SOLVING HARD PROBLEMS QUICKLY USING SAT SOLVERS

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ABOUT THIS TALK

This talk is about solving real world problems using SAT solvers.

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SAT solvers will be used as a black box and we will not cover any of the theory behind them.

We will start by going over the boolean satisfaction (SAT) problem.

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Then we will learn how to drive a SAT solver from C++.

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Then we will learn how to drive a SAT solver from C++.

Then we will apply our newly gained knowledge to two practical examples, Sudoku and Master Key Systems.

INTRODUCTION TO SAT

The boolean satisfaction problem (SAT) is about checking whether a logical formula is *satisfiable*.

The boolean satisfaction problem (SAT) is about checking whether a logical formula is *satisfiable*.

A formula is *satisfiable* if we can assign values to its variables so that the whole formula is true.

```
if (A || B || (!A && !C)) {
    create_new_widget();
} else {
    reuse_old_widget();
}
```

```
if (A || B || (!A && !C)) {
    create_new_widget();
} else {
    reuse_old_widget();
}
```

if (A || B || (!A && !C))

if (A || B || (!A && !C)) { create_new_widget(); } else { reuse_old_widget();

}

$A \lor B \lor (\neg A \land \neg C)$

```
if (A || B || (!A && !C))
```

Negation, also known as NOT [!A]

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 $\neg \alpha$

Negation, also known as NOT [!A]

 $\neg lpha$

Disjunction, also known as OR [A | B]

Negation, also known as NOT [!A]

 $\neg lpha$

Disjunction, also known as OR [A || B] $lpha \lor eta$

Negation, also known as NOT [!A]

 $\neg lpha$

Disjunction, also known as OR [A || B] $lpha \lor eta$

Conjunction, also known as AND [A && B]

Negation, also known as NOT [!A]

 $\neg lpha$

Disjunction, also known as OR [A $~\mid~$ B] $\alpha \lor \beta$

Conjunction, also known as AND [A && B]

 $lpha\wedgeeta$

IMPLICATION

IMPLICATION

 $lpha \implies eta$

IMPLICATION				
	lpha	$\implies \beta$		
lpha	eta	$lpha \implies eta$		
1	1	1		
1	0	0		
0	1	1		
0	0	1		

EQUIVALENCE

$\begin{array}{c} \textbf{EQUIVALENCE} \\ \alpha \iff \beta \end{array}$

EQUIVALENCE			
	lpha	$\iff eta$	
lpha	eta	$lpha\iffeta$	
1	1	1	
1	0	0	
0	1	0	
0	0	1	

All the practical examples in this talk can be formulated using just these logical operators.

All the practical examples in this talk can be formulated using just these logical operators. There is a small problem; SAT solvers do not accept arbitrary logical formulae. All the practical examples in this talk can be formulated using just these logical operators.

There is a small problem; SAT solvers do not accept arbitrary logical formulae.

They only accept logical formulae in the *Conjunctive Normal Form* (CNF). *Conjunctive Normal Form* (CNF) means that the formula is a *conjunction* of *disjunctive* clauses.

Conjunctive Normal Form (CNF) means that the formula is a *conjunction* of *disjunctive* clauses. In other words, the formula is an AND of many ORs.

$A \lor B \lor (\neg A \land \neg C)$

$A \lor B \lor (\neg A \land \neg C)$

How do we convert this to CNF?

CONVERSIONS

CONVERSIONS

Every formula can be converted into an *equivalent* CNF formula.
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Every formula can be converted into an *equivalent* CNF formula.

It helps if you know De Morgan's laws, distributive laws and some simple identities.

Original clause Equivalent clause

$\neg \neg \alpha$	lpha
$ eg(lpha \wedge eta)$	$\neg \alpha \vee \neg \beta$
$ eg(lpha \lor eta)$	$ eg lpha \wedge eg eta$
$(\alpha \wedge \beta) \vee \gamma$	$(\alpha \vee \gamma) \wedge (\beta \vee \gamma)$
$(lpha ee eta) \wedge \gamma$	$(lpha\wedge\gamma)ee(eta\wedge\gamma)$
$lpha \implies eta$	$ eg lpha \lor eta$
$lpha \iff eta$	$(lpha \implies eta) \land (lpha \iff eta)$

$A \lor B \lor (\neg A \land \neg C)$

$A ee B ee (eg A \wedge eg C)$ $\gamma ee (lpha \wedge eta C)$

$egin{aligned} A ee B ee (eg A \wedge eg C) \ & \gamma ee (lpha \wedge eta) \ & (\gamma ee lpha) \wedge (\gamma ee eta) \end{aligned}$





That's all we need to know about (CNF-)SAT.

That's all we need to know about (CNF-)SAT. At least for now.

HOW TO DRIVE SAT SOLVER FROM C++

We will be using MiniSat's C++ interface.

We will be using MiniSat's C++ interface. There is a CMake-integrated fork at https://github.com/master-keying/minisat We will be using MiniSat's C++ interface. There is a CMake-integrated fork at https://github.com/master-keying/minisat It is also in vcpkg as "minisat-master-keying".

• Solver - The solver itself

- Solver The solver itself
- Vec A relocating implementation of std::vector

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and 2 vocabulary types

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• Var - The representation of a logic variable

- Solver The solver itself
- Vec A relocating implementation of std::vector

and 2 vocabulary types

- Var The representation of a logic *variable*
- Lit The concrete *literal* of a variable in a clause

$(A \lor B \lor \neg A) \land (A \lor B \lor \neg C)$

$(A \lor B \lor \neg A) \land (A \lor B \lor \neg C)$ 3 variables, A, B, and C

 $(A \lor B \lor \neg A) \land (A \lor B \lor \neg C)$ 3 variables, A, B, and C4 literals, $A, B, \neg A$, and $\neg C$.

Let's solve the formula $(A \lor B \lor \neg A) \land (A \lor B \lor \neg C)$

```
Let's solve the formula (A \lor B \lor \neg A) \land (A \lor B \lor \neg C)
```

```
#include <minisat/core/Solver.h>
#include <iostream>
int main() {
   using Minisat::mkLit; using Minisat::lbool;
   Minisat::Solver solver;
   auto A = solver.newVar();
   auto B = solver.newVar();
   auto C = solver.newVar();
    solver.addClause( mkLit(A), mkLit(B), ~mkLit(A));
    solver.addClause( mkLit(A), mkLit(B), ~mkLit(C));
```

... and then retrieve the results

... and then retrieve the results

```
auto sat = solver.solve();
if (sat) {
    std::cout << "SAT\n"
        << "Model found:\n"
            << "A := " << (solver.modelValue(A) == 1_True) << '\n'
            << "B := " << (solver.modelValue(B) == 1_True) << '\n'
            << "C := " << (solver.modelValue(C) == 1_True) << '\n';
} else {
    std::cout << "UNSAT\n";
    return 1;
}</pre>
```

So what solution did Minisat find?

So what solution did Minisat find?

\$./example-1
SAT
Model found:
A := 0
B := 0
C := 0

Now we know enough to make a Sudoku solver.

HOW TO CONVERT SUDOKU TO SAT

Sudoku is a puzzle where you put numbers 1-9 onto a 9x9 grid, split into 9 3x3 boxes

5 6	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

Some of the numbers are prefilled and we have to fill in the rest, following some simple rules:

5 6	3			7				
6			1	9	5			
	9	8					6	
8				6				3
8 4 7			8		3			1 6
7				2				6
	6					2	8	
			4	1	9			5 9
				8			7	9

5.3

Some of the numbers are prefilled and we have to fill in the rest, following some simple rules:

5 6	3			7				
6			1	9	5			
	9	8					6	
8				6				3
8 4 7			8		3			1
7				2				6
	6					2	8	
			4	1	9			5 9
				8			7	9

1.	Each row contains all of
	the numbers 1-9

5.3
Some of the numbers are prefilled and we have to fill in the rest, following some simple rules:

5 6	3			7				
6			1	9	5			
	9	8					6	
8				6				3
8 4			8		3			1 6
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

- 1. Each row contains all of the numbers 1-9
- 2. Each column contains all of

the numbers 1-9

5.3

Some of the numbers are prefilled and we have to fill in the rest, following some simple rules:

5 6	3			7				
6			1	9	5			
	9	8					6	
8				6				3
8 4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5 9
				8			7	9

- 1. Each row contains all of the numbers 1-9
- 2. Each column contains all of

the numbers 1-9

3. Each 3x3 box contains all

of the numbers 1-9

5.3

When translating these rules into SAT, we have to start by defining the variables.

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The natural thing to do would be to assign each position a variable that can have values 1-9.

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The natural thing to do would be to assign each position a variable that can have values 1-9.

In SAT, variable can have 2 values, "true", or "false".

The solution is to have a variable per each position *and* each possible value.

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Let's denote these variables as $x_{r,c}^v$

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Let's denote these variables as $x_{r,c}^v$

If the variable $x_{r,c}^v$ is set to true, the r-th row and c-th column contains number v.

1. EACH ROW CONTAINS ALL OF THE NUMBERS 1-9

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$$orall (r,v) \in (rows imes values): x_{r,1}^v ee x_{r,2}^v ee \ldots ee x_{r,9}^v$$

1. EACH ROW CONTAINS ALL OF THE NUMBERS 1-9 $orall (r,v) \in (rows imes values): x_{r,1}^v \lor x_{r,2}^v \lor \ldots \lor x_{r,9}^v$ $orall (r,v) \in (rows imes values): \bigvee_{i=1}^9 x_{r,i}^v$

2. EACH COL CONTAINS ALL OF THE NUMBERS 1-9

2. EACH COL CONTAINS ALL OF THE NUMBERS 1-9

$$orall (c,v) \in (columns imes values): x_{1,c}^v ee x_{2,c}^v ee \ldots ee x_{9,c}^v$$

$$orall (c,v) \in (columns imes values) : igvee_{i=1}^9 x_{i,c}^v$$

3. EACH BOX CONTAINS ALL OF THE NUMBERS 1-9

3. EACH BOX CONTAINS ALL OF THE NUMBERS 1-9

$$orall (b,v) \in (boxes imes values): x^v_{br_1,bc_1} ee x^v_{br_1,bc_2} ee \ldots ee x^v_{br_3,bc_3}
onumber \ orall (b,v) \in (boxes imes values): \bigvee_{(r,c) \in b} x^v_{r,c}$$

We expressed the Sudoku rules as a set of clauses.

We expressed the Sudoku rules as a set of clauses. But an important set of clauses is missing.

$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$								
			$egin{array}{ccccc} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{array}$					
						$egin{array}{cccc} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{array}$		
	$\begin{array}{c}1&2&3\\4&5&6\\7&8&9\end{array}$							
				$\begin{array}{c} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{array}$				
							$egin{array}{cccc} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{array}$	
		$\begin{array}{c}1&2&3\\4&5&6\\7&8&9\end{array}$						
					$\begin{array}{c}1&2&3\\4&5&6\\7&8&9\end{array}$			
								$\begin{array}{c}1&2&3\\4&5&6\\7&8&9\end{array}$

As humans, we assume that each position can contain only a single number.

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This assumption was lost when we split each position into multiple different variables.

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This assumption was lost when we split each position into multiple different variables.

We need to add it back.

 $orall (r,c) \in (rows imes columns): ext{exactly-one}(x^1_{r,c}, \dots, x^9_{r,c})$

 $orall (r,c) \in (rows imes columns): ext{exactly-one}(x^1_{r,c},\ldots,x^9_{r,c})$

The exactly-one helper adds a set of clauses that allows only one of the literals to be true.

 $orall (r,c) \in (rows imes columns): ext{exactly-one}(x^1_{r,c},\ldots,x^9_{r,c})$

The exactly-one helper adds a set of clauses that allows only one of the literals to be true.

Let's take a look at how it works.

We cannot directly limit the number of true literals.

We cannot directly limit the number of true literals. But we can place lower and upper limits on them. We cannot directly limit the number of true literals.
But we can place lower and upper limits on them.
In other words, *exactly one* literal is true when *at least* one is true **and** *at most* one is true.

Making *at least one* literal true is simple:

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 $\bigvee_{lit \in literals} lit$

Forcing *at most one* literal to be true is based on a simple observation

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At most one literal is true when there is no pair of literals where both literals are true at the same time.

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At most one literal is true when there is no pair of literals where both literals are true at the same time.

$$egin{aligned} orall l_1 \in literals, \ l_2 \in literals, \ l_1
eq l_2 :
eg (l_1 \wedge l_2) \end{aligned}$$

Let's write us a C++ Sudoku solver.
Let's write us a C++ Sudoku solver. All the code in this section can be found at https://github.com/horenmar/sudoku-example First we need to figure out addressing variables.

First we need to figure out addressing variables. SAT solvers see variables as integers in range 0..N. First we need to figure out addressing variables. SAT solvers see variables as integers in range 0..N. Luckily, we can easily map $x_{r,c}^v$ into an integer as r * 9 * 9 + c * 9 + v First we need to figure out addressing variables. SAT solvers see variables as integers in range 0..N. Luckily, we can easily map $x_{r,c}^v$ into an integer as r * 9 * 9 + c * 9 + v

Minisat::Var toVar(int row, int column, int value) {
 return row * columns * values + column * values + value;
}

Before we can start adding clauses, we need to allocate all variables

Before we can start adding clauses, we need to allocate all variables

```
void Solver::init_variables() {
    for (int r = 0; r < rows; ++r) {
        for (int c = 0; c < columns; ++c) {
            for (int v = 0; v < values; ++v) {
                static_cast<void>(solver.newVar());
            }
        }
    }
}
```



for (int row = 0; row < rows; ++row) {</pre>

for (int row = 0; row < rows; ++row) {
 for (int value = 0; value < values; ++value) {</pre>

```
for (int row = 0; row < rows; ++row) {
    for (int value = 0; value < values; ++value) {
        Minisat::vec<Minisat::Lit> literals;
```

```
for (int row = 0; row < rows; ++row) {
    for (int value = 0; value < values; ++value) {
        Minisat::vec<Minisat::Lit> literals;
        for (int col = 0; col < columns; ++col) {
            literals.push(Minisat::mkLit(toVar(row, col, value)));
        }
    }
}</pre>
```

```
for (int row = 0; row < rows; ++row) {
    for (int value = 0; value < values; ++value) {
        Minisat::vec<Minisat::Lit> literals;
        for (int col = 0; col < columns; ++col) {
            literals.push(Minisat::mkLit(toVar(row, col, value)));
        }
        solver.addClause(literals);
    }
}</pre>
```

```
for (int col = 0; col < columns; ++col) {
    for (int value = 0; value < values; ++value) {
        Minisat::vec<Minisat::Lit> literals;
        for (int row = 0; row < rows; ++row) {
            literals.push(Minisat::mkLit(toVar(row, col, value)));
        }
        solver.addClause(literals);
    }
}</pre>
```

```
for (int value = 0; value < values; ++value) {</pre>
    for (int r : {0, 3, 6}) {
        for (int c : {0, 3, 6}) {
            Minisat::vec<Minisat::Lit> literals;
            for (int rr : {0, 1, 2}) {
                for (int cc : {0, 1, 2}) {
                    literals.push(Minisat::mkLit(
                        toVar(r + rr, c + cc, value)
                    ));
            solver.addClause(literals);
```

4. EACH POSITION CONTAINS EXACTLY ONE NUMBER

4. EACH POSITION CONTAINS EXACTLY ONE NUMBER

```
for (int row = 0; row < rows; ++row) {
    for (int col = 0; col < columns; ++col) {
        Minisat::vec<Minisat::Lit> literals;
        for (int value = 0; value < values; ++value) {
            literals.push(Minisat::mkLit(toVar(row, col, value)));
        }
        exactly_one(literals);
    }
}</pre>
```

```
void Solver::exactly_one(Minisat::vec<Minisat::Lit> const& lits) {
    // At least one
    solver.addClause(lits);
    // At most one
    for (size_t i = 0; i < lits.size(); ++i) {
        for (size_t j = i + 1; j < lits.size(); ++j) {
            solver.addClause(~lits[i], ~lits[j]);
            }
        }
    }
}</pre>
```

We have a model of Sudoku as a SAT instance.

We have a model of Sudoku as a SAT instance. Now we need to insert an actual instance of the puzzle, and then extract the solution.

Inserting an instance is easy enough, each prefiled square gets an unary clause:

Inserting an instance is easy enough, each prefiled square gets an unary clause:

Extracting a solution is similarly simple, we just need to check which variable for a given square is "true". Extracting a solution is similarly simple, we just need to check which variable for a given square is "true".

```
board Solver::get solution() const {
   board b(rows, std::vector<int>(columns));
   for (int row = 0; row < rows; ++row) {</pre>
      for (int col = 0; col < columns; ++col) {</pre>
         for (int val = 0; val < values; ++val) {</pre>
             if (solver.modelValue(toVar(row, col, val)).isTrue()) {
                b[row][col] = val + 1;
                break;
   return b;
```

Let's take a look at how our solver performs.

Let's take a look at how our solver performs. All benchmarks were run on the same machine, and the binaries were compiled with g++ under WSL. Let's take a look at how our solver performs. All benchmarks were run on the same machine, and the binaries were compiled with g++ under WSL. The inputs were 95 "hard" instances of Sudoku.

Runtimes of different solvers [ms]



Counterintuitively, giving a SAT solver less clauses and/or variables can slow it down.

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Let's see what happens when we encode the sudoku rules differently, and give the solver more information.

1. Each row contains each of the numbers 1-9

1. Each row contains each of the numbers 1-9 exactly once

1. Each row contains each of the numbers 1-9 exactly once

2. Each column contains each of the numbers 1-9
1. Each row contains each of the numbers 1-9 exactly once

2. Each column contains each of the numbers 1-9 exactly once

- 1. Each row contains each of the numbers 1-9 exactly once
- 2. Each column contains each of the numbers 1-9 exactly once
- 3. Each 3x3 box contains each of the numbers 1-9

- 1. Each row contains each of the numbers 1-9 exactly once
- 2. Each column contains each of the numbers 1-9 exactly once
- 3. Each 3x3 box contains each of the numbers 1-9 exactly once

```
for (int row = 0; row < rows; ++row) {
    for (int value = 0; value < values; ++value) {
        Minisat::vec<Minisat::Lit> literals;
        for (int col = 0; col < columns; ++col) {
            literals.push(Minisat::mkLit(toVar(row, col, value)));
        }
        solver.addClause(literals);
    }
}</pre>
```

```
for (int row = 0; row < rows; ++row) {
    for (int value = 0; value < values; ++value) {
        Minisat::vec<Minisat::Lit> literals;
        for (int col = 0; col < columns; ++col) {
            literals.push(Minisat::mkLit(toVar(row, col, value)));
        }
        solver.addClause(literals);
        exactly_one(literals);
    }
}</pre>
```

Runtimes of different solvers [ms]



Be careful to encode *all* of your assumptions.

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More clauses does not mean worse performance.

Be careful to encode *all* of your assumptions. More clauses does not mean worse performance. But it does not mean better performance either.

Be careful to encode *all* of your assumptions. More clauses does not mean worse performance. But it does not mean better performance either. Experiment with different encodings.

HOW TO SOLVE A MASTER KEY SYSTEM WITH A SAT SOLVER

Master Key System (MKS) is a set of keys and locks where a key can open more than one lock. Master Key System (MKS) is a set of keys and locks where a key can open more than one lock.

The relations between keys and locks can be arbitrarily complex, and are described in a lockchart.

The common depiction of a lockchart is a simple table:



Each MKS has a geometry associated with it.

Each MKS has a geometry associated with it. The geometry describes the positions, their depths, and the constraints the keys must satisfy.

Let's take a look at the geometry and inner working of a *pin tumbler* lock.





1. A key has exactly one cutting depth at a position

A key has exactly one cutting depth at a position
 A lock has at least one cutting depth at a position

 A key has exactly one cutting depth at a position
 A lock has at least one cutting depth at a position
 A key must open all locks that the lock-chart specifies it should open

- 1. A key has exactly one cutting depth at a position
- 2. A lock has at least one cutting depth at a position
- 3. A key must open all locks that the lock-chart specifies it should open
- 4. A key must be blocked in all locks that the lock-chart specifies it should not open

- 1. A key has exactly one cutting depth at a position
- 2. A lock has at least one cutting depth at a position
- 3. A key must open all locks that the lock-chart specifies it should open
- 4. A key must be blocked in all locks that the lock-chart specifies it should not open
- 5. A key's cutting must satisfy all constraints

THE VARIABLES

This time we will be using multiple kinds of variables.

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This time we will be using multiple kinds of variables. $key_{p,d}^k,$ which is true when key k is cut at depth d in position p

THE VARIABLES

This time we will be using multiple kinds of variables. $key_{p,d}^k$, which is true when key k is cut at depth d in

position p

 $lock_{p,d}^l,$ which is true when lock l is cut at depth d in position p

1. A KEY HAS EXACTLY ONE CUTTING DEPTH AT A POSITION

1. A KEY HAS EXACTLY ONE CUTTING DEPTH AT A POSITION

$$orall (k,p) \in (keys imes positions): \ ext{exactly-one}(key^k_{p,0}, key^k_{p,1}, \dots, key^k_{p,d})$$

2. A LOCK MUST HAVE AT LEAST ONE CUTTING DEPTH SELECTED FOR EACH POSITION

2. A LOCK MUST HAVE AT LEAST ONE CUTTING DEPTH SELECTED FOR EACH POSITION

$$orall (l,p) \in (locks imes positions): igwedge_{d \in depths(p)} lock_{p,d}^l$$

3. A KEY MUST OPEN ALL LOCKS THAT THE LOCK-CHART SPECIFIES IT SHOULD OPEN

3. A KEY MUST OPEN ALL LOCKS THAT THE LOCK-CHART SPECIFIES IT SHOULD OPEN

A key opens a lock when the lock has the same cutting depths as the key.

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A key opens a lock when the lock has the same cutting depths as the key.

$$orall k \in keys, \ orall l \in ext{opened-by}(k): igwedge_{p \in positions} \left(key_{p,d}^k \implies lock_{p,d}^l
ight) \ p \in positions \ d \in ext{depths}(p)$$

4. A KEY MUST BE BLOCKED IN ALL LOCKS THAT THE LOCK-CHART SPECIFIES IT SHOULD NOT OPEN
4. A KEY MUST BE BLOCKED IN ALL LOCKS THAT THE LOCK-CHART SPECIFIES IT SHOULD NOT OPEN

A key is blocked in a lock if, and only if, it does not open the lock.

4. A KEY MUST BE BLOCKED IN ALL LOCKS THAT THE LOCK-CHART SPECIFIES IT SHOULD NOT OPEN

A key is blocked in a lock if, and only if, it does not open the lock.

A key opens a lock when the lock has the same cutting depths as the key.

A key is blocked in a lock when the lock is missing at least one of key's cutting depths.

A key is blocked in a lock when the lock is missing at least one of key's cutting depths.

$$orall k \in keys, \ orall l \in ext{blocked-in}(k): igvee_{p \in positions} \left(key_{p,d}^k \wedge \neg lock_{p,d}^l
ight) \ _{\substack{p \in positions \ d \in ext{depths}(p)}}$$

We can convert DNF to CNF using distributive laws.

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We can convert DNF to CNF using distributive laws. This creates an exponential number of long clauses. We can do better.

At the start of this talk, we talked about converting formulae into equivalent formulae in CNF.

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It is also possible to create *equisatisfiable* formulae.

$\alpha \lor \beta$ and $(\alpha \lor \neg \gamma) \land (\gamma \lor \beta)$ are not equivalent, but they are equisatisfiable.

We will use trick called *Tseytin transformation*.

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 $block^{k,l}_{p,d} \iff \left(key^k_{p,d} \wedge \neg lock^l_{p,d}
ight)$

 $block^{k,l}_{p,d} \iff \left(key^k_{p,d} \wedge \neg lock^l_{p,d}
ight)$ $lpha \iff eta$

 $block^{k,l}_{p,d} \iff \left(key^k_{p,d} \wedge \neg lock^l_{p,d}
ight)$ $\alpha \iff \beta$ $(lpha \implies eta) \land (lpha \iff eta)$

 $block^{k,l}_{p,d} \iff \left(key^k_{p,d} \land \neg lock^l_{p,d}
ight)$ $\alpha \iff \beta$ $(\alpha \implies \beta) \land (\alpha \iff \beta)$ $(\neg \alpha \lor \beta) \land (\alpha \lor \neg \beta)$

 $block^{k,l}_{p,d} \iff \left(key^k_{p,d} \land \neg lock^l_{p,d}
ight)$ $\alpha \iff \beta$ $(\alpha \implies \beta) \land (\alpha \iff \beta)$ $(\neg lpha \lor eta) \land (lpha \lor \neg eta)$

The first clause can be distributed out:

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$$\left(\neg block_{p,d}^{k,l} \lor \left(key_{p,d}^k \land \neg lock_{p,d}^l
ight)
ight)$$

The first clause can be distributed out:

$$igg(
eg block_{p,d}^{k,l} ee igg(key_{p,d}^k \wedge
eg lock_{p,d}^ligg) igg) \ igg(
eg block_{p,d}^{k,l} ee key_{p,d}^k igg) \wedge igg(
eg block_{p,d}^{k,l} ee
eg lock_{p,d}^{k,l}
eg lock_{p,d}^k igg)
ight)$$

Second clause is simplified with DeMorgan's laws

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$$\left(block_{p,d}^{k,l} \lor \neg \left(key_{p,d}^k \land lock_{p,d}^l
ight)
ight)$$

Second clause is simplified with DeMorgan's laws

$$igg(block_{p,d}^{k,l} ee
eg igg(key_{p,d}^k \wedge lock_{p,d}^ligg)igg) \ igg(block_{p,d}^{k,l} ee
eg key_{p,d}^k ee
eg lock_{p,d}^kigg)$$

With this, the blocking clauses are simple:

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$$orall k \in keys, \ orall l \in ext{blocked-in}(k): igvee_{p \in positions} igvee_{p,d} block_{p,d}^{k,l} \ p \in positions \ d \in ext{depths}(p)$$

We now have a model of a MKS without constraints.

We will explore 2 different constraints:

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• *Jump* constraint

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- *Jump* constraint
- *Key cutting hierarchy* constraint

JUMP CONSTRAINT



To manufacture a key, the cutting depths in two adjacent positions cannot differ by more than j.

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For all keys k_1, k_2 , where opened-by $(k_1) \supset$ opened-by $(k_2), ...$


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For all keys k_1, k_2 , where opened-by $(k_1) \supset$ opened-by (k_2) , for all positions p and depths d_i, d_j , where i > j: For all keys k_1, k_2 , where opened-by $(k_1) \supset$ opened-by (k_2) , for all positions p and depths d_i, d_j , where i > j:

$$key_{p,d_i}^{k_1} \implies \neg key_{p,d_j}^{k_2}$$

C++ IMPLEMENTATION

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A variant of the code is implemented in https://github.com/horenmar/mks-example

C++ IMPLEMENTATION

A variant of the code is implemented in https://github.com/horenmar/mks-example We will not go over it in this talk.

BENCHMARKS

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There are none, sorry.

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There are none, sorry. I do have an anecdote though. ~5 years ago, my university was approached by our local key manufacturer, FAB.

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A team spent ~3 years working on a specialized solver.

~5 years ago, my university was approached by our local key manufacturer, FAB.

A team spent ~3 years working on a specialized solver. It could solve $\sim 80\%$ of test inputs.

Another researcher had the idea to use SAT solvers.

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SAT solvers can be used to solve wildly different problems.

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SAT-based solvers can perform surprisingly well.

But specialized solvers will end up faster.

You need to be careful to encode your assumptions when converting a problem to SAT.

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But there are no guarantees.

Experiment with different encodings of the problem.

Experiment with different encodings of the problem. Experiment with different SAT solvers!

THE END.

QUESTIONS?

- https://github.com/horenmar/sudoku-example
- https://github.com/horenmar/mks-example
- https://github.com/master-keying/minisat
- https://codingnest.com/modern-sat-solvers-fastneat-and-underused-part-3-of-n/