# **Automated Reasoning**

- A Comprehensive Collection -

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# A document presented for the Automated Reasoning

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# Introduction

Welcome to the seminar on Automated Reasoning. This document is a compilation of various seminar materials designed to provide a comprehensive overview of the field. Here, we explore the fundamental concepts, methodologies, and applications of automated reasoning in computer science and logic.

This is an example of referencing Section

# **Chapter 1**

# **Preliminaries**

#### **Truth Function**

**Definition 1.1.** Let  $\mathbb{B} = \{\mathsf{T}, \mathsf{F}\}$  be the *boolean domain*. Let  $k \in \mathbb{N}$ . A mapping

$$f: \mathbb{B}^k \to \mathbb{B}$$

is called a truth function.

**Remark 1.1** (Truth Functions of Connectives). The logical connectives are assumed to be **truth-functional**. Hence, they are represented by certain **truth functions**.

**Logical Negation** The *logical not connective* defines the truth function  $f \neg$  as follows:

$$f^{\neg}(\mathsf{F}) = \mathsf{T}$$
  
 $f^{\neg}(\mathsf{T}) = \mathsf{F}$ 

**Logical Conjunction** The *conjunction connective* defines the truth function  $f^{\wedge}$  as follows:

$$f^{\wedge}(T,T) = T$$
  
 $f^{\wedge}(T,F) = F$   
 $f^{\wedge}(F,T) = F$   
 $f^{\wedge}(F,F) = F$ 

**Logical Disjunction** The *disjunction connective* defines the truth function  $f^{\vee}$  as follows:

$$f^{\vee}(T,T) = T$$
  
 $f^{\vee}(T,F) = T$   
 $f^{\vee}(F,T) = T$   
 $f^{\vee}(F,F) = F$ 

#### **Count of Truth Functions**

**Proposition 1.1.** There are  $2^{(2^k)}$  distinct truth functions on k variables.

*Proof.* Let  $f : \mathbb{B}^k \to \mathbb{B}$  be a truth function for  $k \in \mathbb{N}$ . Then

(Cardinality of Cartesian Product of Finite Sets)

$$\#(\mathbb{B}^{k}) = \#(\mathbb{B} \times \cdots \times \mathbb{B})$$

$$= \#\mathbb{B} \#\mathbb{B} \cdots \#\mathbb{B}$$

$$= k \text{ times}$$

$$= 2 \cdot 2 \cdots 2$$

$$= 2^{k}.$$

(Cardinality of Set of All Mappings.)

$$\#(T^S) := \{ f \subseteq S \times T : f \text{ is a mapping} \} = (\#T)^{(\#S)} \implies \#(\mathbb{B}^{(\mathbb{B}^k)}) = 2^{(2^k)} \}$$

#### **Unary Truth Functions**

**Corollary 1.1.1.** *There are 4 distinct unary truth functions:* 

- *The constant function* f(p) = F
- The constant function f(p) = T
- The identity function f(p) = p
- The logical not function  $f(p) = \neg p$

*Proof.* From Count of Truth Functions there are  $2^{(2^1)} = 4$  distinct truth functions on 1 variable. These can be depicted in a truth table as follows:

 $\circ_1$ : Whether p = T or p = F,  $\circ_1(p) = T$ . Thus  $\circ_1$  is the constant function  $\circ_1(p) = T$ .

 $\circ_2$ : We have

(1) 
$$p = T \implies \circ_2(p) = T$$

(2) 
$$p = F \implies \circ_2(p) = F$$

Thus  $\circ_2$  is the *identity function*  $\circ_2(p) = p$ .

∘<sub>3</sub>: We have

(1) 
$$p = T \implies \circ_3(p) = F$$

(2) 
$$p = F \implies \circ_3(p) = T$$

Thus  $\circ_3$  is the *logical not function*  $\circ_3(p) = \neg p$ .

 $\circ_4$ : Whether p = T or p = F,  $\circ_4(p) = F$ . Thus  $\circ_1$  is the constant function  $\circ_4(p) = F$ .

### **Binary Truth Functions**

**Corollary 1.1.2.** *There are* 16 *distinct unary truth functions:* 

• Two constant operations:

$$-f_{\mathsf{T}}(p,q)=\mathsf{T}$$

$$- f_{\mathsf{F}}(p,q) = \mathsf{F}$$

• Two projections:

- 
$$Proj_1(p,q) = p$$

- 
$$Proj_2(p,q) = q$$

• Two negated projections:

$$- \overline{\mathsf{Proj}_1}(p,q) = \neg p$$

$$- \overline{\mathsf{Proj}_2}(p,q) = \neg q$$

- *The conjunction:*  $p \land q$
- *The disjunction:*  $p \lor q$
- Two conditionals:

$$-p \implies q$$

$$-q \implies p$$

- The biconditional (iff):  $p \iff q$
- The exclusive or (xor):  $\neg(p \iff q)$
- Two negated conditionals:

$$-\neg(p \implies q)$$

$$- \neg (q \implies p)$$

- The NAND  $p \uparrow q$
- The NOR  $p \downarrow q$

*Proof.* From Count of Truth Functions there are  $2^{(2^2)} = 16$  distinct truth functions on 2 variable. These can be depicted in a truth table as follows:

p	01	02	03	$\circ_4$
Т	Т	Τ	F	F
F	F	Т	F	F

# **Chapter 2**

# **Conflict Driven Clause Learning (CDCL)**

#### **Boolean Satisfiability Problem (SAT)**

**Definition 2.1.** Let  $X = \{x_1, x_2, \dots, x_n\}$  be a set of propositional variables. Let L be a set of one or more propositional formulas constructed using only:

- $x_i \in X \text{ for } i = 1, ..., n;$
- the 4 unary logical connectives;
- the 16 binary logical connectives;

I present the CDCL algorithm and its implementation based on existing literature. This algorithm is used to solve SAT problems efficiently...

### 2.0.1 SAT solving basics

The CDCL algorithm is a mix of two older approaches to SAT solving: DPLL and Resolution...

#### Backtracking and unit propagation as in DPLL solvers

When we provide a SAT instance to a DPLL solver it builds up a search tree of assignments...

#### Resolution

If a formula *F* contains the clauses  $\{\neg x\} \cup A$  and  $\{x\} \cup A$ ...

### 2.1 Principles of CDCL

Now that we have seen how Backtracking and Resolution work we are ready to merge these approaches...

#### 2.1.1 The trail

When applying CDCL rather than exploring a search tree of assignments...

### 2.1.2 Conflict clauses and backjumping

Consider our previous example again. When we want to continue building up our trail...

### 2.1.3 The implication graph

A nice way to illustrate the functionality of CDCL are implication graphs...

## 2.1.4 The algorithm

To get a clearer view Algorithm 4.1 shows the pseudocode for the CDCL algorithm...

## 2.2 Implementation

Let us now look at how the algorithm is implemented in real life...

#### 2.2.1 Clauses

We use a monolithic array MEM to hold the original formula's clauses as well as the newly learned clauses...

#### 2.2.2 Literals

Assume the variables are  $x_1, x_2, ..., x_n$ . We represent  $x_k$  by k...

### 2.3 Results

It is important to say that CDCL is a sound and complete algorithm for the propositional satisfiability problem...

# **Bibliography**

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