\epsilon}{2} \leq \eta + (t-1) \cdot \epsilon + \frac{\epsilon}{2} \leq t \cdot \epsilon .
\]

The first inequality is by the preceding explanation. The second inequality uses the inductive hypothesis as previously described. In the first equality, we use that by definition we have \( \eta \cdot \kappa(j) = \frac{\epsilon}{2} \). In the third inequality we use that \( \eta \cdot \epsilon \leq \epsilon \) since \( \eta \leq 1 \) and \( t \geq 1 \); and the final inequality uses that since \( \eta \leq \frac{\epsilon}{4} \) we have \( \eta + \frac{\epsilon}{2} < \epsilon \) and \( \eta \cdot \epsilon < \epsilon \), for \( \epsilon < 1 \); for \( i, m \geq 1 \) which ensures \( \eta \leq \frac{\epsilon}{4} \).

We now combine the above case analysis to establish the inductive proof. We will now consider \( \tilde{\tau}(P_{s}^{rk2(s)-1}, t) \) and our rank preserving split \( (P_{s}^{rk2(s)})_{i \geq 0} \) of \( P_{s}^{rk2(s)-1} \). For all \( i \geq 0 \), let \( t_i \) be the random variable indicating the number of steps \( P_{s}^{rk2(s)-1} \) is exactly \( P_{s}^{rk2(s)} \) among the first \( t \) steps of \( P_{s}^{rk2(s)} \).

We see that \( \tilde{\tau}(P_{s}^{rk2(s)-1}, t) = \sum_{i=0}^{k} \tilde{\tau}(P_{s}^{rk2(s)}, t_i) \) (the random variable \( k \) indicates the highest index such
Lemma 9. \( U \in U \) follows from \( \varepsilon \). The proof of Lemma 8 shows that the strategy 

The combinatorial property established in Lemma 8. The proof of Lemma 8 shows that the strategy \( \sigma_{1,1} \) against all positional counter-strategies of the opponent ensures that in the resulting Markov chain all recurrent classes that intersect with \( U \) are contained in \( U \), all states in \( U \) have successors only in \( U \); (i.e., the recurrent classes in \( U \) are reached with probability 1 from all states in \( U \)); and in every recurrent class in \( U \) the mean-payoff value is at least \( 1 - \varepsilon \).

Lemma 9. (Property 2). Let \( 0 < \varepsilon < \frac{1}{2} \). The strategy \( \sigma_{1}^{s} \) ensures that against all positional strategies \( \sigma_{2} \) for all states \( s \in (U \setminus U_{t-1}) \) we have that

1. given the event \( \text{Safe}(U_{t} \setminus U_{t-1}) \), the mean-payoff is at least \( 1 - \varepsilon \);
2. \( \Pr_{s}^{\sigma_{1}^{s},\sigma_{2}}(\text{Safe}(U_{t} \setminus U_{t-1}) \cup \text{Reach}(U_{t-1} \cup \overline{W})) = 1 \); and
3. \( \Pr_{s}^{\sigma_{1}^{s},\sigma_{2}}(\text{Safe}(U_{t} \setminus U_{t-1}) \cup \text{Reach}(U_{t-1})) \geq 1 - \varepsilon \).

that \( t_{k} \geq 1 \), implying that \( t_{i} \geq 1 \) for \( 0 \leq i \leq k \). Hence, we have that

The first equality follows from our preceding explanation. The first inequality uses our bound on \( \hat{r}(P_{s}^{k}(s_{i}), t_{i}) \) from the respective items above, depending on whether \( s_{i} \in C_{2} \) or \( s_{i} \in C_{3} \). The second inequality uses that there are at most \( \text{pat}(j) \cdot (\delta_{\min})^{-1} \cdot 2 \cdot \kappa(j) \) indices \( i \) such that \( s_{i} \in C_{2} \), from the first item above, and that \( t = \sum_{i=0}^{k} t_{i} \). The third inequality uses that \( (2m)^{j} \leq \frac{(2m)^{j+1}}{2} \) for \( m \geq 2 \) and \( j \geq 1 \). The last follows from \( \frac{m}{4} < \frac{\delta_{\min}}{2} \) and gives the expression we required to establish our inductive claim for \( j \).

This completes the inductive proof and gives us the desired result. \( \square \)
Lemma 11. the event coBuchi and since mean-payoff objectives are independent of finite prefixes, it also follows from Lemma 9 that given Proof. Given $\sigma_1^t, \sigma_2$ be an arbitrary positional counter-strategy for player 2. We see that $\sigma_1^t$ is stationary and follows the distribution $\xi_t^\sigma$ over $\Gamma_1(s)$ for some $0 < \eta < \epsilon$ in state $s \in (W^* \setminus U_{t-1})$. Let $C_{t}^{\sigma_1^t, \sigma_2} = C_i$, i.e., given $\sigma_1^t$ and $\sigma_2$, we have that $C_1, C_2, C_3$ are the set of states of $(U_{t} \setminus U_{t-1})$ that satisfy Equation 4, Equation 5, Equation 6, respectively. Let $R_S$ be the set of states in $(U_{t} \setminus U_{t-1})$, from which $(C_1 \cap (U_{t} \setminus U_{t-1}))$ is not reachable in the Markov chain (i.e., in the graph of the Markov chain given $\sigma_1^t$ and $\sigma_2$, the set $R_S$ is the set of states in $(U_{t} \setminus U_{t-1})$ from which no state in $(C_1 \cap (U_{t} \setminus U_{t-1}))$ is reachable). Equivalently, $R_S$ is the set from which $(U_{t-1} \cup \overline{W^*})$ cannot be reached (the definitions are equivalent, because, from each state $s$ in $(U_{t} \setminus U_{t-1}) = (S \setminus (U_{t-1} \cup \overline{W^*}))$, the set $(U_{t-1} \cup \overline{W^*})$ can be reached in one-step iff $s \in C_1$). Consider now the segment of the play from state $s$ in $(U_{t} \setminus U_{t-1})$ till the play leaves $(U_{t} \setminus U_{t-1})$.

1. First we consider the case when $s \in R_S$. This corresponds to the proof of correctness for states in $U_1$ (note that in the correctness proof of $U_1$, the set $C_i$ was empty; and if $C_i$ is not reached, then the proof is identical to Lemma 8, by construction of the strategy). Hence we have that $\text{Safe}(U_{t} \setminus U_{t-1})$ is ensured with probability 1 (because $(U_{t} \setminus U_{t-1})$ can only be left from states in $C_1 \cap (U_{t} \setminus U_{t-1})$)

$$\lim_{t \to \infty} \sum_{s \in U_{t-1}} \mathbb{P}_s^\sigma_1^t, \sigma_2 \geq 1 - \epsilon$$

as in Lemma 8. This establishes all the required conditions of the lemma.

2. By Markov property 2, we have that $\text{Reach}(U_{t-1} \cup \overline{W^*} \cup R_S)$ happens with probability 1 (since $R_S$ is the set from which $(U_{t-1} \cup \overline{W^*})$ cannot be reached). Note that since $(S \setminus (U_{t-1} \cup \overline{W^*})) = (U_{t} \setminus U_{t-1})$, it follows that $\text{Reach}(U_{t-1} \cup \overline{W^*} \cup R_S)$ with probability 1 implies $\text{Reach}(U_{t-1} \cup \overline{W^*}) \cup \text{Safe}(U_{t} \setminus U_{t-1})$ is also ensured with probability 1, since $(U_{t} \setminus U_{t-1})$ cannot be left once $R_S$ is reached. This also shows that every recurrent class contained in $(U_{t} \setminus U_{t-1})$ must be contained in $R_S$ (and by the first item has mean-payoff value at least $1 - \epsilon$). This shows that given the event $\text{Safe}(U_{t} \setminus U_{t-1})$, the mean-payoff is at least $1 - \epsilon$. From every state in $(U_{t} \setminus U_{t-1})$, in the Markov chain, we have that $\delta(s)(U_{t-1}) \cdot \epsilon \geq \delta(s)(W^*)$ (from states which are not in $C_i$, both probabilities are 0 and $C_i$ by Equation 4). Hence, Markov property 7 implies that event $\text{Reach}(U_{t-1} \cup R_S)$ happens with probability $1 - \epsilon$ (since $R_S$ is the set which $(U_{t-1} \cup \overline{W^*})$ cannot be reached), i.e., we have $\Pr_s^\sigma_1^t, \sigma_2 \cdot (\text{Safe}(U_{t} \setminus U_{t-1}) \cup \text{Reach}(U_{t-1})) \geq 1 - \epsilon$.

The desired result follows.

Remark 10. Lemma 9 proves the desired result only for states in $(U_{t} \setminus U_{t-1})$ and can be considered as the base case of Lemma 12 which proves a similar result for states in $(U_{t-i} \setminus U_{t-i+1})$, for $1 \leq i \leq \ell - 2$. The case for states $(U_1 \setminus U_0) = U_1$ is handled by Lemma 8. Note that $\text{Safe}(U_{t} \setminus U_{t-1}) \subseteq \text{coBuchi}(U_{t} \setminus U_{t-1})$ and since mean-payoff objectives are independent of finite prefixes, it also follows from Lemma 9 that given the event coBuchi$(U_{t} \setminus U_{t-1})$, we have that the mean-payoff is at least $1 - \epsilon$.

Before presenting the proof for Property 3 we first present a lemma that we will use to prove the property.

Lemma 11. Given $0 \leq x \leq \frac{1}{2}$ and $0 \leq \epsilon, \eta \leq 1$, consider the four-state Markov chain $G_{4}^{x, \epsilon, \eta}$ shown in Figure 11. The probability to eventually reach $s_1$ from $s_2$ and $s_3$ is $\frac{x}{\eta + (1 + \frac{1}{2}) \cdot x \cdot (1 - \eta)}$ and $\frac{x \cdot (1 - \eta)}{\eta \cdot (1 + \frac{1}{2}) \cdot x \cdot (1 - \eta)}$, respectively.

Proof. Let $y_2$ and $y_3$ denote the probability to reach $s_1$ from $s_2$ and $s_3$, respectively. Then we have

$$y_2 = x + (1 - (1 + \frac{\epsilon}{2}) \cdot x) \cdot y_3; \quad y_3 = (1 - \eta) \cdot y_2.$$
Hence we have
\[ y_2 = x + (1 - (1 + \frac{\epsilon}{2}) \cdot x) \cdot (1 - \eta) \cdot y_2. \]

Solving for \( y_2 \), and then inserting into \( y_3 = (1 - \eta) \cdot y_2 \), we obtain the desired result. \( \square \)

**Lemma 12.** (Property 3). Let \( 0 < \epsilon < \frac{1}{2} \) and \( 1 \leq i \leq \ell - 2 \). The strategy \( \sigma_1^{\epsilon, \ell-i} \) ensures that against all positional strategies \( \sigma_2 \) for all states \( s \in (U_{t-i+1} \setminus U_{t-i+1}) \) we have that

1. given the event \( \bigcup_{j \leq i} \text{coBuchi}(U_{t-j} \setminus U_{t-(j+1)}) \), the mean-payoff is at least \( 1 - \epsilon \);

2. \( \Pr_{\sigma_1^{\epsilon, \ell-i}, \sigma_2}(\bigcup_{j \leq i} \text{coBuchi}(U_{t-j} \setminus U_{t-(j+1)}) \cup \text{Reach}(U_{t-(i+1)} \cup \overline{W^*})) = 1 \); and

3. \( \Pr_{\sigma_1^{\epsilon, \ell-i}, \sigma_2}(\bigcup_{j \leq i} \text{coBuchi}(U_{t-j} \setminus U_{t-(j+1)}) \cup \text{Reach}(U_{t-(i+1)})) \geq 1 - \epsilon. \)

**Proof.** Given \( \sigma_1^{\epsilon, \ell-i} \), let \( \sigma_2 \) be an arbitrary positional counter-strategy for player 2. Let \( C_i^{\sigma_1^{\epsilon, \ell-i}, \sigma_2} = C_i \), i.e., given \( \sigma_1^{\epsilon, \ell-i} \) and \( \sigma_2 \), we have that \( C_1, C_2, C_3 \) are the set of states of \( (U_t \setminus U_{t-i+1}) \) that satisfy Equation 4, Equation 5, Equation 6, respectively. This proof is similar to the proof of Lemma 9. The proof will be by induction in \( i \), where \( i = 0 \) is the base case. Hence, the base case is settled by Lemma 9. We see that \( \sigma_1^{\epsilon, \ell-i} \) is stationary and follows the distribution \( \xi_i^s \) over \( \Gamma_1(s) \) for some \( \eta > 0 \) in state \( s \in (W^* \setminus U_{t-i+1}) \).

We consider the Markov chain obtained by fixing the two strategies. In the worst case, states in \( \overline{W^*} \) are absorbing with reward 0; and since the target is to reach \( U_{t-(i+1)} \) we consider that the plays end if they leave \( T = (W^* \setminus U_{t-(i+1)}) \), i.e., we are interested in the segment of the play in \( (W^* \setminus U_{t-(i+1)}) \). The play can only end from a state in \( C_1 \cap T \) because \( T = \bigcup_{j \leq i} (U_{t-j} \setminus U_{t-(j+1)}) \) and if a state \( s \) in \( (U_{t-j} \setminus U_{t-(j+1)}) \) satisfies either Equation 5 (in \( C_2 \)) or Equation 6 (in \( C_3 \)), then the set \( (U_{t-j} \setminus U_{t-(j+1)}) \) is not left from \( s \) in one-step. Now consider a play \( P \) in the Markov chain. Let \( R_S \) be the subset of \( T \), from which \( C_1 \cap T \) is not reachable in the Markov chain. There are two cases

1. \( (P \text{ starts in } s \in R_S) \). Let \( (\ell - i', j') = \text{rk}(s) \). Note that \( i' \leq i \), by definition of \( R_S \). Precisely, like in the proof of Lemma 9, we have that \( \text{Safe}(U_{t-i'} \setminus U_{t-(i'+1)}) \) is ensured with probability 1,
because the set \((U_{\ell-i'} \setminus U_{\ell-(i'+1)})\) cannot be left from states in \(C_2\) or \(C_3\). Hence, if \(i' < i\), then we are done, by induction, since \(\sigma_{1}^{i,\ell-i}\) follows \(\sigma_{i}^{n,\ell-i+1}\) in such states, by construction of \(\sigma_{1}^{i,\ell-i}\), for \(\eta = \left(\frac{\epsilon \delta_{\text{min}}}{4}\right)^{(2m)^{k_{\ell-i}}}\) and we have that \(\eta < \epsilon\), for \(m \geq 2\) and \(rk(\ell - i) \geq 1\). If \(i' = i\), then, precisely like in the proof of Lemma 9, the set \((U_{\ell-i} \setminus U_{\ell-(i+1)})\) cannot be left in \(C_2\) or \(C_3\) and hence, using an argument like Lemma 8, we have that \(\lim_{t \to \infty} \sum_{i=0}^{t} \mathbb{P}_{s,\ell}^{i,\ell-i,\sigma_{1},\sigma_{2}}[\sigma_{\ell}] \geq 1 - \epsilon\), because of the similarities between the construction of the strategy \(\sigma_{1}^{i,\ell-i}\) and \(\sigma_{1}^{i,\ell-i+1}\) for states in \((U_{\ell-i} \setminus U_{\ell-(i+1)})\) and states in \(U_1\), respectively. Observe that this case is the same as the corresponding case in Lemma 9 and ensures all the required items of the lemma.

2. \((P \text{ starts outside } R_S:\ \text{Item (1) of the lemma statement})\). First observe that we can only ensure Safe\((U_{\ell-j} \setminus U_{\ell-(j+1)})\), for some \(j \leq i\), from states in \(R_S\), since from all other states \(C_1\) is reachable and for every \(j\) states in \((C_1 \cap (U_{\ell-j} \setminus U_{\ell-(j+1)}))\), can reach \(U_{\ell-(j+1)}\) in one-step with positive probability, by Equation 4. Hence, if \(\bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)})\) is ensured, then given the event \(\bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)})\) a recurrent class that is reached must be contained in \(R_S\). Hence given the event \(\bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)})\), the set \(R_S\) is reached in a finite number of steps with probability 1. Since mean-payoffs are independent of finite-prefixes, the finite prefix to reach \(R_S\) does not change the mean-payoff. Moreover, since if we start in \(R_S\) the mean-payoff is at least \(1 - \epsilon\), it follows that given the event \(\bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)})\) we have that the mean-payoff is at least \(1 - \epsilon\).

3. \((P \text{ starts outside } R_S:\ \text{Item (2) of the lemma statement})\). For \(0 \leq i' \leq i\), let \(E_{i'}\) denote the following event,

\[
E_{i'} = \bigcup_{j \leq i'} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)}) \cup \text{Reach}(U_{\ell-(i'+1)} \cup \overline{W}).
\]

Let \(\text{SP}(s, \ell - i') = \Pr_{s}^{\sigma_{1}^{i,\ell-i'},\sigma_{2}}(E_{i'})\), for all \(0 \leq i' \leq i\), denote the success probability of the event \(E_{i'}\). We need to argue that \(\text{SP}(s, \ell - i) = 1\), for all states in \((U_{\ell} \setminus U_{\ell-(i+1)})\). By induction we have that \(\text{SP}(s, \ell - (i - 1)) = 1\), from states in \((U_{\ell} \setminus U_{\ell-i})\). Since \(\sigma_{1}^{i,\ell-i}\) has the same support as \(\sigma_{1}^{i,\ell-(i-1)}\) for all states in \((U_{\ell} \setminus U_{\ell-i})\), it follows that for each state \(s\) in \((U_{\ell} \setminus U_{\ell-i})\) we have \(\text{SP}(s, \ell - i) = 1\). If the event \(\bigcup_{j \leq i \leq (i-1)} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)}) \cup \text{Reach}(\overline{W})\) happens, then we are done. Thus, in the worst case we have that \(\Pr_{s}^{\sigma_{1}^{i,\ell-i},\sigma_{2}}(\text{Reach}(U_{\ell-i})) = 1\) from state \(s\) in \((U_{\ell} \setminus U_{\ell-i})\) (clearly, from such states \(U_{\ell-i}\) is reachable in the Markov chain since they are reached with probability 1). We only need to argue about the worst case. Let \(R'_S\) be the subset of \((U_{\ell-i} \setminus U_{\ell-(i+1)})\), from which \((C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))\) cannot be reached in the Markov chain. Hence, for each state \(s\) in \((U_{\ell-i} \setminus U_{\ell-(i+1)}),\) the state \(s\) must either be in \(R'_S\) (in which case \(R'_S\) is reachable) or the set \((C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))\) must be reachable from \(s\). From the set \((C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))\), the set \(U_{\ell-(i+1)}\) is reached in one-step with positive probability. We therefore get that from any state in \(T = ((U_{\ell} \setminus U_{\ell-i}) \cup (U_{\ell-i} \setminus U_{\ell-(i+1)}))\), the set \((U_{\ell-(i+1)} \cup R'_S)\) is reachable, by transitivity of reachability. Hence, by Markov property 8 we have that \(\Pr_{s}^{\sigma_{1}^{i,\ell-i'},\sigma_{2}}(\text{Reach}(S \setminus T) \cup U_{\ell-(i+1)} \cup R'_S) = 1\), from any state \(s \in T\). Note that from states in \(R'_S\) no state in \((C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))\) is reachable, and the set \((U_{\ell-i} \setminus U_{\ell-(i+1)})\) can be left only from states in \((C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))\). Hence reachability to \(R'_S\)
ensures $\text{coBuchi}((U_{\ell-i} \setminus U_{\ell-(i+1)}))$. Thus we have that

$$\text{Reach}( (S \setminus T) \cup U_{\ell-(i+1)} \cup R'_S ) = \text{Reach}(U_{\ell-(i+1)} \cup \overline{W}^* \cup U_{\ell-(i+1)} \cup R'_S )$$

$$= \text{Reach}(U_{\ell-(i+1)} \cup \overline{W}^* \cup R'_S )$$

$$\subseteq \text{Reach}(U_{\ell-(i+1)} \cup \overline{W}^* ) \cup \text{coBuchi}(U_{\ell-i} \setminus U_{\ell-(i+1)}) \subseteq \mathcal{E}_i .$$

The first equality uses that $(S \setminus T) = (U_{\ell-(i+1)} \cup \overline{W}^*)$. The first inclusion uses that $\text{Reach}(R'_S)$ ensures $\text{coBuchi}(U_{\ell-i} \setminus U_{\ell-(i+1)})$. Hence, from each state $s \in T$ we have that $\text{SP}(s, \ell - i) = 1$ as desired.

4. (P starts outside $(R_S \cap T)$: Item (3) of the lemma statement). We will now show that the probability of the event $(\bigcup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-(j+1)}) \cup \text{Reach}(U_{\ell-i}))$ is at least $1 - \epsilon$. We will do so by modeling the worst case using the Markov chain $G_{x,\ell,\epsilon,\eta}^i$ of Lemma 11. There is an illustration of the Markov chain $G_{4}^{x,\ell,\epsilon,\eta}$ in Figure 11. We have one state representing each of the following sets

1. $(U_{\ell-(i+1)} \cup R_S)$
2. $(U_{\ell-i} \setminus (U_{\ell-(i+1)} \cup R_S))$
3. $(U_i \setminus (U_{\ell-i} \cup R_S))$
4. $\overline{W}^*$

We will refer to the states as $s_1, s_2, s_3$ and $s_4$, respectively. We will now argue about the transition probabilities, and first consider the absorbing states.

The state $s_1$. We are interested in the probability that $(U_{\ell-(i+1)} \cup R_S)$ is eventually reached. This probability does not depend on what happens after $(U_{\ell-(i+1)} \cup R_S)$ is reached. Hence, we consider $s_1$ as absorbing, like in $G_{x,\ell,\epsilon,\eta}^i$.

The state $s_4$. In the worst case $\overline{W}^*$ cannot be left, once reached. Thus $s_4$ is an absorbing state, like in $G_{x,\ell,\epsilon,\eta}^i$.

The state $s_2$. For each state $s \in (U_{\ell-i} \setminus (U_{\ell-(i+1)} \cup R_S)) \subseteq (U_{\ell-i} \setminus U_{\ell-(i+1)})$, we must eventually reach a state in either $(C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)})) = ((C_1 \cap T) \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))$ or $(R_S \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))$, with probability 1, by Markov property 3 (recall that we cannot reach states outside $(U_{\ell-i} \setminus U_{\ell-(i+1)})$, except from states in $(C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))$ by Equation 4, Equation 5 and Equation 6. Also, $(R_S \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))$ is the subset of $(U_{\ell-i} \setminus U_{\ell-(i+1)})$ from which $(C_1 \cap T)$ cannot be reached. If we reach $R_S$, an argument similar to the first item in the proof of this lemma shows that we satisfy the desired statement. Thus, in the worst case we always reach $(C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))$.

For each state $s$ in $(C_1 \cap (U_{\ell-i} \setminus U_{\ell-(i+1)}))$, let $x_s = \delta(s, \sigma_1^{\ell-i}, \sigma_2)(U_{\ell-(i+1)})$ be the one-step transition probability to $U_{\ell-(i+1)}$. By Equation 4, and the construction of the strategy, we have that

$\frac{\epsilon}{2} \cdot x_s > \delta(s, \sigma_1^{\ell-i}, \sigma_2)(\overline{W}^*)$.

Clearly, in the worst case we have that

$\frac{\epsilon}{2} \cdot x_s = \delta(s, \sigma_1^{\ell-i}, \sigma_2)(\overline{W}^*)$ implies that $x_s > 0$ and therefore we have that

$x_s \geq \frac{\delta_{\text{min}}}{\text{pat}(\ell - i)}$, where $\text{pat}(\ell - i) = \left(\frac{c \cdot \delta_{\text{min}}}{4} \right)^{-(\frac{2m}{\epsilon} - \frac{\ell - i}{2})}$, is an upper bound on the patience of the distribution $\sigma_1^{\ell-i}(s)$, by Lemma 6. Thus with probability $x_s$ we go to $U_{\ell-(i+1)}$, with probability $\frac{\epsilon}{2} \cdot x_s$ we go to $\overline{W}^*$, and with the remaining probability of $(1 - (1 + \frac{\epsilon}{2}) \cdot x_s)$ we go to a state in $T$, which in the worst case is a state in $(U_{\ell} \setminus (U_{\ell-i} \cup R_S))$. This is so, because, in
the worst case, to reach \((U_{\ell-i} \cup R_S)\) from \((U_\ell \setminus (U_{\ell-i} \cup R_S))\) we must go through a state in \((U_{\ell-i} \setminus (U_{\ell-i+1} \cup R_S))\), and hence the probability to reach \(U_{\ell-i+1}\) is minimized when \(x_s\) is as small as possible, for all \(s\). That is, \(x_s = \delta_{\text{pat}(\ell-i)}\), for all \(s \in (C_1 \cap (U_{\ell-i} \setminus U_\ell))\). Let \(x = \frac{\delta_{\text{pat}(\ell-i)}}{\text{min} \cdot \epsilon} \).

Thus, the transition probabilities are as follows: (i) from \(s_2\) to \(s_1\) is \(\frac{1}{2} \cdot x\); (ii) from \(s_2\) to \(s_1\) is \(x\); and (iii) from \(s_2\) to \(s_3\) is \(1 - (1 + \frac{1}{2}) \cdot x\). Thus, \(s_2\) is like in \(G_{4}^{x,\epsilon,\eta}\).

**The state \(s_3\).** For each state \(s \in (U_\ell \setminus (U_{\ell-i} \cup R_S)) \subseteq (U_\ell \setminus U_{\ell-i})\), by induction and since \(\sigma_{1,\ell,\epsilon,\eta}\) follows \(\sigma_{1,\ell,\epsilon,\eta redesign}\), we satisfy that \(\text{Pr}_{s_{\ell-i}} \sigma_{1,\ell,\epsilon,\eta} \cdot (\cup_{j \leq i-1} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-j+1}) \cup \text{Reach}(U_{\ell-i})) \geq 1 - \eta\), where \(\eta = \left(\frac{\epsilon \cdot \delta_{\text{min}}}{4}\right)^{(2m)^{\eta(x,\epsilon,\eta)}}\). By item (2) of the lemma statement, we enter \(T\) with the remaining probability (which is absorbing). Hence, the worst case must be where \(\text{Pr}_{s_{\ell-i}} \sigma_{1,\ell,\epsilon,\eta} \cdot (\cup_{j \leq i-1} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-j+1}) \cup \text{Reach}(U_{\ell-i})) = 1 - \eta\) (and thus \(\text{Pr}_{s_{\ell-i}} \sigma_{1,\ell,\epsilon,\eta} \cdot \text{Reach}(T') = \eta\)). As previously argued, in the first item and second item of this lemma, the event \(\cup_{j \leq i-1} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-j+1})\) ensures reachability to \(R_S\) (i.e., ensures Reach\((R_S))\). In the worst case for the proof the probability to reach \((R_S \cup U_{\ell-i-1})\) is minimized, and thus in the worst case we have \(\text{Pr}_{s_{\ell-i}} \sigma_{1,\ell,\epsilon,\eta} \cdot \text{Reach}(((U_{\ell-i} \setminus U_{\ell-i+1}) \cup R_S)) = 1 - \eta\) and \(\text{Pr}_{s_{\ell-i}} \sigma_{1,\ell,\epsilon,\eta} \cdot \text{Reach}(T') = \eta\). Thus, from \(s_3\) the transition probability to \(s_2\) and \(s_4\) are \(1 - \eta\) and \(\eta\), respectively. Thus, \(s_3\) is like in \(G_{4}^{x,\epsilon,\eta}\).

**The probability to eventually reach \(s_1\) from \(s_2\) or \(s_3\).** We have that \(x = \frac{1}{2}\) (since \(\text{pat}(\ell-i) < \frac{1}{2}\), for \(m \geq 2\) and \(rk(\ell-i) \geq 1\)). Also, \(0 < \eta, \epsilon < 1\) (in the case of \(\eta\), because \(m \geq 2\) and \(rk(\ell-i) \geq 1\)). Hence we can apply Lemma 11 and get that the probability to eventually reach \(s_1\) from \(s_2\) and \(s_3\) is \(\frac{x \cdot (1 - \eta)}{\eta + (1 + \frac{x}{2}) \cdot x \cdot (1 - \eta)}\) and \(\frac{x \cdot (1 - \eta)}{\eta \cdot (1 + \frac{x}{2}) \cdot x \cdot (1 - \eta)}\), respectively. Clearly, the probability from \(s_3\) is the smallest. We will show that it is greater than \(1 - \epsilon\). We have that

\[
\frac{x \cdot (1 - \eta)}{\eta + (1 + \frac{x}{2}) \cdot x \cdot (1 - \eta)} = \frac{1}{x \cdot (1 - \eta)} > 1 + \epsilon \geq 1 - \epsilon.
\]

We will argue about the first inequality last. The second inequality follows from \(1 > 1 - \epsilon^2 = (1 + \epsilon) \cdot (1 - \epsilon) \Rightarrow \frac{1}{1 + \epsilon} > 1 - \epsilon\). To show the first inequality we will argue that \(\frac{\eta}{x \cdot (1 - \eta)} \leq \frac{\rho}{\eta} \) or, equivalently, that \(\frac{2 \eta}{x \cdot (1 - \eta) \cdot \epsilon} \leq 1\), since \(\epsilon > 0\). We have that

\[
\frac{2 \cdot \eta}{x \cdot (1 - \eta) \cdot \epsilon} \leq \frac{4 \cdot \eta}{x \cdot \epsilon} = \frac{4 \cdot \eta \cdot \text{pat}(\ell-i)}{\delta_{\text{min}} \cdot \epsilon} = \eta \cdot \frac{\epsilon}{\delta_{\text{min}}} = \frac{(2m)^{\eta(x,\epsilon,\eta)}}{4} = \eta^2 < 1.
\]

The inequalities come from \(\eta < \frac{1}{2}\) (which is the case because \(m \geq 2\) and \(rk(\ell-i) \geq 1\)). The first equality is because \(x = \frac{\delta_{\text{min}}}{\text{pat}(\ell-i)}\), by definition. The second equality is because \(\text{pat}(\ell-i) = \left(\frac{\epsilon \cdot \delta_{\text{min}}}{4}\right)^{(2m)^{\eta(x,\epsilon,\eta)}}\), by definition. The third equality uses that \(\eta = \left(\frac{\epsilon \cdot \delta_{\text{min}}}{4}\right)^{(2m)^{\eta(x,\epsilon,\eta)}}\), by definition.

**Ensuring item (3) of the lemma statement.** We see that the probability to reach \((U_{\ell-i+1} \cup R_S)\) from \(T\) is more than \(1 - \epsilon\) (by recalling the definition of \(s_1, s_2 \) and \(s_3\)) and thus item (3) of the lemma statement is ensured, because from states in \(R_S\) the event \(\cup_{j \leq i} \text{Safe}(U_{\ell-j} \setminus U_{\ell-j+1})\) is ensured (as argued in the beginning of the lemma) and hence reaching \(R_S\) ensures \(\cup_{j \leq i} \text{coBuchi}(U_{\ell-j} \setminus U_{\ell-j+1})\).
The desired result follows.

\begin{lemma}
Let \(0 < \epsilon < \frac{1}{2}\). The stationary strategy \(\sigma_1^*\) ensures that for all states \(s \in W^*\) and all strategies \(\sigma_2\) we have \(E_s^{\sigma_1^*,\sigma_2}[\text{LimSupAvg}] \geq E_s^{\sigma_1^*,\sigma_2}[\text{LimInfAvg}] \geq 1 - \epsilon\).
\end{lemma}

\begin{proof}
By construction \(\sigma_1^*\) plays as \(\sigma_1^{\beta,1}\) in \(U_1\) and \(\sigma_1^{\beta,2}\), for \(\beta = \frac{\epsilon}{2}\), in the remaining states. Therefore \(\sigma_1^*\) ensures that the mean-payoff of any play that starts in \(U_1\) is at least \(1 - \beta\), by Lemma 8. Since \(\sigma_1^*\) is stationary, once \(\sigma_1^*\) is fixed we obtain an MDP for player 2, and in MDPs positional strategies always suffice to minimize mean-payoff objectives [13]. Hence, Lemma 12 shows that if the play starts in \(s \in (U_\epsilon \setminus U_1)\), then with probability \(1 - \beta\) the play either stays in \((U_j \setminus U_{j-1})\) for some \(j \geq 2\) and ensures mean-payoff of at least \(1 - \beta\) or reaches \(U_1\), from which we will get mean-payoff \(1 - \beta\). By simple multiplication (using that rewards are at least 0) we therefore see that we get mean-payoff at least
\[
(1 - \beta)^2 = 1 + \beta^2 - 2\beta \geq 1 - \epsilon.
\]
The desired result follows.
\end{proof}

Lemma 13 implies the following inclusion.

\begin{lemma}
We have \(W^* \subseteq \text{val}_1(\text{LimInfAvg}(r), \Sigma_1^*) \subseteq \text{val}_1(\text{LimSupAvg}(r), \Sigma_2^*)\).
\end{lemma}

### 3.2.2 Second inclusion: \(\overline{W}^* \subseteq S \setminus \text{val}_1(\text{LimInfAvg}, \Sigma_1^*)\)

We will now show that for all states \(s \in \overline{W}^*\) that there exists a constant \(c > 0\) such that no finite-memory strategy \(\sigma_1\) for player 1 can ensure value more than \(1 - \frac{c}{\pi}\). Again the statement is trivially true if \(\overline{W}^*\) is empty, and hence we assume that this is not the case.

**Computation of \(\overline{W}^*\).** We first analyze the computation of \(\overline{W}^*\). To analyze the computation of \(\overline{W}^*\) we consider the iterative computation \(W^*\)

- Let \(W_0 = \emptyset\) and \(W_i = \mu U.\nu X.\mu Y.\nu Z.\text{LimAvgPre}(W_{i-1}, U, X, Y, Z)\).
- Let \(X_{i,0} = \emptyset\) and \(X_{i,j} = \nu X.\mu Y.\nu Z.\text{LimAvgPre}(W_{i-1}, W_i, X_{i,j-1}, Y, Z)\).
- Also let \(Z_{i,j,0} = \emptyset\) and \(Z_{i,j,k} = \text{LimAvgPre}(W_{i-1}, W_i, X_{i,j-1}, X_{i,j}, Z_{i,j,k-1})\).

Let \(\ell \geq 0\) be the smallest number such that \(W_\ell = W_{\ell+1} = W^*\). Let \(\text{rk}(i)\), be the smallest number \(j\) such that \(X_{i,j} = X_{i,j+1}\). Also, let \(\text{rk}(i,j)\), be the smallest number \(k\) such that \(Z_{i,j,k} = Z_{i,j,k+1}\). We have that for any state \(s\) in \(\overline{W}^*\), there must be some smallest number \(i\) such that \(s\) is not in \(W_i\) (since \(W_0 = \emptyset\), we have that \(i > 0\)). Also, there must be some smallest \(j\) such that \(s\) is not in \(X_{i,j}\) and similar for \(k\) and \(Z_{i,j,k}\). We define the rank of a state \(s\) in \(\overline{W}^*\) as \(\text{rk}(s) = (i, j, k)\), where \(i\) (resp. \(j\), and \(k\)) is the smallest number such that \(s\) is not in \(W_i\) (resp. \(X_{i,j}\) and \(Z_{i,j,k}\)). By definition of \(\overline{W}^*\), there exists a constant \(c > 0\), such that for a state \(s\), with \(\text{rk}(s) = (i, j, k)\), for all distributions \(\xi_1\) over \(\Gamma_1(s)\) there must exist an counter-action \(a_2^s\xi_1 \in \Gamma_2(s)\) for player 2 such that all the following conditions hold (i.e., the negation of the conditions of LimAvgPre hold):

\[
(c \cdot \delta(s, \xi_1, a_2^s)(W_i) \leq \delta(s, \xi_1, a_2^s)(W_{i-1}))
\]

\[
\land(\delta(s, \xi_1, a_2^s)(X_{i,j-1}) < 1 \lor \delta(s, \xi_1, a_2^s)(X_{i,j}) = 0)
\]

\[
\land(\delta(s, \xi_1, a_2^s)(X_{i,j-1}) < 1 \lor \text{ExpRew}(s, \xi_1, a_2^s < 1 - c \lor \delta(s, \xi_1, a_2^s)(Z_{i,j,k-1}) < 1 - c))
\]
If the above conditions hold, then one of the following three conditions hold as well. We first explain the following cases: (i) if \( \delta(s, \xi_1, a_2^{s, \xi_1})(W_i) > 0 \), then \( c \cdot \delta(s, \xi_1, a_2^{s, \xi_1})(W_i) \leq \delta(s, \xi_1, a_2^{s, \xi_1})(W_{i-1}) \) must hold to ensure the first condition above (this corresponds to Case (3) below); (ii) if \( \delta(s, \xi_1, a_2^{s, \xi_1})(W_i) = 0 \), then the first condition above is satisfied; then we have two sub-cases: (a) if \( \delta(s, \xi_1, a_2^{s, \xi_1})(X_{i,j}) = 0 \) then the first condition above is satisfied; then we have two sub-cases: (a) if \( \delta(s, \xi_1, a_2^{s, \xi_1})(W_{i-1}) < 0 \), then both the second and third condition is satisfied (this corresponds to Case (2) below); (b) otherwise we must have \( \delta(s, \xi_1, a_2^{s, \xi_1})(X_{i,j}) = 0 \) to satisfy the second condition above and \( (\text{ExpRew}(s, \xi_1, a_2^{s, \xi_1}) < 1-c \lor \delta(s, \xi_1, a_2^{s, \xi_1})(Z_{1,j,i-1}) < 1-c) \) to satisfy the third condition above (this corresponds to Case (1) below). Thus we have that either

- **Case (1).** There is a \( a_2^{s, \xi_1} \) such that

\[
\delta(s, \xi_1, a_2^{s, \xi_1})(W_i) = 0 \\
\land \\
\delta(s, \xi_1, a_2^{s, \xi_1})(X_{i,j}) = 0 \\
\land \\
(\text{ExpRew}(s, \xi_1, a_2^{s, \xi_1}) < 1-c \lor \delta(s, \xi_1, a_2^{s, \xi_1})(Z_{1,j,i-1}) < 1-c)
\]

or;

- **Case (2).** There is a \( a_2^{s, \xi_1} \) such that

\[
(\delta(s, \xi_1, a_2^{s, \xi_1})(W_i) = 0) \land (\delta(s, \xi_1, a_2^{s, \xi_1})(X_{i,j-1}) < 1)
\]

or;

- **Case (3).** There is a \( a_2^{s, \xi_1} \) such that

\[
(c \cdot \delta(s, \xi_1, a_2^{s, \xi_1})(W_i) \leq \delta(s, \xi_1, a_2^{s, \xi_1})(W_{i-1})) \land (\delta(s, \xi_1, a_2^{s, \xi_1})(W_i) > 0)
\]

We will use the above three cases explicitly in our proof.

**The counter-strategy \( \sigma_2 \) given \( \sigma_1 \).** Fix an arbitrary finite-memory strategy \( \sigma_1 \) for player 1. Let the finite set of memories used by \( \sigma_1 \) be Mem. A counter-strategy \( \sigma_2 \) given \( \sigma_1 \) is defined as follows: given the current state \( s \) of the game, and current memory state \( m \in \text{Mem} \), let \( \xi_1 \) be the distribution played by \( \sigma_1 \). The strategy \( \sigma_2 \) for player 2 plays an action \( a_2^{s, \xi_1} \) (if there are more than one option for \( a_2^{s, \xi_1} \), pick one arbitrarily) with probability one. If \( \sigma_1 \) uses memory set Mem, then \( \sigma_2 \) also uses the memory set Mem and has the same memory update function.

**Upper bound on value ensured by \( \sigma_1 \).** We will show that given \( \sigma_1 \) and the counter-strategy \( \sigma_2 \) the mean-payoff value is at most \( 1 - c \frac{m}{n} \) for all starting states in \( \text{Mem} \). Also note that the upper bound on the value is independent of the size of the memory, and this shows that in the complement of \( W^* \) the values achievable by finite-memory strategies is strictly bounded below 1.

**The game \( G \times \text{Mem} \).** Consider the game \( G \) and a product with any deterministic automaton \( A \) with state space \( Q \). Every state in \( \text{Mem} \) \( Q \) in the synchronous product game belongs to the set \( \text{Mem} \) \( Q \) in the product game and the ranks also coincide (by the properties of \( \mu \)-calculus formulae). Consider the synchronous product game \( G \times \text{Mem} \) of \( G \) and the memories of \( \sigma_1 \) and \( \sigma_2 \), where states corresponds to pairs in \( \langle S, \text{Mem} \rangle \) and where \( \delta((t, m), a, b)((t', m')) = \delta(s, a, b)(t) \) where \( \sigma_1^m(t, a, b, m) = m' \) and hence also \( \sigma_2^m(t, a, b, m) = m' \). In this game the strategy corresponding to \( \sigma_1 \) can be interpreted as a stationary strategy \( \sigma_1' \). Also the strategy corresponding to \( \sigma_2 \) can be interpreted as a positional strategy \( \sigma_2' \) in \( G \times \text{Mem} \). Hence given the strategies \( \sigma_1 \) and \( \sigma_2 \) we can obtain a Markov chain on \( G \times \text{Mem} \), considering the stationary
strategies $\sigma'_1$ and $\sigma'_2$ on the product game. Also for all states $t \in W^*$ in $G$, all the corresponding states $(t, m)$ in $G \times \text{Mem}$ belong to $W^*$ computed in the product game and has the same rank as $t$ in $G$.

**Upper bound on value ensured by $\sigma_1$.** We show that given $\sigma_1$ and the counter-strategy $\sigma_2$ the mean-payoff value is at most $1 - \frac{c^n}{n}$ for all starting states in $W^*$. The proof is split in the following cases, and the basic intuitive arguments are as follows:

1. **Consider a play that starts in $X_{1,1}$.** We show that the play always stays in $X_{1,1}$ and Case (1) is always satisfied. Thus we show that from every state there is a path of length at most $n$ where reward 0 occurs at least once.

2. For a play that starts in $W_1 \setminus X_{1,1}$, we always satisfy either Case (1) or Case (2). First we establish that the event of Case (2) being satisfied infinitely often has probability 0. Hence from some point on Case (1) is always satisfied, and then the argument is similar to the previous case.

3. Finally we consider a play that starts in $W^* \setminus W_1$. Whenever Case (3) is satisfied, and if the current state is $W_j$, for $j > 1$, then $W_{j-1}$ is reached with positive probability in one-step. We establish that either (i) we are similar to the previous case or (ii) reach $W$ or $W_1$ and the probability to reach $W_1$ is at least $c^n$.

Intuitively, in the first two cases above, we reach a recurrent class that consists of states satisfying Case (1) only, and in such recurrent classes the mean-payoff value is at most $1 - c^n$. In the last case, either we reach a recurrent class of the above type, or whenever we satisfy Case (3) with positive probability $c > 0$ we make progress to a recurrent class of the above type. The above case analysis establish the proof. We now present the formal proof.

**Lemma 15.** Fix an arbitrary finite-memory strategy $\sigma_1$ and consider the counter-strategy $\sigma_2$ given $\sigma_1$. For all states in $W^*$ we have that $\mathbb{E}_{s, G}^{\sigma_1, \sigma_2}[\text{LimSupAvg}] \leq 1 - \frac{c^n}{n}$.

**Proof.** In game $G \times \text{Mem}$, let $\overline{C}_i$ be the set of states where Case $(i)$ is satisfied$^3$. That is $\overline{C}_1, \overline{C}_2$, and $\overline{C}_3$ satisfy Case (1), Case (2), and Case (3), respectively. We consider the Markov chain given $\sigma_1$ and $\sigma_2$, and consider a play $P^s$ starting from state $s$. We will consider three cases to establish the result.

1. **Plays starting in $s \in X_{1,1}$.** Recall that $\overline{X}_{1,1}$ is the complement of $X_{1,1}$. Consider state $s$ in $\overline{Z}_{1,1}$, for some $k \geq 1$ (that is: states in $\overline{X}_{1,1} \setminus \overline{X}_{1,k}$). Since $W_0 = X_{1,0} = S$, we have that the play corresponding to $P^s$ in $G \times \text{Mem}$ is always in $\overline{C}_1$ (note that only in Case (1) do we have probability 0 to go to $W_0$ and $\overline{X}_{1,0}$). Hence the play $P^s$ always stays in $\overline{X}_{1,1}$. Hence, for states in $\overline{Z}_{1,1,k}$, if player 1 plays according to $\sigma_1$ and player 2 plays $\sigma_2$, with probability $c$ we either (i) reach a state in $\overline{Z}_{1,1,k-1}$, or (ii) get a reward of 0. Since $Z_{1,1,0} = S$ we must get a reward of 0 with at least probability $c$ when in $\overline{Z}_{1,1,k}$. Hence, for all states in $\overline{X}_{1,1}$, given player 1 follows $\sigma_1$ and player 2 follows $\sigma_2$, there is a path of play of length at most $rk(1, 1) > rk(1)$ where each step happens with probability at least $c$ and the reward 0 happens at least once. Thus, for any state $s$ in $\overline{X}_{1,1}$, the play $P^s$ stays in $\overline{X}_{1,1}$ and gives a expected average reward of at most $1 - \frac{c^j}{j}$, with probability 1, where $j = rk(1)$. In other words, we have established the following property: in the Markov chain all recurrent classes that intersect with $(\overline{X}_{1,1} \times \text{Mem})$ are contained in $(\overline{X}_{1,1} \times \text{Mem})$ and have mean-payoff at most $1 - \frac{c^n}{n}$.

2. **Plays starting in $s \in (\overline{W}_1 \setminus \overline{X}_{1,1})$.** Consider now state $s$ in $(\overline{W}_1 \setminus \overline{X}_{1,1})$. Since $W_0 = S$, we have that the play $P^s_{\text{Mem}}$, corresponding to $P^s$ in $G \times \text{Mem}$, is always in $(\overline{C}_1 \cup \overline{C}_2)$ (note that in Case (3) we have positive probability to goto $W_0$). This is the only property of $(\overline{W}_1 \setminus \overline{X}_{1,1})$ we will use. Notice

$^3$Note that $\overline{C}_i \neq (S \setminus C_i)$, for $i \in \{1, 2, 3\}$, in general, where $C_i$ is the set defined in Subsection 3.2.1, but this notation is used because $\overline{C}_1, \overline{C}_2, \overline{C}_3$ serve similar roles for properties of $W^*$ as $C_1, C_2, C_3$ did for properties of $W^*$.
that this ensures that $P^s$ always stays in $\overline{W}_1$. Let $R_S$ be the set of states from which no state in $\overline{C}_2$ can be reached. There are now two cases, either $P^s_{\text{Mem}}$ reaches a state in $R_S$ or it does not.

- **The play $P^s_{\text{Mem}}$ reaches a state in $R_S$.** Let $j = \overline{r}(1)$. Then the mean-payoff is at most $1 - \frac{c^j}{j}$ after reaching $R_S$, by a argument similar to the one for states in $\overline{X}_{1,1}$. Therefore, in this case, the mean-payoff of $P^s$ is at most $1 - \frac{c^j}{j}$, since the mean-payoff is independent of the finite-prefix.

- **The play $P^s_{\text{Mem}}$ does not reach a state in $R_S$.** In this case, we must visit states in $\overline{C}_2$ infinitely often with probability 1, by Markov property 1. Whenever we are in a state $s'$ in $\overline{C}_2 \cap ((\overline{X}_{1,j} \setminus \text{Mem}) \setminus \overline{X}_{1,j-1} \times \text{Mem}))$, we have probability at least $p \cdot \delta_{\text{min}}$ to reach $((\overline{X}_{1,j} \times \text{Mem})$ in one-step where $\frac{1}{p}$ is the maximum patience of any distribution played by $\sigma_1$. Whenever we are in a state $s'$ in $\overline{C}_2 \cap ((\overline{X}_{1,j} \times \text{Mem}) \setminus (\overline{X}_{1,j-1} \times \text{Mem}))$, we have probability 0 to leave $((\overline{X}_{1,j} \times \text{Mem}) \setminus (\overline{X}_{1,j-1} \times \text{Mem}))$ in one-step. Therefore we must reach $((\overline{X}_{1,1} \times \text{Mem})$ in a finite number of steps with probability 1 and from $((\overline{X}_{1,1} \times \text{Mem})$ we get a mean-payoff of at most $1 - \frac{c^j}{j}$, where $j = \overline{r}(1)$, as we have already established in the first item$^4$.

Therefore, in both cases we get a mean-payoff of at most $1 - \frac{c^j}{j}$ with probability 1, where $j = \overline{r}(1)$, i.e., all recurrent classes have mean-payoff of at most $1 - \frac{c^j}{j}$.

3. **Plays starting in $s \in (\overline{W}^* \setminus \overline{W}_1)$.** Consider now state $s$ in $(\overline{W}^* \setminus \overline{W}_1)$. Consider the play $P^s$ in $G$ and the corresponding play $P^s_{\text{Mem}}$ in $G \times \text{Mem}$. For $i \geq 1$, let $L_i = W_i \setminus \overline{W}_{i-1}$ and note that $L_i = W_i \setminus \overline{W}_{i-1}$. Let $\overline{R}_i$ be the set of states in $\overline{L}_i$ from which no state in $\overline{C}_3 \cap \overline{L}_i$ is reachable; (note that $\overline{R}_i \subseteq \overline{L}_i \cap (\overline{C}_3 \cup \overline{C}_2)$). Note that from $\overline{L}_i$, the set $\overline{L}_i$ can be left only from states in $\overline{C}_3 \cap \overline{L}_i$. We now consider two sub-cases.

- **We first consider the case where we reach $\overline{R}_i$.** Let $j = \overline{r}(i)$. In this case, the mean-payoff is at most $1 - \frac{c^j}{j}$ by an argument similar to the argument for $s$ in $\overline{W}_1 \setminus \overline{X}_{1,1}$. The argument for $s$ in $\overline{W}_1 \setminus \overline{X}_{1,1}$ only uses that states in $\overline{C}_1 \cup \overline{C}_2$ are visited. Once $\overline{R}_i$ is reached we are guaranteed that only states in $\overline{R}_i$ are visited, and hence the recurrent classes in $\overline{R}_i$ has mean-payoff of at most $1 - \frac{c^j}{j}$.

- **If $\overline{R}_i$ is not reached, then since from every state $\overline{C}_3 \cap \overline{L}_i$ we have positive transition probability to $L_i$, it follows that $L_i$ is reached with probability 1, by Markov property 4. But if we reach either $W_i$ or $\overline{W}_{i-1}$, we have a probability of at least $c^j$ that it will be $\overline{W}_{i-1}$ (since it can only be done whenever $P^s_{\text{Mem}}$ is in $\overline{C}_3 \cap L_i$, which ensures so).

Each time we repeat the second case, all states in $\overline{L}_i$, will never be visited again, in the worst case. Since each set $\overline{L}_i$ must contain at least one state, we see that, if we repeat the second case $k$ times and thereafter enter $\overline{R}_i$ (and are thus in the first case), then $n - k \geq \overline{r}(i')$. We have a probability of $c^k$ to follow such a play and we then get value at most $1 - \frac{c^k}{n-k}$. Even if we got mean-payoff 1 with the remaining probability of $1 - c^k$, we still have an expected mean-payoff of at most $1 - \frac{c^n}{n-k}$. Thus, we see that in the worst case $k = 0$ with probability 1, in which case we get mean-payoff at most $1 - \frac{c^n}{n}$.

The desired result follows. 

$^4$In fact, alternatively we can prove this case using contradiction, since $(\overline{X}_{1,1} \times \text{Mem}) \subseteq \overline{C}_1$ and therefore $(\overline{X}_{1,1} \times \text{Mem}) \subseteq R_S$, since $(\overline{X}_{1,1} \times \text{Mem})$ cannot be left in the Markov chain.
Lemma 15 implies the following inclusion.

**Lemma 16.** We have $\text{val}_1(\text{LimSupAvg}(r), \Sigma_1^F) \subseteq W^*$. 

## 4 Improved Rank-Based Algorithm

In this section we present an improved rank-based algorithm, which is based on the same principle as the small-progress measure algorithm [19] (for parity games). While the naive computation of the $\mu$-calculus formula for the value 1 set requires $O(n^4)$ iterations, the improved algorithm will require $O(n^2)$ iterations.

**Basic idea.** The basic idea of the algorithm is to consider the ranking function $\text{rk}$ from Section 3.2.1 and use that to obtain an algorithm. Notice that $\text{rk}(s)$ for $s \in W^*$ is always a pair $(i, j)$ such that $2 \leq i + j \leq n + 1$ and where $1 \leq i, j \leq n$. We see that for any number $k$ there are $k - 1$ pairs $(i, j)$ such that $i + j = k$ and such that $1 \leq i, j \leq k - 1$. Hence, there are $\sum_{k=1}^{n} k = \frac{n(n+1)}{2}$ such pairs $(i, j)$ such that $2 \leq i + j \leq n + 1$ and where $1 \leq i, j \leq n$. Furthermore we also have a special rank $\top$ for not being in $W^*$. The ranks are lexicographically ordered as follows:

$$(1, 1) < (1, 2) < \cdots < (1, n) < (2, 1) < \cdots < (n, 1) < \top.$$ 

We will thus say that $(i, j) < \top$ for all $i, j$ and $(i, j) < (i', j')$ if $i < i'$ or $i = i'$ and $j < j'$; (and for $(i, j) \leq (i', j')$ we change $j \leq j'$). To distinguish with the ranking function in Section 3.2.1, we denote the ranking function of the improved algorithm as $\text{rk}'(s)$.

**Definition of matrix.** Consider a given assignment of ranks to states. Let $s$ be some state of rank $\text{rk}'(s) \neq \top$ and therefore of rank $(i, j)$ for some $i$ and $j$; and also consider a state $s'$ of rank $(i', j')$. We define some sets, $U_s, Y_s, Z_s, X_s, W_s$ as follows:

1. The state $s'$ is in $U_s$, if $i > i'$.
2. The state $s'$ is in $Y_s$, if $i > i'$ or $i' = i$ and $j > j'$.
3. The state $s'$ is in $Z_s$, if $i > i'$ or $i' = i$ and $j \geq j'$.
4. The state $s'$ is in $X_s$, if $i \geq i'$.
5. The state $s'$ is in $W_s$ independent of $s$.

Also if a state $s''$ has rank $\top$, then it is in the set $\overline{W}_s$. This set also does not depend on $s$. Let $M_{a_1, a_2}^s \in \{\overline{W}_s, U_s, W_s, Y_s, X_s, Z_s^1, Z_s^0\}$, for $a_1 \in \Gamma_1(s)$ and $a_2 \in \Gamma_2(s)$, be the matrix similar to the matrix $M$ from Section 3.1, except that instead of set $\overline{W}$ use $\overline{W}_s$ and similar for $U, Y, Z, X$ and $W$.

**The RANKALGO algorithm.** We will refer to our algorithm as RANKALGO and the description is as follows:

1. For each state $s$ set $\text{rk}'(s) \leftarrow (1, 1)$
2. Let $i \leftarrow 0$ and $S^0 \leftarrow S$.
3. (Iteration) While $S^i$ is not the empty set:
   
   (a) Let $Q^i = S^i \cup \{s \mid \exists a_1 \in \Gamma_1(s), \exists a_2 \in \Gamma_2(s). \text{Succ}(s, a_1, a_2) \cap S^i \neq \emptyset\}$ be the set of states in $S^i$ and their predecessors.
We now analyze the running time of the algorithm. We first analyze the work done for updating matrices.

4.1 Running time of algorithm

We now analyze the running time of the algorithm. We first analyze the work done for updating matrices $M^s$ and then analyze the work done for ALGOPRED computation.

- **Work to update matrix.** For a state $s$ of rank $(i, j)$, notice that we do not need to recalculate the entire $M^s$ whenever some successor $s'$ of $s$ changes rank, but only the entries $(a_1, a_2)$ such that $s' \in \text{Succ}(s, a_1, a_2)$. Also notice that we do not need to change $M^s$ at all whenever $s'$ changes rank to ranks other than in $\{(i, 1), (i, j), (i, j + 1), (i + 1, 1), \mathbb{T}\}$. Hence, as long as $s$ has some rank $(i, j)$, we can do all updates of $M^s$ in time $O(\sum_{a \in \Gamma_1(s)} |\text{Supp}(s, a, b)|)$. We also recalculate $M^s$ whenever $s$ changes rank, and since each state has at most $O(n^2)$ different ranks therefore we use $O(n^2 \cdot \sum_{s \in S} \sum_{a \in \Gamma_1(s), b \in \Gamma_2(s)} |\text{Supp}(s, a, b)|)$ times to do all updates of $M^s$ for all states $s$.

- **Work of ALGOPRED.** Note that each entry of $M^s$ can take at most 7 different values, and as long as $s$ has a fixed rank each update comes for some entry worse than before. Hence as long as $s$ has some fixed rank $(i, j)$ we can do no more than $6 \cdot |\Gamma_1(s)| \cdot |\Gamma_2(s)|$ updates of $M^s$. Hence we run ALGOPRED at most $\frac{n(\alpha+1)}{2} \cdot 6 \cdot |\Gamma_1(s)| \cdot |\Gamma_2(s)|$ times for a fixed $s$.

Therefore, we get a total running time of $O(n^2 \cdot \sum_{s \in S} (|\Gamma_1(s)|^3 \cdot |\Gamma_2(s)|^3 + \sum_{a_1 \in \Gamma_1(s), a_2 \in \Gamma_2(s)} |\text{Supp}(s, a_1, a_2)|))$, using Lemma 4.

4.2 Proof of correctness of algorithm RANKALGO

The correctness proof is similar to the results of [19]. The proof of [19] shows the equivalence of $\mu$-calculus formula and a rank-based algorithm (called small-progress measure algorithm) for parity games; and the crucial argument of the correctness was based on the fact that the predecessor operator is monotonic. Our correctness proof is similar and uses that LimAvgPre is monotonic. We just present the proof of one inclusion and the other inclusion is similar. For simplicity we will say that the rank of $s$ is $\text{rk}(s) = \mathbb{T}$ if $s \in \overline{W}^*$. Let $W^*$ be the output of the algorithm. We show that $\overline{W}^* \subseteq W^* : \text{rk}(s) \leq \text{rk}(s')$. We only need to show the statement for $\text{rk}(s) \neq \mathbb{T}$ since otherwise the statement follows by definition. Hence, assume towards contradiction that $\text{rk}(s) > \text{rk}(s)$ and let $\text{rk}(s) = (i, j)$. Also, we can WLOG assume that $s$ gets assigned a rank higher than $\text{rk}(s)$ in the first iteration for which any state $s'$ gets assigned rank higher than $\text{rk}(s')$ by the algorithm. Therefore in that iteration all states $s'$ are such that the rank assigned by the algorithm is at most $\text{rk}(s')$ and $s$ has rank $\text{rk}(s)$ assigned. Therefore $W^* \subseteq W_\mathbb{T}, U_{i-1} \subseteq U_s, U_i \subseteq X_s, Y_{i,j-1} \subseteq Y_s, Y_{i,j} \subseteq Z_s$. But $s$ is in LimAvgPre($W^*, U_{i-1}, U_i, Y_{i,j-1}, Y_{i,j}$) by definition since $s$ is such that $\text{rk}(s) = (i, j)$. By monotonicity of LimAvgPre we have that $s$ is also in LimAvgPre($W_s, U_s, X_s, Y_s, Z_s$), contradicting that $s$ changes rank.

Lemma 17. The algorithm RANKALGO correctly computes the set $\text{val}_1(\text{LimInfAvg}(r), \Sigma_i^F)$ of states in time $O(n^2 \cdot \sum_{s \in S} (|\Gamma_1(s)|^3 \cdot |\Gamma_2(s)|^3 + \sum_{a_1 \in \Gamma_1(s), a_2 \in \Gamma_2(s)} |\text{Supp}(s, a_1, a_2)|))$. 

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5 Main Result and Concluding Remarks

We now summarize the main result, and conclude with an open question.

**Theorem 18.** The following assertions hold for concurrent mean-payoff games.

1. **(Value 1 set characterization).** Let $W^* = \nu W, \mu U, \nu X, \mu Y, \nu Z \cdot \text{LimAvgPre}(W, U, X, Y, Z)$, then we have

   $$W^* = \text{val}_1(\text{LimSupAvg}(r), \Sigma_1^S) = \text{val}_1(\text{LimSupAvg}(r), \Sigma_1^F)$$

   $$= \text{val}_1(\text{LimInfAvg}(r), \Sigma_1^S) = \text{val}_1(\text{LimInfAvg}(r), \Sigma_1^F)$$

2. **(Running time).** The value 1 sets $\text{val}_1(\text{LimSupAvg}(r), \Sigma_1^S) = \text{val}_1(\text{LimSupAvg}(r), \Sigma_1^F)$ can be computed in time $O(n^2 \cdot \sum_{s \in S} (O(|\Gamma_1(s)|^3 \cdot |\Gamma_2(s)|^3 + \sum_{a_1 \in \Gamma_1(s), a_2 \in \Gamma_2(s)} |\text{Supp}(s, a_1, a_2)|))$.

3. **(Optimal patience).** For all $\epsilon > 0$, there exist stationary $\epsilon$-optimal strategies in the set $\text{val}_1(\text{LimSupAvg}(r), \Sigma_1^S)$ with patience at most $\left(\frac{\epsilon \delta_{\text{min}}}{4} - (2m)^n\right)$.

**Proof.** The first item follows from Lemma 16 together with Lemma 14. The second item comes from Lemma 17. The third item follows from Lemma 7.

Notice that the patience closely matches the patience obtained for the concurrent reachability game Purgatory, by Hansen, Ibsen-Jensen and Miltersen [15, Theorem 10] (the bound for $m = 2$ is also in [17]). Concurrent reachability games is a subclass of concurrent mean-payoff games and always have $\epsilon$-optimal stationary strategies, for all $\epsilon > 0$, and all states in Purgatory have value 1. Thus the example provides a closely matching lower bound for patience.

**Robustness.** Our results show that the value 1 set computation can be achieved by an iterative algorithm with the LimAvgPre operator. Our algorithm for the LimAvgPre operator computation is based on the matrix construction $M$, and observe that the entries in the matrix depends only on the support set, but not the precise probabilities. It follows that given two concurrent games where the support sets of the transition functions match, but the precise transition probabilities may differ, the value 1 set remains unchanged.

**Concluding remarks.** In this work we considered concurrent mean-payoff games and presented a polynomial-time algorithm to compute the value 1 set for finite-memory strategies for player 1. An interesting open question is whether the value 1 set with infinite-memory strategies can also be computed in polynomial time.

**References**


6 Technical appendix — Computation of LPre

We now present the details of the computation of LPre(s, W, U, A1, A2). We will establish the Reject property and Accept properties a—d of LPre. We first recall the properties:

(Accept properties of LPre). Accepts and returns the set A3 ⊆ A2 and a parametrized distribution ξ1, for 0 < ε < \frac{1}{2}, with support Supp(ξ1) ⊆ A1, such that the following properties hold:

- (Accept property a). For all a2 ∈ A3, the distribution ξ1 satisfies Equation 1 for a2.
- (Accept property b). For all a2 ∈ (A2 \ A3), we have Succ(s, ξ1, a2) ∩ W = ∅ and Succ(s, ξ1, a2) ∩ U = ∅.
- (Accept property c). For all a1 ∈ (A1 \ Supp(ξ1)), there exists an action a2 in (A2 \ A3) such that Succ(s, a1, a2) ∩ W ≠ ∅.
- (Accept property d). The set A3 is largest in the sense that for all a2 ∈ (A2 \ A3) and for all parametrized distributions ξ1 over A1, the Equation 1 cannot be satisfied, while satisfying actions in A2 using Equation 1, or Equation 2, or Equation 3, for any X, Y, Z such that U ⊆ Y ⊆ Z ⊆ X ⊆ W.

The computation of LPre(s, W, U, A1, A2) will be done similar to the computation of the similar named LPre(s, W, U) in [9, 8], and we will follow notations from [8]. We will use the two methods Stay and Cover, defined as follows:

\[
\text{Stay}(s, W, A1, A2, A) = \{a1 ∈ A1 | ∀a2 ∈ (A2 \ A). \left[\left(Succ(s, a1, a2) ∩ W = ∅\right)\right] \}
\]

\[
\text{Cover}(s, U, A1, A2, A) = \{a2 ∈ A2 | ∃a1 ∈ (A1 ∩ A). \left[\left(Succ(s, a1, a2) ∩ U = ∅\right)\right] \}
\]

The algorithm LPre(s, W, U, A1, A2) is then as follows:

1. Let \(A^* ← \mu A.\left[\text{Stay}(s, W, A1, A2, A) ∪ \text{Cover}(s, U, A1, A2, A)\right]\) and for all a1 ∈ (A* ∩ A1) let \(ℓ(a1)\) be the level of a1 in the formula.

2. If (A* ∩ A1) is empty, return reject. Otherwise, return accept and (A* ∩ A2, ξ1), where ξ1 is the parametrized distribution, with support (A* ∩ A1), and the ranking function of a1 ∈ (A* ∩ A1) is \(\frac{ℓ(a1) - 1}{2}\).

The algorithm for LPre(s, W, U) of [9, 8] can be obtained as a special case of our description above as follows:

1. Let \((A3, ξ^1) ← \text{LPre}(s, W, U, Γ1(s), Γ2(s))\). If either (i) LPre(s, W, U, Γ1(s), Γ2(s)) rejects; or (ii) A3 ≠ Γ2(s), then return reject, otherwise return accept and ξ^1.

We will now show that LPre(s, W, U, A1, A2) satisfies the desired properties.

Lemma 19. The algorithm LPre(s, W, U, A1, A2) satisfies the Reject property of LPre and Accept properties a—d. Also, the patience of ξ1 is at most \(\left(\frac{c \cdot \mu_{\min}}{2}\right)^{|A1|-1}\).

Proof. We establish the desired properties.

The reject property of LPre. We see that LPre(s, W, U, A1, A2) only rejects if (A* ∩ A1) is empty. By definition of Stay(s, W, A1, A2, A) we have (A* ∩ A1) is empty iff for all a1 ∈ A1 there exists a2 ∈ (A2 \ A*)
such that \((\text{Succ}(s, a_1, a_2) \cap W) \neq \emptyset\). We also see the reverse, since we see that also \((A_2 \in A^*) is empty if \((A^* \in A_2) is empty by definition of Cover(s, U, A_1, A_2, A). This implies that the empty set is a fixpoint of \(\mu A \cdot [\text{Stay}(s, W, A_1, A_2, A) \cup \text{Cover}(s, U, A_1, A_2, A)]\) and thus must be \(A^*\). Since \(A^*\) is empty, it follows that for all \(a_1 \in A_1\), there exists \(a_2 \in (A_2 \setminus A^*) = A_2\) such that \((\text{Succ}(s, a_1, a_2) \cap W) \neq \emptyset\). Hence, if \(\text{LPre}(s, W, U, A_1, A_2)\) rejects, then the reject property of \(\text{LPre}\) is satisfied.

**Properties of the set \(A^*\).** We have that if \(\text{LPre}(s, W, U, A_1, A_2)\) returns \((A_3, \xi_1^*)\), then \(A^* = (\text{Supp}(\xi_1^*) \cup A_3)\) and \(A^*\) is a fixpoint of \(\mu A \cdot [\text{Stay}(s, W, A_1, A_2, A) \cup \text{Cover}(s, U, A_1, A_2, A)]\).

**Accept property a.** We note that if we restrict the set of actions of player 1 to \(\text{Accept}\) property b. the proof of [8, Lemma 4] ensures \(\text{Accept}\) property a and the desired patience.

**Accept property b.** We see that for an action \(a_1\) to be in \((A^* \cap A_1) = \text{Supp}(\xi_1^*)\), by definition of \(\text{Stay}(s, W, A_1, A_2, A^*)\), for all \(a_2\) in \((A^* \cap A_2) = A_2\) we have that \((\text{Succ}(s, a_1, a_2) \cap W) = \emptyset\) (or equivalently that \((\text{Succ}(s, \xi_1^*, a_2) \cap W) = \emptyset\)). This establishes the first half of \(\text{Accept}\) property b. Also, we see that if an an action \(a_2\) is in \((A_2 \setminus A^*) = (A_2 \setminus A_3)\), then by definition of \(\text{Cover}(s, U, A_1, A_2, A^*)\) for all \(a_1\) in \((A^* \cap A_1) = \text{Supp}(\xi_1^*)\) we have that \((\text{Succ}(s, a_1, a_2) \cap U) = \emptyset\) (or equivalently that \((\text{Succ}(s, \xi_1^*, a_2) \cap U) = \emptyset\)). This establishes the second half of \(\text{Accept}\) property b.

**Accept property c.** For \(A^*\) to be a fixpoint we must have, by definition of \(\text{Stay}(s, W, A_1, A_2, A^*)\), that for each action \(a_1 \in (A_1 \setminus A^*) = (A_1 \setminus \text{Supp}(\xi_1^*))\) that the condition to be in \(\text{Stay}(s, W, A_1, A_2, A^*)\) must be violated and thus, there exists \(a_2 \in (A_2 \setminus A^*) = (A_2 \setminus A_3)\) such that \((\text{Succ}(s, a_1, a_2) \cap \emptyset) = \emptyset\). This establishes \(\text{Accept}\) property c.

**Accept property d.** Along with \(U\) and \(W\) consider any \(X, Y, Z\) such that \(U \subseteq Y \subseteq Z \subseteq X \subseteq W\). Consider a real number \(0 < \epsilon < \frac{\delta_{\min}}{|A_1|}\) and a distribution \(\xi_1\) over \(A_1\). We will show that if Equation 1 is satisfied by \(\xi_1\) for some action \(a_2 \in (A_2 \setminus A_3)\), then there is some action \(a_2^* \in A_2\) which is not satisfied by either (i) Equation 1; or (ii) Equation 2; or (iii) Equation 3. The proof will be by contradiction and assume towards contradiction that such an action \(a_2^*\) exists. Let \(A_1 \subseteq A_2\) be the set of actions which does satisfy Equation 1 by \(\xi_1\) and let the remaining actions be satisfied by either Equation 2 or Equation 3. Notice that \(A_1 \not\subseteq A_3\), since \(a_2 \in A_4\) and \(a_2 \not\in A_3\).

We consider two cases depending on whether or not \(\text{Supp}(\xi_1) \subseteq \text{Supp}(\xi_1^*)\) to establish the result.

- We first consider the case, where \(\text{Supp}(\xi_1) \subseteq \text{Supp}(\xi_1^*)\). Then Equation 1 is violated for all \(a_2^* \in (A_2 \setminus A_3)\), since \(U\) cannot be reached by \(\text{Accept}\) property b. In particular, it must be violated for \(a_2^*\). That is a contradiction.

- We next consider the case, where \(\text{Supp}(\xi_1) \not\subseteq \text{Supp}(\xi_1^*)\). Let \(a_1 \in (\text{Supp}(\xi_1) \setminus \text{Supp}(\xi_1^*))\) be an action, such that \(a_1 \in \arg \max_{a_1' \in (\text{Supp}(\xi_1) \setminus \text{Supp}(\xi_1^*))} \xi_1(a_1')\). By \(\text{Accept}\) property c, there exists an action \(a_2^* \in (A_2 \setminus A_3)\) such that \((\text{Succ}(s, a_1, a_2^*) \cap W = \emptyset)\), since \(a_1 \in (\text{Supp}(\xi_1) \setminus \text{Supp}(\xi_1^*)) \subseteq (A_1 \setminus \text{Supp}(\xi_1^*))\). We again split into two cases. Either \(a_2^*\) is in \(A_4\) or not.

  - We first consider the case then \(a_2^* \in A_4\). We will show that we go to \(W\) with too high probability, compared to the probability with which we go to \(U\). We see that \(\delta(s, \xi_1, a_2^*)(W) = \delta_{\min} \cdot \xi_1(a_1)\), by definition of \(a_2^*\). Each action \(a_1' \in \text{Supp}(\xi_1^*)\) ensures that \((\text{Succ}(s, a_1', a_2^*) \cap U = \emptyset)\) by \(\text{Accept}\) property b, since \(a_2^* \not\in A_3\). It follows that \(\delta(s, \xi_1, a_2^*)(U) = \xi_1(a_1) \cdot destroyer\). This is because each action \(a_1'\) such that \(\xi(a_1') \geq \xi(a_1)\) are in \(\text{Supp}(\xi_1^*)\) by definition of \(a_1\) and there are at most \(|A_1| - 1\) actions in \((\text{Supp}(\xi_1) \setminus \text{Supp}(\xi_1^*))\) (since \(\xi_1\) and \(\xi_1^*\) are distributions over \(A_1\) and \(|\text{Supp}(\xi_1)| \geq 1\). But then \(\delta(s, \xi_1, a_2^*)(U) < \delta \cdot \delta(s, \xi_1, a_2^*)(W)\) and thus Equation 1 is violated by \(\xi_1\) and \(a_2^*\). This contradicts either that \(a_2^* \in A_4\) or the definition of \(A_4\).
We next consider the case then \( a'_2 \in (A_2 \setminus A_4) \). Recall that \( \text{Succ}(s, \xi_1, a'_2) \cap \overline{W} \neq \emptyset \). Hence, Equation 2 and Equation 3 are violated, since \( \text{Succ}(s, \xi_1, a'_2) \cap X \neq \emptyset \) (because \( X \subseteq W \) and if \( \overline{W} \) is reached with positive probability, then \( X \) is reached with positive probability). Moreover, Equation 1 cannot be satisfied either, since \( a'_2 \not\in A_4 \). Thus we have a contradiction.

Thus, in all cases we reach contradiction and, hence Accept property d is satisfied.

The desired result follows.