

# On the Hardness of Finding Symmetries in Markov Decision Processes

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# Outline

- 1 Overview
- 2 Introduction
  - Markov Decision Processes
  - Formal Problem Definition
- 3 Symmetries in MDPs
  - Finding Symmetries
  - Exploiting Symmetries
- 4 Experiments and Results
- 5 Conclusions

# Overview

- Markov Decision Processes (MDPs)
  - Used to model sequential decision problems
  - Current solution techniques do not scale well with the size of the MDP
  - Real world problems when modeled as MDPs exhibit high degree of redundancy
  - Reduction in size possible if we exploit redundancy
- Finding Symmetries in MDPs
  - We use the symmetry as a notion of redundancy as introduced in (Ravindran, 2004)
  - Believed to be hard however exact hardness is unknown
  - Intuitively, because of the additional structure of MDPs it seems harder
- We show that finding symmetries in MDPs is no harder than the problem of Graph Isomorphism (GI)
- We also show the use of existing GI solvers for finding symmetries in MDPs

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# Stochastic Sequential Decision Making

- Markov Decision Process,  $\mathcal{M}: \langle S, A, \Psi, P, R \rangle$ 
  - Set of States :  $S$
  - Set of Actions :  $A$
  - Set of Permissible Actions :  $\Psi \subseteq S \times A$
  - Transition Probabilities :  $P : \Psi \times S \rightarrow [0, 1]$
  - Expected Reward :  $R : \Psi \rightarrow \mathbb{R}$
- Policy,  $\pi : S \rightarrow A$
- Value of a state  $s$  under policy  $\pi : E^\pi$  (discounted sum of future rewards got by following  $\pi$  from  $s$ )
- Bellman Equation

$$V_\pi(s) = R(s, a) + \gamma \sum_{s' \in S} P(s, a, s') V_\pi(s')$$

where,  $0 \leq \gamma < 1$

# Solution of an MDP

- Is a policy  $\pi^*$  such that, for any policy  $\pi$ ,  $V_{\pi^*}(s) \geq V_{\pi}(s)$ ,  $\forall s \in \mathcal{S}$
- Bellman Optimality Equation

$$V_{\pi^*}(s) = \max_{a \in A} \{R(s, a) + \gamma \sum_{s' \in \mathcal{S}} P(s, a, s') V_{\pi^*}(s')\}$$

- Iterative algorithm using the Bellman Optimality equation

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## Reduced Model - Formal definition

### Definition

An MDP homomorphism from  $\mathcal{M}$  to  $\mathcal{M}'$  is a surjection  $h : \Psi \rightarrow \Psi'$  defined by  $h(s, a) = (f(s), g_s(a))$ , where  $f : S \rightarrow S'$  and  $g_s : A_s \rightarrow A'_{f(s)}$  are surjections satisfying,

$$P'(f(s), g_s(a), f(s')) = \sum_{s'' \in f^{-1}(f(s'))} P(s, a, s'')$$

$$R'(f(s), g_s(a)) = R(s, a)$$

### Definition

An MDP  $\mathcal{M}'$  is said to be a *reduced model* of an MDP  $\mathcal{M}$ , iff there exists an MDP homomorphism  $h : \mathcal{M} \rightarrow \mathcal{M}'$ .

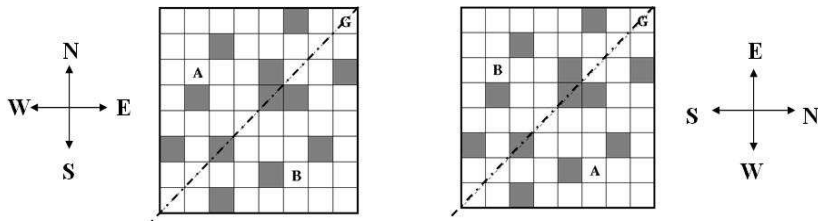


# Reduced Model - Significance

- Reduced Model:
  - Preserves dynamics by definition
  - Preserves optimal value functions and policies
  - Functionally equivalent to the original model but significantly smaller

# Symmetry informally

- A symmetric system is one that is invariant under certain transformation onto itself.
  - This gridworld is invariant under reflection along diagonal



# Symmetry Formal Definition

## Definition

A bijective MDP homomorphism from  $\mathcal{M}$  to  $\mathcal{M}$  is called an MDP automorphism which represents a symmetry. We have,

$$\begin{aligned}P(f(s), g_s(a), f(s')) &= P(s, a, s') \\R(f(s), g_s(a)) &= R(s, a)\end{aligned}$$

## Definition

The set of all automorphisms of an MDP,  $\mathcal{M}$ , form a group under composition called the automorphism group of  $\mathcal{M}$ , represented as  $\text{Aut } \mathcal{M}$ . The orbits of the natural action of any subgroup  $\mathcal{G}$  on  $\mathcal{M}(\Psi)$  defines a partition  $B_{\mathcal{G}}$  of  $\Psi$  using which a quotient MDP  $\mathcal{M} / B_{\mathcal{G}}$ , called the  $\mathcal{G}$ -Reduced Image can be defined.

# Problem

- Given an MDP  $\mathcal{M}$ 
  - 1 Find  $\text{Aut} \mathcal{M}$
  - 2 Find  $\text{Aut} \mathcal{M}$ -Reduced Image

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## Problem Simplification

- Given an MDP  $\mathcal{M}$ , find  $\text{Aut.}\mathcal{M}$
- A group is completely specified by its generators
- $\text{AMGEN}(\mathcal{M})$ : Find generators of  $\text{Aut.}\mathcal{M}$

# Isomorphism Completeness

## Definition

$A$  is *Isomorphism Complete* iff  $A$  is polynomially equivalent to finding Graph Isomorphisms

## Definition

$A$  is *polynomially equivalent* to  $B$  iff  $A$  is polynomially reducible( $\infty$ ) to  $B$  and  $B \infty A$ , denoted  $A \equiv_{\infty} B$

## List of relevant Isomorphism Complete Problems

- $ISO(G_1, G_2)$ : Isomorphism recognition for  $G_1$  and  $G_2$ , where  $G_1$  and  $G_2$  are simple
- $IMAP(G_1, G_2)$ : Isomorphism Map from  $G_1$  to  $G_2$  (if it exists), where  $G_1$  and  $G_2$  are simple
- $AGEN(G)$ : Generators of the automorphism group,  $AutG$ , where  $G$  is simple
- $DGEN(G)$ : Generators of the automorphism group,  $AutG$ , where  $G$  is a digraph
- So,  $DGEN(G) \equiv_{\infty} AGEN(G) \equiv_{\infty} IMAP(G_1, G_2) \equiv_{\infty} ISO(G_1, G_2)$



# Outline

- 1 Pose  $AMGEN(\mathcal{M})$  as a problem on weighted pseudographs
- 2 Prove that  $AMGEN(\mathcal{M}) \equiv_{\infty} DGEN(G)$ 
  - $DGEN(G) \propto AMGEN(\mathcal{M})$  (trivial)
  - $AMGEN(\mathcal{M}) \propto DGEN(G)$
- 3 Hence,  $AMGEN(\mathcal{M})$  is Isomorphism Complete

# Set Bijections

- 1 A generator of  $Aut.\mathcal{M}$  has 2 components:
  - A function  $f$  that permutes the states
  - A set of functions  $\{g_u\}$  that permute the actions called the State-Dependent Action Recoding (SDAR) functions.
- 2 Solution to  $DGEN(G)$  accounts only for  $f$
- 3 Factorially many SDAR functions in the worst case, rendering explicit representations useless
- 4 To obtain the SDAR functions, we define the notion of a *set bijection*
- 5 Represents a set of bijections compactly
- 6 Polynomially computable operations of intersection, composition and inverse

## Set Bijections example

For example, the following set of bijections from  $A = \{1, 2, 3, 4\}$  to  $B = \{N, E, W, S\}$

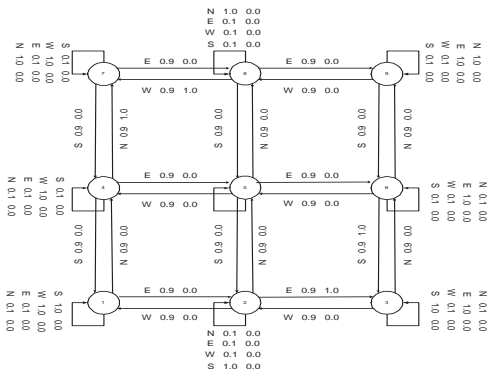
$$\begin{array}{cccc}
 1 \rightarrow N, & 2 \rightarrow E, & 3 \rightarrow W, & 4 \rightarrow S \\
 1 \rightarrow N, & 2 \rightarrow E, & 3 \rightarrow S, & 4 \rightarrow W \\
 1 \rightarrow E, & 2 \rightarrow N, & 3 \rightarrow W, & 4 \rightarrow S \\
 1 \rightarrow E, & 2 \rightarrow N, & 3 \rightarrow S, & 4 \rightarrow W
 \end{array}$$

can be represented compactly using a *set bijection*,  $X_1$ , from  $U_A^1 = \{\{1, 2\}, \{3, 4\}\}$  to  $U_B^1 = \{\{N, E\}, \{W, S\}\}$  as follows:

$$\begin{array}{l}
 X_1(\{1, 2\}) = \{N, E\} \\
 X_1(\{3, 4\}) = \{W, S\}
 \end{array}$$

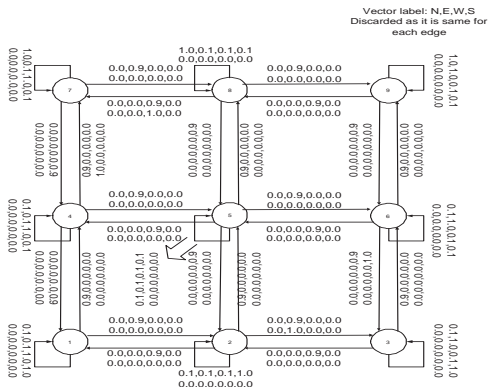
# An example

MDP as PseudoGraph



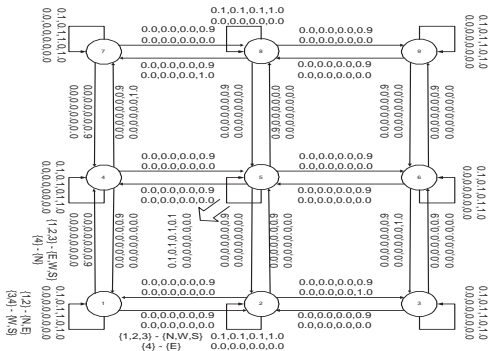
# An example

Vector Weighted Graph



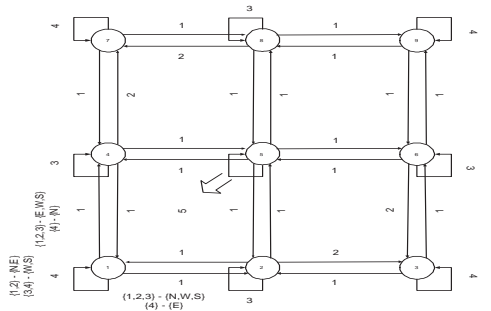
# An example

Sorted Vector Weighted Graph  
 with Set Bijections



# An example

Weighted DiGraph (WG)

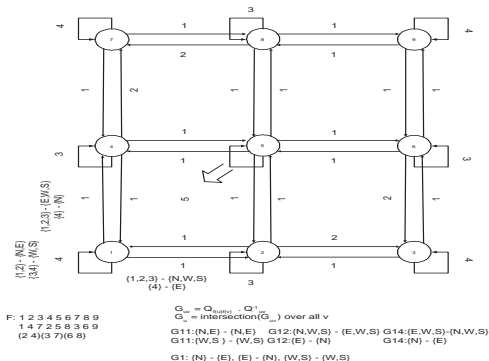


An automorphism in AutWG :

F: 1 2 3 4 5 6 7 8 9  
 1 4 7 2 5 8 3 6 9  
 (2 4)(3 7)(6 8)

# An example

Finding State Dependent Action  
 Recoding Functions





# Construction provides the Generators of $Aut.\mathcal{M}$

## Outline of the proof

- 1 Prove that  $Aut.\mathcal{M}$  can be partitioned into  $\{ \langle f, \{G_u\} \rangle \}$ .
- 2 Define a group homomorphism  $\phi : Aut.\mathcal{M} \rightarrow Aut.WG$ .
- 3 Prove that  $Aut.\mathcal{M}$  as partitioned above represents the set of all cosets of the kernel,  $ker(\phi)$ .
- 4 Since, the kernel is a normal subgroup, we know that,  $Aut.\mathcal{M} / ker(\phi) \cong im(\phi)$ .
- 5 Using the isomorphism, prove that the set  $\{ \langle f, \{G_u\} \rangle \}$  found using the above procedure is the set of generators of  $Aut.\mathcal{M}$ .

# Significance

- 1 Theoretically significant
- 2 Allows the use of off-the-shelf Graph Isomorphism solvers to find symmetries on MDPs.

## Nauty - No Automorphisms, Yes?

- Solves DGEN
  - Worst case complexity is exponential
  - On avg on a graph of  $n$  vertices takes  $n^2$  time
- Uses backtracking and a refinement procedure to find the canonical labelings
- Allows the use of a variety of vertex invariants to solve harder problems

# Nauty Integration

## Procedure

- 1 Construct the weighted pseudograph from the given MDP
- 2 Construct the weighted digraph using the above procedure
- 3 Construct a simple digraph from the weighted digraph using standard procedure
- 4 Get the generators of the digraph using Nauty
- 5 Use set bijections to find state-dependent action recoding functions for each generator
- 6 Generate the partition of  $|\Psi|$  induced by the group generated by the above functions
- 7 Use the partition to construct a reduced model and follow explicit model minimization

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# $\mathcal{G}$ -Reduced Image Algorithm

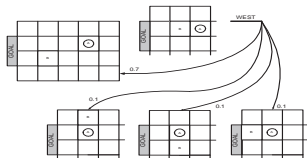
- Given an MDP  $\mathcal{M}$  and a Symmetry Group  $\mathcal{G}$ , finds the reduced model  $\mathcal{M}'$  induced by  $\mathcal{G}$
- Straightforward way by explicit enumeration takes  $|\Psi| \times |\mathcal{G}|$
- Breadth First Search with pruning
- Terminates when at least one representative from each equivalence class of  $\mathcal{G}$  has been examined
- With certain assumptions time complexity is  $O(|\Psi'| \times |\mathcal{G}|)$

## Experimental Setup - Probabilistic GridWorld

- **States:** An  $N \times N$  GridWorld
- **Actions:** Four probabilistic actions of going UP, DOWN, RIGHT and LEFT having a 90% success probability
- **Initial state:**  $(0,0)$
- **Goal states:**  $\{(0, N - 1), (N - 1, 0)\}$ .

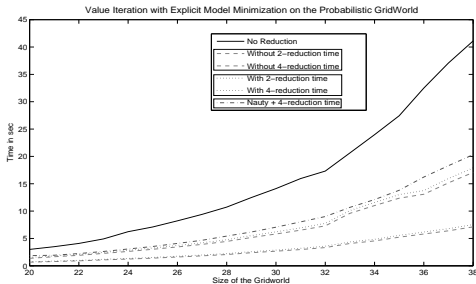
## Experimental Setup - GridWorld Soccer

- Slightly modified version of that described in (Bowling, 2003) with an  $M \times N$  grid with two agents (Attacker-**A** and Defender-**B**)
- **States:** The non-identical positions of the attacker and the defender leading to  $(MN)^2 - (MN)$  states
- **Actions:** The four compass directions: **N**, **E**, **W**, **S** and the hold action **H**
- **Goal States:** **W** action from the squares in front of the goal



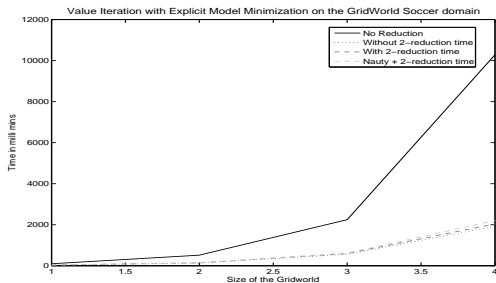


## Results - Probabilistic GridWorld



- Able to find the partition corresponding to the symmetry group
- For a grid of size  $N \times N$ , states  $(x,y)$ ,  $(y,x)$ ,  $(N-1-x,N-1-y)$  and  $(N-1-y,N-1-x)$  are equivalent

## Results - GridWorld Soccer



- Intuition gets it wrong; domain is not symmetric!
- The algorithm also finds another interesting symmetry due to the existence of the hold action.

# Summary

- In this work, we have provided a constructive proof for the *Isomorphism Completeness* of the problem of finding symmetries.
- We have also proposed the use of this constructive proof along with an efficient minimization algorithm to solve an MDP using symmetries and demonstrated it empirically.
- We are looking at adapting approximation algorithms for finding graph isomorphisms to finding approximate symmetries in MDPs.

# Thank You!

## $\mathcal{G}$ – Reduced Image Algorithm

```

01 Given  $\mathcal{M} = \langle S, A, \Psi, P, R \rangle$  and  $\mathcal{G} \leq \text{Aut}\mathcal{M}$ ,
02 Construct  $\mathcal{M}/B_{\mathcal{G}} = \langle S', A', \Psi', P', R' \rangle$ .
03 Set Que to some initial state  $\{s_0\}$ ,  $S' \leftarrow \{s_0\}$ 
04 While Que is non-empty
05    $s = \text{dequeue}\{\text{Que}\}$ 
06   For all  $a \in A_s$ 
07     If  $(s, a) \not\equiv_{\mathcal{G}} (s', a')$  for any  $(s', a') \in \Psi'$ , then
08        $\Psi' \leftarrow \Psi' \cup (s, a)$ 
09        $A' \leftarrow A' \cup a$ 
10        $R'(s, a) = R(s, a)$ 
11     For all  $t \in S$  such that  $P(s, a, t) > 0$ 
12       If  $t \equiv_{\mathcal{G}} s'$ , for some  $s' \in S'$ ,
13          $P'(s, a, s') \leftarrow P'(s, a, s') + P(s, a, t)$ 
14       else
15          $S' \leftarrow S' \cup t$ 
16          $P'(s, a, t) = P(s, a, t)$ 
17         add  $t$  to Que

```