Motivation

- Previous lectures: How to determine satisfiability of propositional formulas
- But in some contexts, this is not enough
- Sometimes we need to efficiently represent the set of all solutions (i.e., satisfying assignments) to the formula
- Binary decision diagrams (BDDs): compact representation of all satisfying assignments of formula

Historical Context

- Invented by Randal Bryant from CMU; introduced in very influential 1986 paper
- BDDs have many applications: hardware and software verification, computer aided design of circuits, relational databases, ...
- Don Knuth: “One of the really fundamental data structures that came out in the last twenty years”

Binary Decision Trees

- Before talking about BDDs, let us first consider a simpler data structure called binary decision tree
- Binary decision tree: A tree data structure with two kinds of vertices, terminal and non-terminal
- Terminal vertices: boolean constants $\top$ (1) and $\bot$ (0)
- Non-terminal vertex labeled $v$ corresponds to boolean variable $v$ in propositional formula

Binary Decision Trees, cont.

- Each non-terminal vertex has two successors (i.e., edges)
- Low successor of non-terminal vertex $v$ (labeled with dashed edge) corresponds to assigning 0 to $v$
- High successor of vertex $v$ (labeled with solid edge) corresponds to assigning 1 to $v$
- Each path from root to a terminal node corresponds to an interpretation for the formula
- Paths ending in 1 correspond to satisfying interpretations
- Paths ending in 0 correspond to falsifying interpretations

Example: Binary Decision Tree

- Binary decision tree for formula with variables $x_1, x_2, x_3$:

  ![Binary Decision Tree Diagram]

- Question: Is interpretation $x_1 = \bot, x_2 = \bot, x_3 = \top$ satisfying?
- Question: What about $x_1 = \top, x_2 = \bot, x_3 = \top$?
- This BDT is ordered: Any path from the root to a terminal contains variables in the same order (order: $x_1 < x_2 < x_3$)
Binary Decision Tree vs. Truth Table

- Binary decision tree encodes all satisfying assignments, but how does it compare to truth tables?

- Good news: Not as bad as it looks; there is a lot of redundancy! (e.g., different subparts of the tree are isomorphic)

- Idea: Merge redundant subparts and compress BDT into a much more space-efficient DAG representation!

Reduced Ordered Binary Decision Diagram

- To create compact representation, start with an ordered binary decision tree and apply a set of reduction rules

- There are three reduction rules; we apply these rules until none of them can be further applied

- The resulting data structure is called a reduced ordered binary decision diagram (ROBDD)

- When we talk about BDDs, we really mean ROBDDs (and so does everyone else)

Reduction Rule #1

Reduction rule #1: Merge all terminal nodes 1 into one node, and merge all terminal nodes 0 into one node.

Example: Merging Isomorphic Subtrees

- Which subgraphs are isomorphic?

Reduction Rule #2

- Reduction rule #2: Merge isomorphic subgraphs

  - Two subgraphs are isomorphic if:

    1. Their root represents the same variable
    2. The subgraphs rooted at their low successors are isomorphic
    3. The subgraphs rooted at their high successors are also isomorphic

Reduction Rule #3

- Reduction rule #3: Remove redundant nodes.

  - Node \( v \) is redundant if its low and high successors are the same.

  - Why?

  - Eliminating redundant node \( v \): Remove \( v \) from the graph, and redirect incoming edge to \( v \) to \( v \)'s children
Example: Removing Redundant Nodes

Which nodes are redundant?

Exposing New Reductions

Question: Can removing redundant nodes expose new isomorphic subtrees? (i.e., do we need to apply reduction 2 again after reduction 3?)

Example: Are there any isomorphic subparts in this graph?

Exposing New Reductions, cont.

Question: Can merging isomorphic subgraphs expose new redundant nodes? (i.e., do we need to apply reduction 3 again after reduction 2?)

Example: Are there any redundant nodes in this graph?

Applying Reductions

As examples illustrate, we may need to apply reduction rules again after each reduction.

Thus, have to apply reductions 2 and 3 until no isomorphic subgraphs and no redundant nodes left.

Resulting data structure after exhaustive application of reduction rules is a ROBDD.

ROBDD is more space efficient compared to the binary decision tree because it eliminates redundancies.

Building ROBDDs

Starting with BDT and applying reduction rule useful way to understand BDD invariants.

But no one builds BDDs this way. Why?

Idea: Build the ROBDD for a formula directly without building the binary decision tree!

Building BDDs directly from Formulas

Consider a formula $\phi$ of the form $\phi_1 \ast \phi_2$ where $\ast$ is any boolean connective.

To construct the ROBDD for $\phi$, first recursively construct the ROBDDs for $\phi_1$ and $\phi_2$.

Then, combine BDDs for $\phi_1$ and $\phi_2$ to form the BDD for $\phi$.

To combine BDDs for $\phi_1$ and $\phi_2$, will use a technique called Shannon’s decomposition.
Cofactoring and Shannon’s Decomposition

- Shannon’s decomposition involves an operation called **cofactoring**.
- Cofactoring a boolean formula restricts the formula to a particular value of a variable.
- Example: What is the resulting formula when we restrict $x_1$ to $\top$ in $x_1 \land x_2$?
  - The positive cofactor $\phi \downarrow x_i$ is the resulting formula when $x_i$ is replaced by $\top$.
  - The negative cofactor $\phi \downarrow \neg x_i$ is $\phi$ with $x_i$ replaced by $\bot$.
- Example: What is $(x_1 \lor (\neg x_2 \land x_3)) \downarrow \neg x_2$?

Cofactoring Using BDDs

- If we have a BDD for $\phi$, it is easy to build BDD for positive and negative cofactors of $\phi$ with respect to $x$.
- Given BDD for $\phi$, how do we build BDD for $\phi \downarrow x$?
  - How do we build BDD for $\phi \downarrow \neg x$?

Shannon’s Decomposition

- Can now define Shannon’s decomposition using cofactors.
- Shannon’s decomposition:
  \[
  \phi \equiv (x \land \phi \downarrow x) \lor (\neg x \land \phi \downarrow \neg x)
  \]
  - Basically a case analysis on $x$’s truth value.
  - Either $x$ is $\top$ or $\bot$.
  - If $x$ is $\top$, then the positive cofactor must be true.
  - If $x$ is $\bot$, then the negative cofactor must be true.

Using Shannon’s Decomposition to Build BDD

- Now, we can directly build BDD for a formula $\phi_1 \ast \phi_2$ using Shannon’s decomposition.
- First, build BDD for subformulas $\phi_1$ and $\phi_2$.
- Then, use operation called **Apply** to build BDD for $\phi$ from BDDs for $\phi_1$ and $\phi_2$.
- The Apply operation considers three cases.

Apply: Case #1

- Case #1: Suppose that the BDDs for $\phi_1$ and $\phi_2$ have root nodes $x$ and $x'$ and both are boolean constants.
  - Then, what is the BDD for $\phi_1 \ast \phi_2$?
  - This is the base case for our Apply procedure.
An Example

Consider formula $\phi_1 \lor \phi_2$ where $\phi_1$ is $x_1 \leftrightarrow x_2$, and $\phi_2$ is $\neg x_2$

Suppose $x_1$ precedes $x_2$ in variable order

Assume we have BDDs for $\phi_1$ and $\phi_2$:

![BDD Diagram]

We want to use Apply to compute BDD for $\phi_1 \lor \phi_2$
Example, continued

- Assuming we computed the BDDs for negative and positive cofactors, BDD for $\phi_1 \lor \phi_2$ looks like:

  ![BDD for $\phi_1 \lor \phi_2$]

- Here, the positive cofactor is just 1
- Negative cofactor is:

  ![BDD for negative cofactor]

- What is the final BDD?

Example 2

- Give the BDD representing the negation of the following BDD:

  ![BDD for negation]

Rest Of Lecture

- So far: talked about what BDDs are and how to construct them
- In addition to compactly representing all satisfying interpretations, BDDs have some other useful properties
- Rest of lecture: Talk about some interesting properties of BDDs

Important Property of BDDs: Canonicity

- BDDs are a canonical representation of boolean formulas.
- Canonical means two equivalent formulas have same representation
- Thus, if we construct BDDs for two equivalent formulas using same variable order, resulting BDDs are the same!
- Are any of the normal forms we talked about (NNF, CNF, DNF) canonical?
- Example:

Consequences of Canonicity

- Corollary 1: Given BDDs for $\phi_1$ and $\phi_2$ constructed with same variable order, equivalence of $\phi_1$ and $\phi_2$ just syntactic check
- Corollary 2: Given BDD for formula $\phi$, $\phi$ is unsatisfiable if and only if its BDD representation is the boolean constant 0.
- How does this corollary follow from canonicity?
- Corollary 3: Given BDD for formula $\phi$, $\phi$ is valid if and only if its BDD representation is the boolean constant 1.
BDD Size and Variable Order

- Another important BDD property: Size of a BDD for a given formula $\phi$ is very sensitive to variable order!
- For some variable orders, the size of the BDD may be only polynomial in the number of variables.
- For some other variable orders, the size of the BDD for the same formula may be exponential.
- Furthermore, there are boolean formulas for which any variable order causes an exponential blow-up.

Choosing Variable Order

- Since size of BDD is so sensitive to variable order, we would like to construct BDD using a good variable order.
- Unfortunately, NP-complete to decide whether a given order is optimal.
- Typically, heuristics are used to predict good variable order.
- Heuristics for finding good variable order can be either static (i.e., determined up-front) or dynamic (i.e., change as BDD operations proceed).
- Dynamic orders typically yield more compact BDDs, but slower.

Summary

- BDDs can be used to compactly represent all satisfying assignments to a boolean formula.
  - Pros:
    + Canonical representation $\Rightarrow$ checking equivalence, validity, satisfiability constant time operations once BDD is built
    + If we have good variable order, can yield a compact representation of all satisfying assignments of formula.
  - Cons:
    - Compactness very sensitive to variable order.
    - Can cause an exponential blow-up in the representation of the formula.