

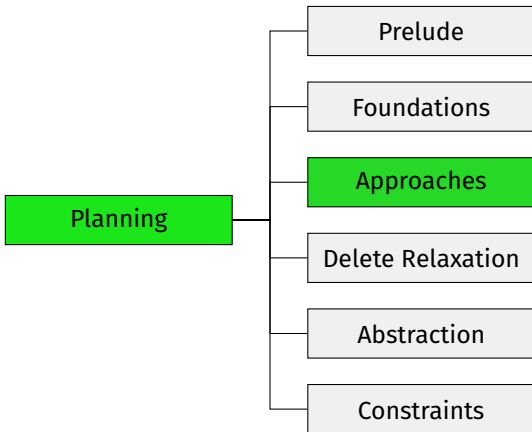
# Automated Planning

## C4. Symbolic Search: Binary Decision Diagrams

Jendrik Seipp

Linköping University

# Content of this Course



# Motivation

## Symbolic Search Planning: Basic Ideas

- come up with a good **data structure** for **sets of states**
- **hope:** (at least some) exponentially large state sets can be represented as polynomial-size data structures
- simulate a standard search algorithm like **breadth-first search** using these set representations

# Symbolic Breadth-First Progression Search

## Symbolic Breadth-First Progression Search

```

def bfs-progression( $V, I, O, \gamma$ ):
    goal_states := models( $\gamma$ )
    reached0 := {I}
    i := 0
    loop:
        if reachedi  $\cap$  goal_states  $\neq \emptyset$ :
            return solution found
        reachedi+1 := reachedi  $\cup$  apply(reachedi, O)
        if reachedi+1 = reachedi:
            return no solution exists
        i := i + 1
  
```

$\leadsto$  If we can implement operations **models**, **{I}**,  $\cap$ ,  $\neq \emptyset$ ,  $\cup$ , **apply** and = efficiently, this is a reasonable algorithm.

# Data Structures for State Sets

## Representing State Sets

We need to represent and manipulate state sets (again)!

- How about an explicit representation, like a **hash table**?
- And how about our good old friend, the **formula**?

# Time Complexity: Explicit Representations vs. Formulas

Let  $k$  be the **number of state variables**,  
 $|S|$  the **number of states** in  $S$  and  
 $\|S\|$  the **size of the representation** of  $S$ .

	Hash table	Formula
$s \in S?$	$O(k)$	$O(\ S\ )$
$S := S \cup \{s\}$	$O(k)$	$O(k)$
$S := S \setminus \{s\}$	$O(k)$	$O(k)$
$S \cup S'$	$O(k S  + k S' )$	$O(1)$
$S \cap S'$	$O(k S  + k S' )$	$O(1)$
$S \setminus S'$	$O(k S  + k S' )$	$O(1)$
$\bar{S}$	$O(k2^k)$	$O(1)$
$\{s \mid s(v) = \mathbf{T}\}$	$O(k2^k)$	$O(1)$
$S = \emptyset?$	$O(1)$	<b>co-NP-complete</b>
$S = S'?$	$O(k S )$	<b>co-NP-complete</b>
$ S $	$O(1)$	<b>#P-complete</b>



## Which Operations are Important?

- **Explicit representations** such as hash tables are unsuitable because their size grows linearly with the number of represented states.
- **Formulas** are very efficient for some operations, but not for other important operations needed by the breadth-first search algorithm.
  - Examples:  $S \neq \emptyset?$ ,  $S = S'?$

# Canonical Representations

- One of the problems with formulas is that they allow **many different representations** for the same set.
  - For example, all unsatisfiable formulas represent  $\emptyset$ .This makes equality tests expensive.
- We would like data structures with a **canonical representation**, i.e., with only **one possible representation** for every state set.
- Reduced ordered **binary decision diagrams** (BDDs) are an example of such a canonical representation.

## Time Complexity: Formulas vs. BDDs

Let  $k$  be the **number of state variables**,  
 $|S|$  the **number of states** in  $S$  and  
 $\|S\|$  the **size of the representation** of  $S$ .

	Formula	BDD
$s \in S?$	$O(\ S\ )$	$O(k)$
$S := S \cup \{s\}$	$O(k)$	$O(k)$
$S := S \setminus \{s\}$	$O(k)$	$O(k)$
$S \cup S'$	$O(1)$	$O(\ S\  \ S'\ )$
$S \cap S'$	$O(1)$	$O(\ S\  \ S'\ )$
$S \setminus S'$	$O(1)$	$O(\ S\  \ S'\ )$
$\bar{S}$	$O(1)$	$O(\ S\ )$
$\{s \mid s(v) = \mathbf{T}\}$	$O(1)$	$O(1)$
$S = \emptyset?$	co-NP-complete	$O(1)$
$S = S'?$	co-NP-complete	$O(1)$
$ S $	#P-complete	$O(\ S\ )$

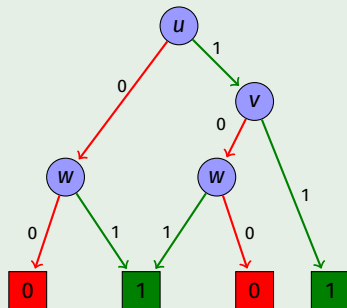
**Remark:** Optimizations allow BDDs with complementation ( $\bar{S}$ )  
 in constant time, but we will not discuss this here.

# Binary Decision Diagrams

# BDD Example

## Example

Possible BDD for  $(u \wedge v) \vee w$



# Exercise

## BDD exercise

Draw a BDD for  $(y \wedge \neg x) \vee z$

## Binary Decision Diagrams: Definition

### Definition (BDD)

Let  $V$  be a set of propositional variables.

A **binary decision diagram (BDD)** over  $V$  is a directed acyclic graph with labeled arcs and labeled vertices such that:

- There is exactly one node without incoming arcs.
- All sinks (nodes without outgoing arcs) are labeled **0** or **1**.
- All other nodes are labeled with a variable  $v \in V$  and have exactly two outgoing arcs, labeled **0** and **1**.

A note on notation:

- In BDDs, **1** stands for **T** and **0** for **F**.
- We follow this customary notation in BDDs, but stick to **T** and **F** when speaking of logic.

# Binary Decision Diagrams: Terminology

## BDD Terminology

- The node without incoming arcs is called the **root**.
- The labeling variable of an internal node is called the **decision variable** of the node.
- The nodes reached from node  $n$  via the arc labeled  $i \in \{0, 1\}$  is called the  **$i$ -successor** of  $n$ .
- The BDDs which only consist of a single sink are called the **zero BDD** and **one BDD**.

**Observation:** If  $B$  is a BDD and  $n$  is a node of  $B$ , then the subgraph induced by all nodes reachable from  $n$  is also a BDD.

- This BDD is called the **BDD rooted at  $n$** .



## BDD Semantics

### Testing whether a BDD Includes a Variable Assignment

**def** *bdd-includes*(*B*: BDD, *l*: variable assignment):

Set *n* to the root of *B*.

**while** *n* is not a sink:

Set *v* to the decision variable of *n*.

Set *n* to the 1-successor of *n* if  $l(v) = \mathbf{T}$  and  
to the 0-successor of *n* if  $l(v) = \mathbf{F}$ .

**return true** if *n* is labeled 1, **false** if it is labeled 0.

### Definition (Set Represented by a BDD)

Let *B* be a BDD over variables *V*.

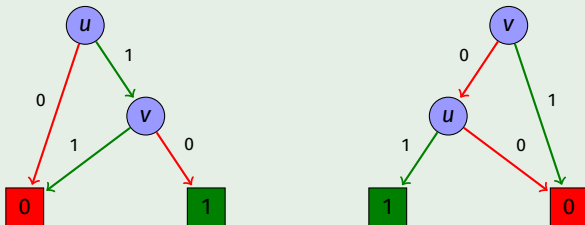
The **set represented by *B***, in symbols  $r(B)$ ,  
consists of all variable assignments  $l : V \rightarrow \{\mathbf{T}, \mathbf{F}\}$   
for which *bdd-includes*(*B*, *l*) returns true.

# BDDs as Canonical Representations

## Ordered BDDs: Motivation

In general, BDDs are not a canonical representation for sets of interpretations. Here is a simple counter-example ( $V = \{u, v\}$ ):

Example (BDDs for  $u \wedge \neg v$  with Different Variable Order)



Both BDDs represent the same state set, namely the singleton set  $\{\{u \mapsto \mathbf{T}, v \mapsto \mathbf{F}\}\}$ .

## Ordered BDDs: Definition

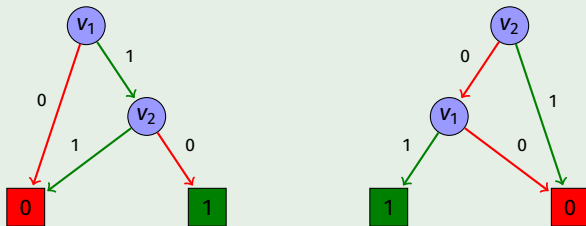
- As a first step towards a canonical representation, we now require that the set of variables is **totally ordered** by some ordering  $\prec$ .
- In particular, we will only use variables  $v_1, v_2, v_3, \dots$  and assume the ordering  $v_i \prec v_j$  iff  $i < j$ .

### Definition (Ordered BDD)

A BDD is **ordered** (w.r.t.  $\prec$ ) iff for each arc from a node with decision variable  $u$  to a node with decision variable  $v$ , we have  $u \prec v$ .

## Ordered BDDs: Example

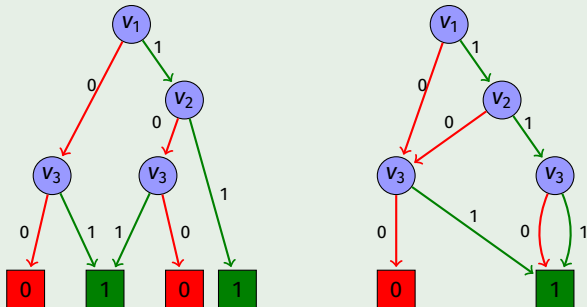
### Example (Ordered and Unordered BDD)



The left BDD is ordered w.r.t. the ordering we use in this chapter, the right one is not.

## Reduced Ordered BDDs: Are Ordered BDDs Canonical?

### Example (Two equivalent BDDs that can be reduced)



- Ordered BDDs are still not canonical:  
both ordered BDDs represent the same set.
- However, ordered BDDs can easily be **made** canonical.

## Reduced Ordered BDDs: Reductions (1)

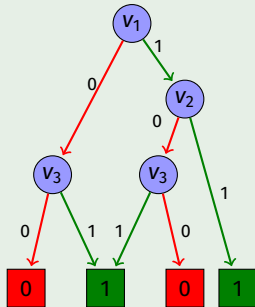
There are two important operations on BDDs that do not change the set represented by it:

### Definition (Isomorphism Reduction)

If the BDDs rooted at two different nodes  $n$  and  $n'$  are **isomorphic**, then all incoming arcs of  $n'$  can be redirected to  $n$ , and all BDD nodes unreachable from the root can be removed.

## Reduced Ordered BDDs: Reductions (2)

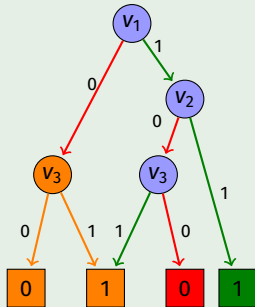
### Example (Isomorphism Reduction)





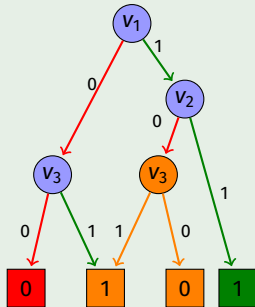
## Reduced Ordered BDDs: Reductions (2)

### Example (Isomorphism Reduction)



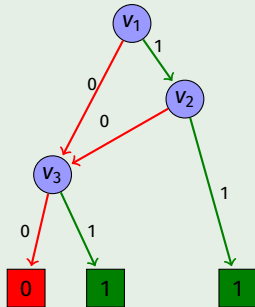
## Reduced Ordered BDDs: Reductions (2)

### Example (Isomorphism Reduction)



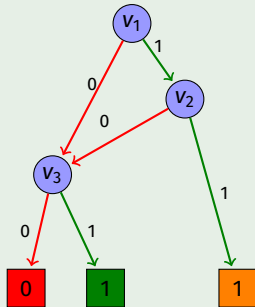
## Reduced Ordered BDDs: Reductions (2)

### Example (Isomorphism Reduction)



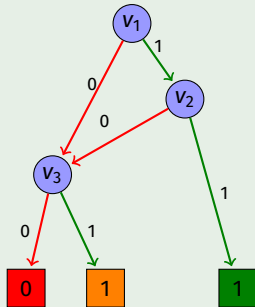
## Reduced Ordered BDDs: Reductions (2)

### Example (Isomorphism Reduction)



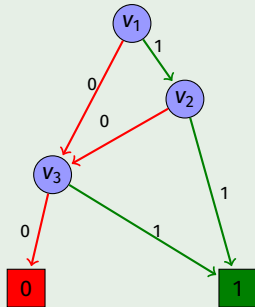
## Reduced Ordered BDDs: Reductions (2)

### Example (Isomorphism Reduction)



## Reduced Ordered BDDs: Reductions (2)

### Example (Isomorphism Reduction)



## Reduced Ordered BDDs: Reductions (3)

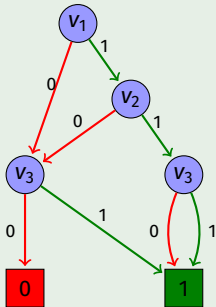
There are two important operations on BDDs that do not change the set represented by it:

### Definition (Shannon Reduction)

If both outgoing arcs of an internal node  $n$  of a BDD lead to the same node  $m$ , then  $n$  can be removed from the BDD, with all incoming arcs of  $n$  going to  $m$  instead.

## Reduced Ordered BDDs: Reductions (4)

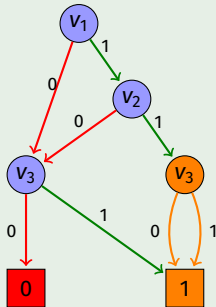
### Example (Shannon Reduction)





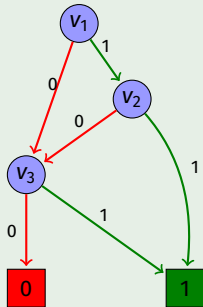
## Reduced Ordered BDDs: Reductions (4)

### Example (Shannon Reduction)



## Reduced Ordered BDDs: Reductions (4)

### Example (Shannon Reduction)



## Reduced Ordered BDDs: Definition

### Definition (Reduced Ordered BDD)

An ordered BDD is **reduced** iff it does not admit any isomorphism reduction or Shannon reduction.

### Theorem (Bryant 1986)

*For every state set  $S$  and a fixed variable ordering, there exists exactly one reduced ordered BDD representing  $S$ .*

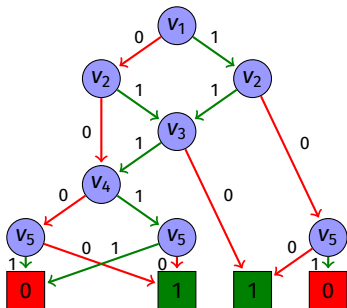
*Moreover, given any ordered BDD  $B$ , the equivalent reduced ordered BDD can be computed in linear time in the size of  $B$ .*

↪ Reduced ordered BDDs are the canonical representation we are looking for.

From now on, we simply say **BDD** for **reduced ordered BDD**.

## Reduced Ordered BDDs: Exercise

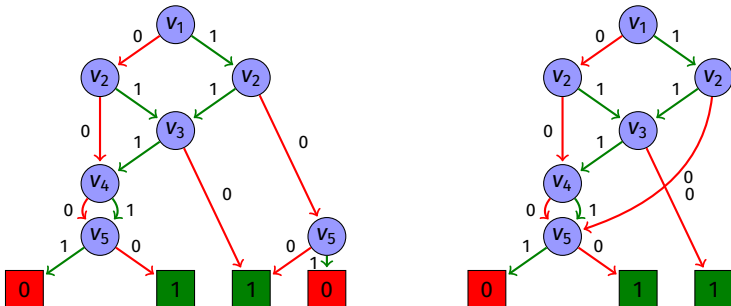
Consider the following ordered BDD over variables  $v_1, \dots, v_5$ :



Provide the equivalent reduced ordered BDD.

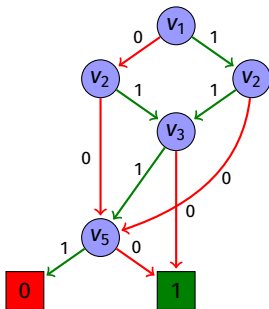
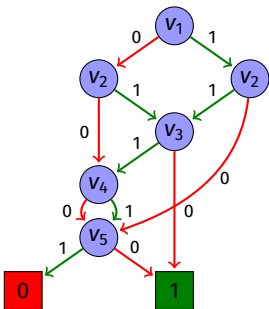
## Reduced Ordered BDDs: Exercise Solution (1)

In the first two steps we can combine the three isomorphic sub-BDDs with root  $v_5$ .



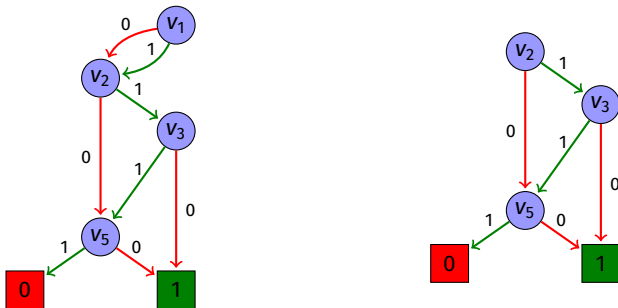
## Reduced Ordered BDDs: Exercise Solution (2)

In addition to the isomorphism reduction that combines the two 1-leaves, a Shannon reduction at the node with decision variable  $v_4$  is now also possible.



## Reduced Ordered BDDs: Exercise Solution (3)

Now the two sub-BDDs whose roots are the nodes with decision variable  $v_2$  are isomorphic. Combining them allows a Shannon reduction at  $v_1$ .



The BDD represents the formula  $(v_2 \vee \neg v_5) \wedge (\neg v_3 \vee \neg v_5)$  and the following 20 states: 00000, 00010, 00100, 00110, 01000, 01001, 01010, 01011, 01100, 01110, 10000, 10010, 10100, 10110, 11000, 11001, 11010, 11011, 11100, 11110.

# Summary



## Summary

- **Symbolic search** is based on the idea of performing a state-space search where many states are considered “at once” by operating on **sets of states** rather than individual states.
- **Binary decision diagrams** are a data structure to compactly represent and manipulate sets of variable assignments.
- **Reduced ordered** BDDs are a **canonical representation** of such sets.