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Oxiflex - A Constraint Programming Solver for MiniZinc written in Rust

Bachelor's thesis

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Abstract

Constraint Satisfaction Problems (CSPs) are typical NP-complete combinatorial problems in the field of Artificial Intelligence. As part of this thesis, we introduce Oxiflex, a CSP solver written from scratch in Rust. Oxiflex is built on the MiniZinc tool chain and supports a subset of FlatZinc constraint builtins. Starting with a naive backtracking approach, we enhance Oxiflex by applying variable ordering and inference. Both forward checking and arc consistency enforcing algorithms like AC-1 and AC-3 are used for inference. Results show that for Oxiflex, variable ordering and forward checking have a positive impact on time measurements, but AC-1 and AC-3 do not. However, by measuring the number of iterations, results show that AC-1 and AC-3 can significantly reduce the number of iterations needed for backtracking. This work shows that inference does tighten the problem size, but careful implementation is needed to make it fast.

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1 Introduction

Constraint Satisfaction Problems (CSPs) represent a common category of NP-complete combinatorial issues within Artificial Intelligence, involving a collection of variables and constraints that establish how these variables interact. The main goal of this thesis is the development of a CSP solver entirely from scratch.
In Chapter 2 we will discuss how we can write down CSPs in both a formal way and in way that is useful for solvers. For the latter we will be using MiniZinc [NSB+07], a CSP modeling language developed at and by Monash University in Australia. MiniZinc comes with tools for users that want to solve CSPs, and tools for solvers as well. The main idea of MiniZinc is to be translated to a simpler language called FlatZinc that solvers are able to use directly. MiniZinc is only the language and does not provide a solver. MiniZinc problems are independent from solvers and make it really easy to give the same problem to multiple solvers. At the end of this chapter we will showcase an example problem domain called 8-Queens Problem as an easy to understand CSP that will also be used for benchmarking the solver later.
Afterwards in Chapter 3 we will explore how we can actually solve CSPs. We will start from a naive backtracking algorithm approach that resembles depth first search. Next we will improve on this algorithm by changing which variables the solver tries out first. This is called variable ordering. In a last step we will introduce a method to enhance solving CSPs by using inference. Inference is a way to tighten the problem size and reduce the amount of search we have to do with backtracking. To apply inference there will be two methods discussed: Forward checking and enforcing arc consistency. The former being a simpler approach that is a special case of enforcing arc consistency. The latter can be done in multiple ways, we will be discussing the algorithms called AC-1 and AC-3.
Furthermore in Chapter 4 we introduce our new CSP solver called Oxiflex written from scratch in Rust. Rust [MI14] is a general purpose programming language focused on security and, importantly for Oxiflex, performance. Oxiflex supports a subset of FlatZinc builtin constrains. Builtin constraints are a type of constraint that has to be supported by any solver in order to support FlatZinc and in turn MiniZinc. The architecture of Oxiflex is made up of tree parts: parser, model and solver. Building a solver from scratch has the additional benefit that we can build it in a way so that we can provide flags to turn on each

improvement for the algorithm separately. This structure will allow us then in a next step to measure each algorithm combination by its own.

We then proceed in Chapter 5 to conduct experiments with Oxiflex. There are two problem domains used: N-Queens (introduced in Chapter 2) and Slow Convergence which is a problem from the MinZinc benchmarks repository [Min18]. The improvements to the solver algorithm discussed in Chapter 3 will be compared to each other and visualized using diagrams. Both time and and number of iterations are part of the measurements. Time is great to showcase how fast the solving is for the user and iterations is great to see how much we tightened the problem size after each inference step. As we will see those can vary a lot. Results will show that arc consistency enforcing algorithms in Oxiflex do not outperform forward checking or even the naive approach of the algorithm in time measurements. However, they do decrease iterations significantly. We will also see that variable ordering improves the N-Queens problem solving by a lot and even enables Oxiflex to solve the Slow Convergence problem at all.

Finally in Chapter 6 we will finish with a discussion of the thesis.

2

Constraint Satisfaction Problems

2.1 Overview

Constraint Satisfaction Problems (CSP) [Mac87] are mathematical questions defined as a finite set of variables whose value must satisfy a number of constraints or limitations. When solely talking about the problem without the algorithmic finding of a solution, these are called Constraint Networks. CSPs are typical NP-complete combinatorial problems in the field of Artificial Intelligence. See Example 2.1.1 for an simple constraint network.

Example 2.1.1: Simple Constraint Network

$w = \{1, 2, 3, 4\}$	**where:**
$y = \{1, 2, 3, 4\}$	$w = 2 \cdot x$
$x = \{1, 2, 3\}$	$w < z$
$z = \{1, 2, 3\}$	$y > z$

We define variables w, y, x and z. Variables w and y can both have one value from $\{1, 2, 3, 4\}$ and variables x and z can have one value from $\{1, 2, 3\}$. The constraints then restrict which values are valid from their respective domains. Here $w = 2 \cdot x$ restricts the value of x to be double of w for example. If there are no constraints for variables, the constraints are still there but they allow every assignment. These constraints are called trivial constraints and are usually omitted.

In this example we define constraints in a mathematical notation. There are no formal restrictions on stating constraints neither by their complexity nor by the number of variables involved. To make it easier to reason about and easier to understand, we model constraints as binary constraint sets within this explanation. This is not needed when implementing the constraints later. Constraints are then sets of valid value pairs for two specific variables. Instead of stating the desired relation between any variables, we list all valid value pair tuples in a set. Constraint $w < z$ then becomes $(R_{wz} = \{(1, 2), (1, 3), (2, 3)\}$ which contains all possible value pairs for the two variables w and z.

We define constraint networks formally:

A (binary) constraint network is a 3-tuple $C = \langle V, \mathrm{dom}, (R_{uv}) \rangle$ such that:

- V is a non-empty and finite set of variables,
- dom is a function that assigns a non-empty and finite domain to each variable $v \in V$, and
- $(R_{uv})_{u,v \in V, u \neq v}$ is a family of binary relations (constraints) over V where for all $u \neq v : R_{uv} \subseteq \mathrm{dom}(u) \times \mathrm{dom}(v)$

And we define our example formally:

$C = \langle V, \mathrm{dom}, (R_{uv}) \rangle$ with

- variables:
  $V = \{w, x, y, z\}$
- domains:
  $\mathrm{dom}(w) = \mathrm{dom}(y) = \{1, 2, 3, 4\}$
  $\mathrm{dom}(x) = \mathrm{dom}(z) = \{1, 2, 3\}$
- constraints:
  $R_{wx} = \{(2, 1), (4, 2)\}$
  $R_{wz} = \{(1, 2), (1, 3), (2, 3)\}$
  $R_{yz} = \{(2, 1), (3, 1), (3, 2), (4, 1), (4, 2), (4, 3)\}$

The goal of a CSP is then to find an assignment that satisfies all constraints. For this simple example a possible assignment would be $(w \mapsto 2), (x \mapsto 1), (y \mapsto 4), (z \mapsto 3)$. If a value pair from an partial assignment is not within a constraint set, the partial assignment is in **conflict**. A CSP is called **inconsistent** if each total assignment results in a conflict.

2.2 MiniZinc

MiniZinc [NSB+07] is a free and open-source constraint modeling language developed at and by Monash University in Australia. It allows us to express Constraint Satisfaction Problems in a mathematical notation-like way. MiniZinc also holds an annual competition of constraint programming solvers on a variety of benchmarks. Here we will be talking about the modeling language. See our simple previous Example 2.1.1 written in the MiniZinc language: Example 2.2.1.

Example 2.2.1: MiniZinc Translation

```
var 1..4: w;
var 1..4: y;
var 1..3: x;
var 1..3: z;

constraint w = 2 × x;
constraint w < z;
constraint y > z;

solve satisfy;
```

Remember that MiniZinc is only the language to express a problem domain. Once a problem domain is specified we can give the problem to multiple solvers to solve them. This way we can compare the performance of various solvers on the same problem domain. Note that in MiniZinc we also specify how we want the problem to be solved. With `solve satisfy;` we can tell the solver to give us any solution that satisfies the constraints. MiniZinc also supports `solve maximize` and `solve minimize` for optimization problems. We will be focusing on finding any solution.

MiniZinc also provides a way to parameterize a problem domain. This is a great way to scale a problem size up and see how increasing the problem size affects the solving speed. A great example for this is the Queens Problem (See Section 2.3). We define the Queens Problem domain once and can then run specific problem instances for different n. This makes it really easy to compare the solving speed for the queens problem when $n = 8$, $n = 10$ or $n = 14$ for example. Those files where we specify parameters for MiniZinc files are called data files and have the extension `dzn`. Files where we define the problem domain like in Example 2.2.1 are called MiniZinc files and have the file extension `mzn`. We can combine `mzn` files with `dzn` files to created FlatZinc files that a solver is able to read and solve.

2.2.1 FlatZinc

FlatZinc is a simpler problem specification language provided by the MiniZinc tool chain. It is designed to be used by solvers directly. MiniZinc files in combination with data files are translated to FlatZinc files in a pre-solving step. FlatZinc files have the file extension `fzn` and can directly be read by solvers.

Translating from MiniZinc to FlatZinc maps more advanced instructions from MiniZinc to primitives supported in FlatZinc. An analogy to this translation is compiling a C program to Assembly where MiniZinc is C and FlatZinc is Assembly. FlatZinc therefore requires solvers to support a set of standard constraints called FlatZinc builtins. Builtins need to be implemented to be a fully compatible FlatZinc solver. See Example 2.2.2 for an FlatZinc translation using our Simple Example 2.2.1.

Example 2.2.2: FlatZinc Translation (Simplified)

```
array [1..2] of int: x_introduced_2_ = [1,-2];
array [1..2] of int: x_introduced_3_ = [1,-1];
array [1..2] of int: x_introduced_4_ = [-1,1];
var 2..4: w:: output_var;
var 1..4: y:: output_var;
var 1..3: x:: output_var;
var 1..3: z:: output_var;
constraint int_lin_eq(x_introduced_2_,[w,x],0);
constraint int_lin_le(x_introduced_3_,[w,z],-1);
constraint int_lin_le(x_introduced_4_,[y,z],-1);
solve satisfy;
```

The translation of the variable declarations is straight forward. For the constraints, MiniZinc translated all constraints into FlatZinc builtin constraints. For our simple example MiniZinc used two builtins: `int_lin_eq` and `int_lin_le`. See the lines that start with `constraint`. We will look at `int_lin_eq` further to see how FlatZinc builtins work. Example 2.2.3 shows the signature of the builtin `int_lin_eq` that was used for the constraint $w = 2 \cdot x$.

Example 2.2.3: FlatZinc builtin: int_lin_eq

```
predicate int_lin_eq(array [int] of int: as,
                     array [int] of var int: bs,
                     int: c)
```

Note that the builtin `int_lin_eq` expects 3 parameters. The first `as` is an array of `int` constants. This is what FlatZinc translated to `x_introduced_2`. This array is called a parameter, because it has concrete values assigned to it. Here `x_introduced_2` has the value `[1,-2]` assigned. The second parameter `bs` is an array of `int` variables, that is an array of variables that we want to solve for. Here the variables w and x are passed in also as an array `[w,x]`. The third parameter `c` is also a parameter because it is also a constant value that needs to be passed. Here the value for `c` is 0.

Every FlatZinc builtin also has a description for when the constraint is valid or violated respectively. For `int_lin_eq` the description is given with Eq. (2.1).

$$c = \sum_i \mathrm{as}[i] \cdot \mathrm{bs}[i] \tag{2.1}$$

For this builtin, MiniZinc therefore translated our constraint into a linear combination. With our example we can fill in the passed parameters to the constraint and we get $0 = w - 2x$ which can be rearranged to $w = 2 \cdot x$.

Note that MiniZinc created these parameter arrays by itself. The `x` within `x_introduced_2_` is not the same as our variable x that we defined ourselves. Also does the 2 in the name

have nothing to do with our model but is instead defined by the MiniZinc translation. Additionally note that for the translation MiniZinc already does some basic level of inference. The FlatZinc variable w can only have values between 2 and 4 in the translated FlatZinc. Whereas in the MiniZinc version we defined w with the domain $\{1, 2, 3, 4\}$. This means MiniZinc infers that w can not be value 1 and removes it from its domain declaration. Due to the constraint $w = 2 \times x$, the variable w has to be double of x and x must have at least value 1. Therefore excluding 1 as possible value for w.

2.3 Queens Problem

Also called the Eight Queens Puzzle, the Queens Problem is an example of a classic Constraint Satisfaction Problem that involves placing eight queens on an 8x8 chessboard in such a way that no two queens threaten each other. That is, no two queens can share the same row, column, or diagonal. See Fig. 2.1 for an example solution to the 8-Queens Problem.

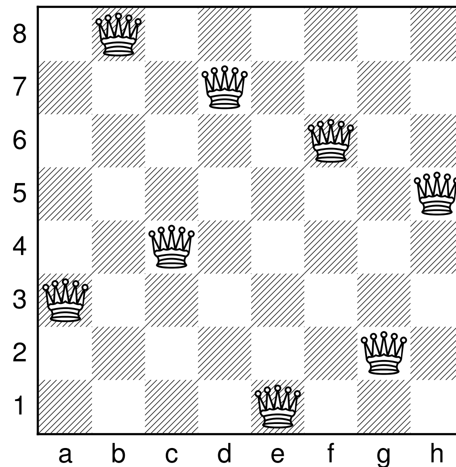

Figure 2.1: Possible solution to the 8-Queens problems.

The Queens Problem is really good suited as an example problem domain for CSPs because it is easy to understand and can also easily be scaled up to increase complexity for a solver. By generalizing the problem from a fixed 8×8 grid size to an $n \times n$ grid with n queens, the problem remains the same in principle, but gets way harder to solve. See Example 2.3.1 [RR06] for the N-Queens Problem modeled in MinZinc.

Example 2.3.1: N-Queens Problem MiniZinc Model

```
int: n;

array [1..n] of var 1..n: q;

predicate
    noattack(int: i, int: j, var int: qi, var int: qj) =
        qi != qj /\
        qi + i != qj + j /\
        qi - i != qj - j;

constraint
    forall (i in 1..n, j in i+1..n) (
        noattack(i, j, q[i], q[j])
    );

solve satisfy;
```

This MiniZinc model defines an array of variables q where each index corresponds to a column on the chessboard and the value at each index represents the row position of the queen in that column. The constraints ensure that no two queens are on the same row, column or diagonal. Remember that this model receives a parameter n and is therefore not specific to 8 queens.

3

Solving Constraint Satisfaction Problems

Constraints Satisfaction Problems on finite domains are typically solved using a form of search. We search for a solution to the constraint network by trying out possible values until a solution is found or we find that there is no solution. A solution is a valid assignment of all variables with a value of their respective domain satisfying all constraints within the constraint network.

3.1 Backtracking

Backtracking is a technique used to search a problem space for potential solutions [BR75]. It systematically organizes the search process by attempting to extend a partial solution step-by-step. If an extension of the current partial solution proves to be leading to no solution, the algorithm "backtracks" to a previous, shorter partial solution and tries a different path. This method is particularly useful in solving CSPs, as we can do partial assignments of variables and expand them step by step by assigning more variables. We can start by using backtracking without any enhancements. See function 3.1.1 for reference with the following notes:

Input: constraint network C and partial assignment α for C. On first invocation of Naive-Backtracking we pass an empty assignment $\alpha = \emptyset$.

Result: Total assignment (solution) of C or **inconsistent** no solution is found.

function 3.1.1: NaiveBacktracking(C, α)

```
⟨V, dom, (R_uv)⟩ := C
if α is inconsistent with C:
    return inconsistent

if α is a total assignment:
    return α

select some variable v for which α is not defined
for each d ∈ dom(v) in some order:
    α′ := α ∪ {v ↦ d}
    α″ := NaiveBacktracking(C, α′)
    if α″ ≠ inconsistent:
        return α″

return inconsistent
```

This algorithm corresponds to Depth First Search. It assigns values to variables from their domains to form a partial assignment. This process continues until either all variables are assigned and a solution is found, or a constraint is violated. If a constraint is violated, the algorithm backtracks and tries a different value from the domain until a solution is found. If all possible assignments violate constraints, there is no solution and **inconsistent** is returned. Finding a total assignment, that is, an partial assignment that gives all variables a valid value from their domain, is finding a solution.
Backtracking is great as an easy to understand solving technique, but is far from the best way to solve CSPs [BG95].

3.1.1 Variable Ordering

Backtracking in general does not specify in which order the search is done. For CSPs we want to assign critical variables early. Critical variables are variables that tighten the search size the most by their assignment. This can be done in multiple ways:

- **static order**
  Fixed order defined prior to search.
- **dynamic order**
  Order depends on current search state and is calculated after each assignment.

Dynamic ordering is more powerful but also requires computational overhead during search for each iteration. The following are two commonly used variable ordering criteria:

- **minimum remaining values:**
  Prefer variables that have small domains.

- **most constraining variable:**
  Prefer variables involved in many constraints.

Dynamic variable ordering is usually more effective combined with inference.

3.2 Inference

Inference allows us to modify our constraint network by tightening the constraint network. Tightening works by excluding values from domains of variables that we know are not possible. For example in the Queens Problem (See Section 2.3) if we place a Queen on $d4$, we can exclude the value 4 from all other columns. We can also exclude all diagonally positioned squares like $a1$, $b2$, $c3$ and so forth. See Fig. 3.1 for reference. Note that we do not need to do anything with the column the queen is on because we modeled the column to be a variable to solve for and a variable can only be one value anyways. The Queen can not be in multiple rows of the same column.

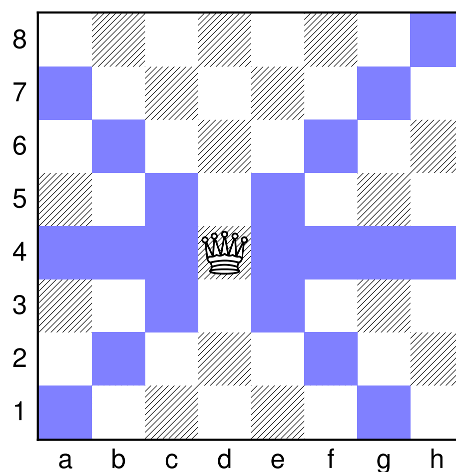

Figure 3.1: We apply inference after placing Queen on $d4$ tightening the problem size.

By removing values from the remaining domains we can tighten the resulting constraint network and have a smaller search space. We adjust our NaiveBacktracking approach by applying inference after each assignment of a variable. See function 3.2.1 for the adjusted algorithm.

function 3.2.1: BacktrackingWithInference(C, α)

$\langle V, \text{dom}, (R_{uv})\rangle := C$
if α is inconsistent with C:
    return inconsistent

if α is a total assignment:
    return α

$C' := \langle V, \text{dom}', (R'_{uv})\rangle :=$ copy of C
apply inference to C'
if $\text{dom}'(v) \neq \emptyset$ for all variables v:
    select some variable v for which α is not defined
    for each $d \in$ copy of $\text{dom}'(v)$ in some order:
        $\alpha' := \alpha \cup \{v \mapsto d\}$
        $\text{dom}'(v) := \{d\}$
        $\alpha'' :=$ BacktrackingWithInference(C', α')
        if $\alpha'' \neq$ **inconsistent**:
            return α''

return inconsistent

Note that we now have to copy the constraint network after each assignment which can introduce significant overhead for large problems. The copying is needed because we still have to backtrack if we find an inconsistent assignment. When backtracking we have to restore the domain for each variable again because it is possible that the domain had values that are valid again after backtracking.

3.2.1 Forward Checking

We start with a simple inference method called Forward Checking [HE80]. See function 3.2.2 for reference.

function 3.2.2: ForwardChecking(C, α)

$\langle V, \text{dom}, (R_{uv})\rangle := C$
for each $v \in$ unassigned variable in α:
    for each R_{vx} in (R_{uv}):
        for each $d \in \text{dom}(v)$:
            if $\exists$ **conflict** in $\alpha \cup (v \mapsto d)$
                $\text{dom}(v) = \text{dom}(v) \setminus d$

Forward checking is basically looking ahead in the future to see which values can be excluded from search after an assignment. By looking ahead we can omit the backtracking part that

would result by finding a dead end. We check each value for each variable with the new assignment and remove all values that are not valid anymore from their respective domain.

3.2.2 Arc Consistency

Originally developed to address vision problems, arc consistency represents a generalization of forward checking [Wal72]. Forward checking enforces arc consistency for all variables with respect to the just assigned variable. Arc consistency does this for all variables. This makes forward checking a special case of arc consistency. We can define arc consistency formally:

Let $C = \langle V, \text{dom}, (R_{UV})\rangle$ be a constraint network.

- The variable $v \in V$ is arc consistent with respect to another variable $v' \in V$, if for every value $d \in \text{dom}(v)$ there exists a value $d' \in \text{dom}(v')$ with $\langle d, d'\rangle \in R_{vv'}$.
- The constraint network C is arc consistent, if every variable $v \in V$ is arc consistent with respect to every other variable $v' \in V$.

Note that for a variable pair the definition is not symmetrical. That means if v is arc consistent with respect to v', v' does not have to be arc consistent with respect to v'.

3.2.2.1 Enforcing Arc Consistency

There are multiple algorithms to enforce arc consistency [Mac77] [Bes94]. The simplest is called AC-1. It works by making use of a function called revise. The function 3.2.3 revise ensures arc consistency in one direction between two variables.

function 3.2.3: revise(C, v, v')

$\langle V, \text{dom}, (R_{uv})\rangle := C$
for each $d \in \text{dom}(v)$:
    if there is no $d' \in \text{dom}(v')$ with $\langle d, d'\rangle \in R_{vv'}$:
        remove d from $\text{dom}(v)$

The function 3.2.4 called AC-1 iterates over each constraint and applies `revise` in both directions to each variable pair for each constraint until there was no change within its iteration of using revise.

function 3.2.4: AC-1(C)

$\langle V, \text{dom}, (R_{uv})\rangle := C$
repeat
    for each nontrivial constraint R_{uv}:
        revise(C, u, v)
        revise(C, v, u)
until no domain has changed in this iteration

Building on AC-1, AC-3 tries to save redundant checks made by AC-1. Instead of repeatedly going over all constraints, AC-3 iterates over all constraint once and revises variable pairs again only if needed. We can achieve this by using a queue. See function 3.2.5 for reference.

function 3.2.5: AC-3(C)

$\langle V$, dom, $(R_{uv})\rangle := C$
queue $:= \emptyset$
for each nontrivial constraint R_{uv}:
    insert $\langle u, v\rangle$ into *queue*
    insert $\langle u, v\rangle$ into *queue*

while *queue* $\neq \emptyset$:
    remove an arbitrary element $\langle u, v\rangle$ from *queue*
    revise(C, u, v)
    if dom(u) changed in the call to revise:
        for each $w \in V \setminus \{u, v\}$ where R_{wu} is nontrivial:
            insert $\langle w, u\rangle$ into *queue*

4
Implementation

4.1 Oxiflex

As part of this thesis we present **Oxiflex**, a minimal CSP solver from scratch for MiniZinc written in Rust. Oxiflex is a FlatZinc solver that can be used as an backend to MiniZinc. This means Oxiflex minimally supports the requirements for a solver to take advantage of the MiniZinc tool chain and its language. The goal is to have a minimal solver that is able to measure the impact of our improvements like forward checking and enforcing arc consistency on CSP solving.
Oxiflex is open-source, licensed under the MIT license and available on Github[1].

4.2 Rust

Rust [MI14] is a general purpose systems programming language focused on safety and performance. It achieves these goals without using a garbage collector by ensuring memory safety through a system of ownership with strict compile-time checks enforced by the borrow checker. This makes Rust particularly well-suited for creating performance-critical applications like CSP solvers where control over resources is crucial. This makes Rust an ideal choice for developing Oxiflex.

4.2.1 Limitations

Not all FlatZinc builtins are supported in Oxiflex. The idea is to implement just the needed builtins for any given interesting problem domain. Further are only `ints` supported, no floating point values. With that, there are no optimization solving structures available in Oxiflex to be able to search for an optimal solution instead of just any solution.

[1] https://github.com/glklimmer/oxiflex

4.3 Dependencies

4.3.1 flatzinc

The library flatzinc [Thi20] is a FlatZinc parser for Rust. It parses the FlatZinc format into Rust structures and variables. Oxiflex uses version `0.3.20` of flatzinc.

4.3.2 structopt

The library structopt [Pin20] is utilized to parse command-line arguments in Oxiflex. This library simplifies setting up custom commands and flags for Oxiflex. Oxiflex uses version `0.3.26` of structopt.

4.4 Architecture

Oxiflex is made up of three parts: parser, model and solver. The solver part can be fine tuned from outside by using command line flags that enable different solving strategies. The output is printed to standard output in a format given by the MiniZinc tool chain.

4.4.1 parser

Using the library flatzinc Oxiflex reads an FlatZinc `fzn` file and collects all parts needed to then construct a constraint satisfaction network. These include a list for parameters, variables and constraints. In order to also output the solution after solving the problem, Oxiflex has to know which variables it has to output. MiniZinc does this by making use of annotations on FlatZinc elements. Variables that are needed for the output are annotated as `output_var`. There are two possible output annotations in FlatZinc: `output_var` and `output_array`.

4.4.2 model

After parsing a FlatZinc file into Rust structures that can be used directly, Oxiflex starts to build useful structures to solve a given CSP. This is where Oxiflex creates a model containing variables with their respective domains and constraints. Models use HashMaps to keep track of its variables and their respective domains. This allows for constant access time to domains to either read or modify them after inference for example. Constraints are saved by the model as a list (In Rust this is a pointer, capacity, length triplet). Usually when checking if constraints are violated we either want all constraints or all constraints related to a variable. For this reason an additional HashMap is created called `constraint_index`, that uses variable ids as keys and points to a list of constraints on the heap. In Rust this can be done by using reference counting. This results in two ways to access constraints. One that is just a list to iterate over all constraints and one where a HashMap is used to get all constraints involved by a specific variable.
Variables all have an id. All variable ids are strings. Oxiflex also uses reference counting to store variable ids. As it is often also needed to pass variable ids around, we can mitigate the cost of calling `clone` on variable ids by using reference counting. Instead of actually cloning

variable ids, we just pass a pointer to the variable id needed. With reference counting we can ensure the actual memory for the variable id is freed after all pointers to it have been deleted.

4.5 Solver

The solver is the core part of Oxiflex. By allowing control over what optimization is turned on or off we can measure the impact of each optimization individually. As discussed in Chapter 3 there are various optimizations for solving CSPs. See Fig. 4.1 for an overview of how the optimizations can turned on.

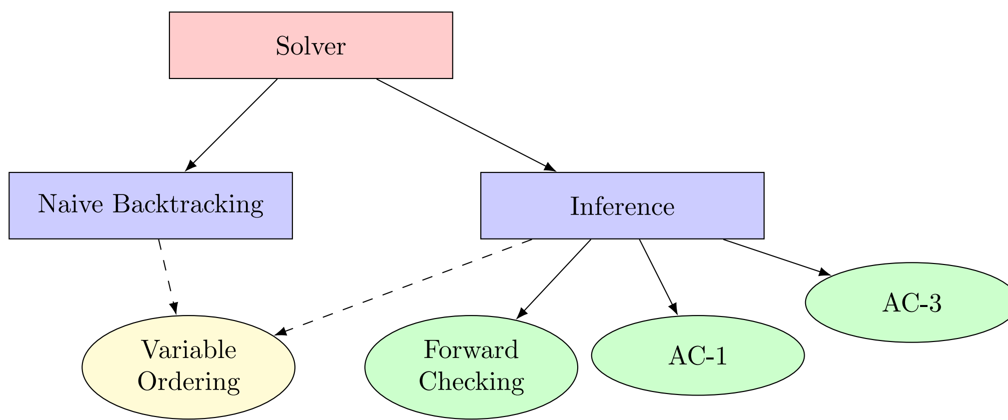

Figure 4.1: Architecture of the Solver options. Blue: choose one of general solver plans, Yellow: turn on or off, Green: choose one.

By default each optimization in Oxiflex is turned on. By passing flags named after each optimization we can disable the respective optimization. The help menu can be printed using `oxiflex --help` from the console.

```
FLAGS:
    -f, --forward-checking
    Use forward checking as inference

    -n, --naive-backtracking
    Use naive backtracking, e.g. no forward_checking

    -r, --random-variable-order
    Use random order for variable ordering.

    -a, --arc-consistency <arc-consistency>
    Specify arc consistency version [default: 3]
```

4.5.1 Value Ordering

Oxiflex is able to use dynamic ordering of variables during search based on the number of constraints. Enabled by default, Oxiflex orders variables from most constraints involvement to least for an assignment. So variables that are involved with the most constraints are chosen first to be assigned. This fail early approach to ordering can be used both for NaiveBacktracking and Inference based algorithms. For the calculation for which a variable has the most constraints, we use the HashMap called `constraint_index` mentioned in Section 4.4.2: model. This gives us a list of constraints that we can count based on number of constraints and then choose the variable with the most.

4.5.2 Forward Checking

Forward checking in Oxiflex works by removing values of domains that are no longer valid for some constraints. Domains in Oxiflex are lists of type `Vec`, which are pointer, capacity and length triplets. The removal of values happens in-place. That is, values within the `Vec` are removed without copying the whole domain. We use the function `retain` for that. It iterates over all values in a `Vec` and only "retains" values that pass the constraint checks. Removing single values from a `Vec` has a complexity of $\mathcal{O}(n)$, but as `retain` iterates over all elements either way, the complexity stays there even when removing multiple elements. Forward checking also uses `constraint_index` mentioned in Section 4.4.2: model to only get the constraints that are needed instead of checking all constraints.

4.5.3 Arc Consistency

Both AC-1 and AC-3 use the function `revise` which ensures arc consistency in one direction for two variables. The main computational work happens within this function. The role of AC-1 and AC-3 is to arrange the calls to `revise`. Within `revise` we also use the `constraint_index` (See 4.4.2: model) to get only constraints that are involved with the given variable for `revise`.
Checking constraints works by checking a `PartialAssignment`. The actual type for `PartialAssignment` is a HashMap with variable id for keys and assignments of variables as values. Therefore within `revise` the given `PartialAssignment` α is expanded with each combination of values from both variables given to `revise`. That means for each value pair within the two domains, α is expanded with two assignments. The first assignment of the first variable and the second assignment of the second variable.

5 Results

5.1 Method

For benchmarking two metrics were measured:

- **Time**
  Seconds until a solution is found.
- **Iterations**
  How many times the recursive algorithm was called.

For Time measurements hyperfine [Pet23] is used. Each Time Benchmark includes 3 warm up runs and is averaged. The longer the solver takes, the fewer runs are done. This is default behavior of hyperfine. However, at least 10 runs made were made for each benchmark. Time is given in seconds. Iterations were measured by doing 5 runs and averaging them.
A benchmark is a pair of problem size with a combination of algorithmic modifications to the solver. As Oxiflex allows us to enable each optimization individually, we can create 8 optimization combinations.

- `-n -r`
  NaiveBacktracking
- `-n`
  NaiveBacktracking with variable ordering
- `-f -r`
  Inference with forward checking
- `-f`
  Inference with forward checking and variable ordering
- `-a 1 -r`
  Inference with AC-1
- `-a 1`
  Inference with AC-1 and variable ordering

- `-r`
  Inference with AC-3

- `no flags`
  Inference with AC-3 and variable ordering

The following Problem Domains where measured:

- N-Queens
- Slow Convergence

All benchmarks were performed on the same machine.

CPU:	Intel i7-6700K (8) @ 4.200GHz
Memory:	6051MiB / 32021MiB
hyperfine version:	1.16.1
Rust version:	1.76.0
Operating System:	Pop!_OS 22.04 LTS

5.2 N-Queens

Fig. 5.1[2] shows the runtime comparison for the N-Queens Problem (See Section 2.3: Queens Problem) with $n = 8..20$ for all combinations. It shows that arc consistency enforcing methods AC-1 and AC-3 in Oxiflex take much more Time then the naive and forward checking approach. We can also see that variable ordering seems to improve all approaches significantly.
Fig. 5.2 does not include arc consistency enforcing methods making it clear to see the impact of forward checking on Time measurements for the N-Queens Problem. This shows that although the naive approach without variable ordering performs much worse then forward checking without variable ordering, it outperforms forward checking with variable ordering.
Fig. 5.3 shows benchmarks with the same parameters for measurements of Iterations. It shows that the number of Iterations grows significantly up from $n = 20$. And although we could see that arc consistency enforcing methods worsen the performance Time wise, they provide huge improvements for number of Iterations.
In Fig. 5.4 we provide benchmarks for Iterations without the naive approach with $n = 14$ up to $n = 24$. As expected forward checking performed the worst out of the three.
Table 5.1 and Table 5.2 contain results for Time and Iterations including standard deviation. Time values are rounded to 2 decimal places. If there is a standard deviation for the measurements it is given after the $\pm$ symbol. If there is no variable ordering the measurements can vary greatly because variables are chosen randomly to be assigned a value.

[2] ChatGPT 4 was used to help write scripts that create the plots. https://chatgpt.com

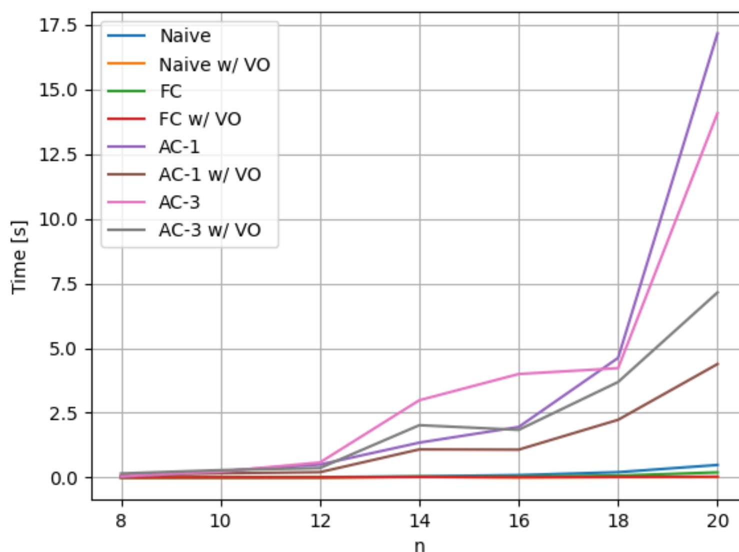

Figure 5.1: N-Queen Time measurements averaged over multiple runs (at least 10).

n	14	16	18	20
Naive	0.05 ± 0.08	0.09 ± 0.12	0.21 ± 0.45	0.49 ± 1.29
FC	0.03 ± 0.03	0.04 ± 0.04	0.07 ± 0.10	0.20 ± 0.66
AC-1	1.35 ± 0.73	1.95 ± 1.06	4.62 ± 3.25	17.17 ± 31.87
AC-3	2.99 ± 1.92	4.00 ± 2.67	4.23 ± 0.97	14.09 ± 9.93
Naive w/ VO	0.03	0.00	0.02	0.02
FC w/ VO	0.02	0.01	0.02	0.03
AC1 w/ VO	1.09 ± 0.02	1.08 ± 0.03	2.23 ± 0.04	4.39 ± 0.06
AC3 w/ VO	2.02 ± 0.04	1.84 ± 0.05	3.69 ± 0.06	7.15 ± 0.05

Table 5.1: N-Queens Time in seconds averaged over multiple runs (at least 10), Mean±SD, w/ VO: with variable ordering.

n	14	16	18	20
Naive	3538 ± 1148	1749 ± 907	2760 ± 1145	21479 ± 11183
FC	110 ± 51	415 ± 76	79 ± 16	270 ± 63
AC-1	51 ± 9	396 ± 343	195 ± 67	104 ± 19
AC-3	103 ± 41	34 ± 6	91 ± 68	86 ± 30
Naive w/ VO	3536	137	1018	1011
FC w/ VO	112	17	46	52
AC1 w/ VO	52	17	25	36
AC3 w/ VO	49	17	24	34

Table 5.2: N-Queens Iterations averaged over 5 runs, Mean±SD, w/ VO: with variable ordering.

5.3 Slow Convergence

The Slow Convergence Problem is from the MiniZinc benchmarks repository [Min18]. Benchmarks for this problem without variable ordering took over 300 seconds and are therefore

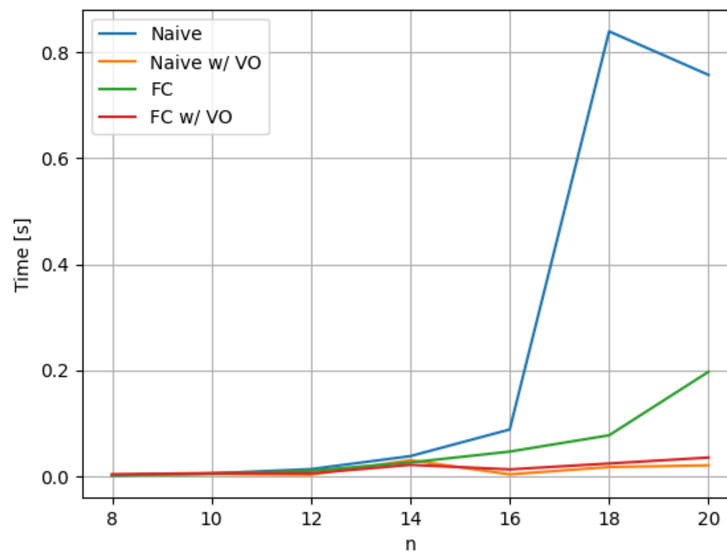

Figure 5.2: N-Queens Time measurements without arc consistency averaged over multiple runs (at least 10).

omitted. Fig. 5.5 shows benchmarks for $n = 2..10$ with combinations using variable ordering. We can see that Time measurements for AC-1 and AC-3 grow exponentially and it seems that the naive and forward checking approach grow linearly.
Fig. 5.6 shows benchmarks with the same parameters for measurements of Iterations. Note the huge spike in Iterations at $n = 3$. This spike is not a measurement error. The benchmarks were run multiple times and provided the same results. We can see that when measuring Iterations, inference methods help reducing the number of Iterations.
Next, increasing n for non arc consistency enforcing benchmarks. Fig. 5.7 shows Time measurements on the left and iteration measurements on the right for $n = 10..60$. Note the inverse correlation between Iterations and Time for the two options. Although naive backtracking (`-n`) takes more Iterations, it is still faster than forward checking (`-f`). We can also observe that it looks like forward checking was growing linearly in Fig. 5.5, and Fig. 5.7 on the left clearly show also exponential growth for forward checking. Further we can again observe that the naive approach seems to be growing linearly, but as we will see, it also grows exponentially.
Table 5.3 and Table 5.4 contain results for Time and Iterations with standard deviation for the $n = 10..60$ range.

5.4 Gecode

For comparison Fig. 5.8 shows Oxiflex compared to Gecode [Tea06]. Gecode is a CSP solver compatible with MiniZinc with state-of-the art performance. Note the steep increase in $n = 100..600$. And we can again observe that the naive approach grows exponentially.

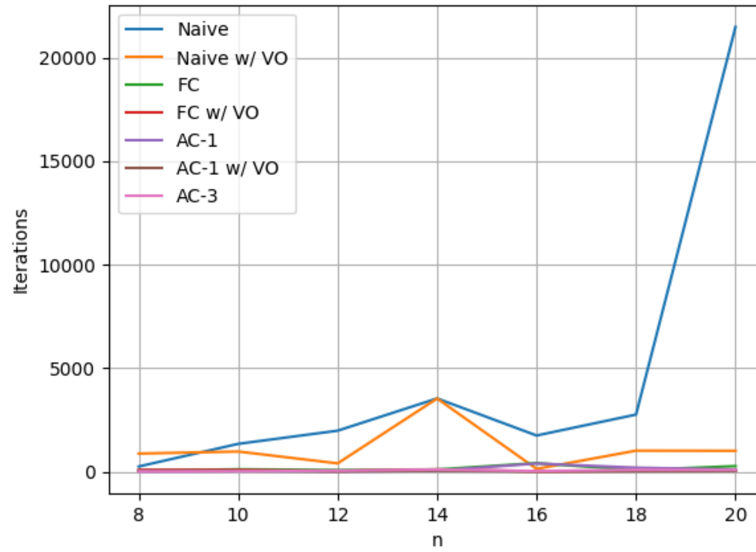

Figure 5.3: N-Queens iteration measurements averaged over 5 runs.

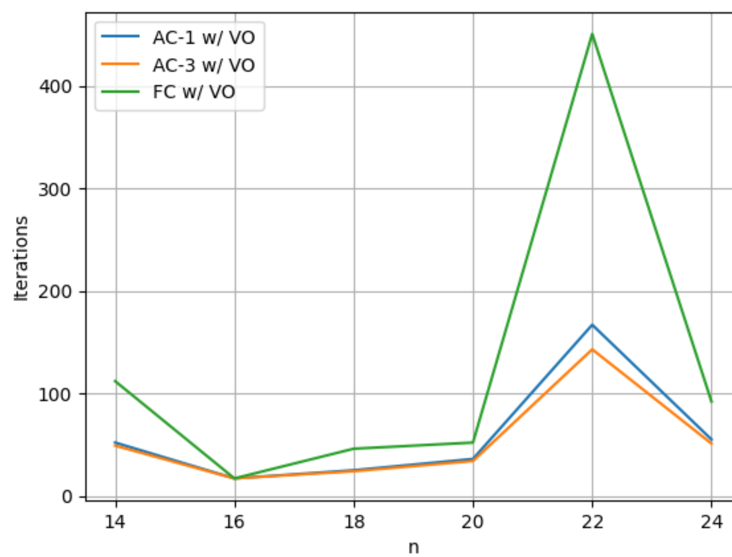

Figure 5.4: N-Queens Iterations only inference averaged over 5 runs.

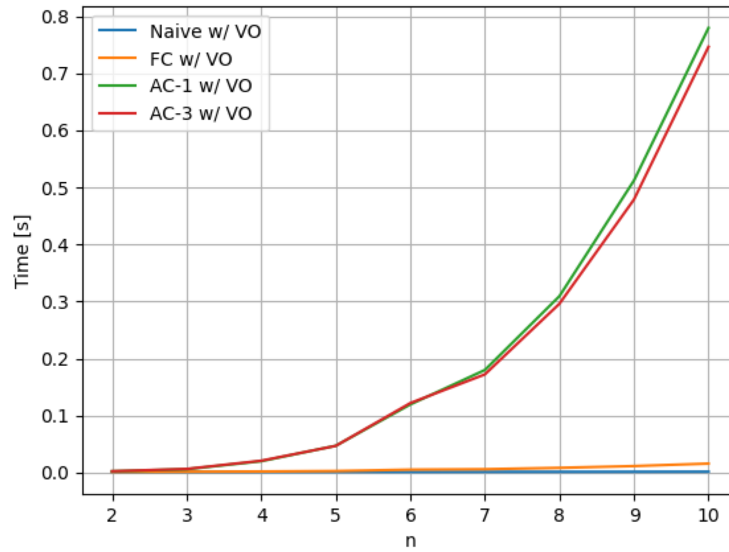

Figure 5.5: Slow Convergence Time measurements averaged over multiple runs (at least 10).

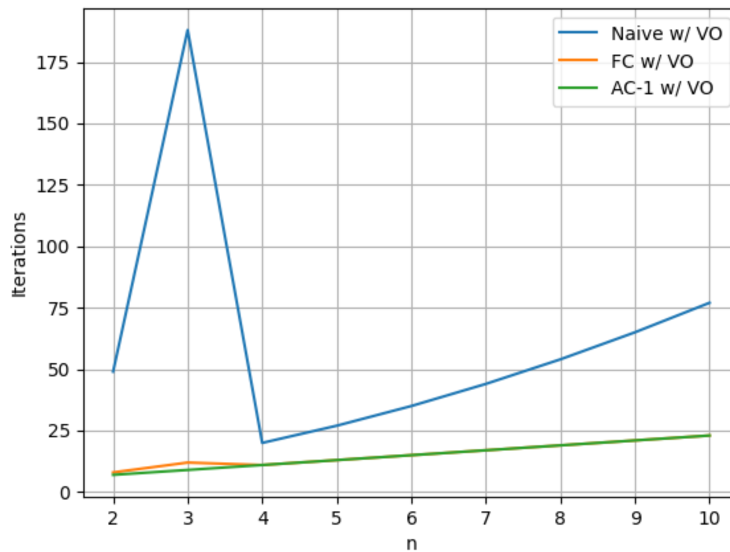

Figure 5.6: Slow Convergence iteration measurements averaged over 5 runs.

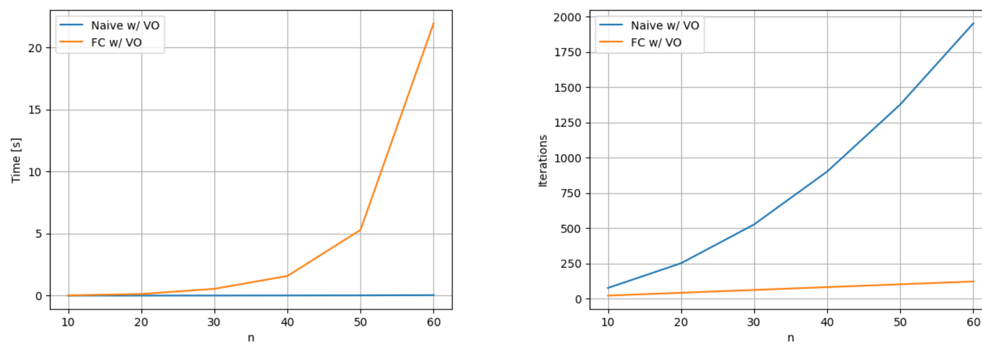

Figure 5.7: Comparison for higher $n = 10..60$. Left: Time, right: Iterations.

n	Naive w/ VO	FC w/ VO
10	0.00	0.01
20	0.00	0.13
30	0.01	0.54 ± 0.01
40	0.01	1.58 ± 0.08
50	0.02	5.29 ± 0.14
60	0.04	21.94 ± 0.5

Table 5.3: Slow Convergence Time in seconds averaged over multiple runs (at least 10), Mean±SD, w/ VO: with variable ordering.

n	Naive w/ VO	FC w/ VO
10	77	23
20	252	43
30	527	63
40	902	83
50	1377	103
60	1952	123

Table 5.4: Slow Convergence number of Iterations over 5 runs, w/ VO: with variable ordering.

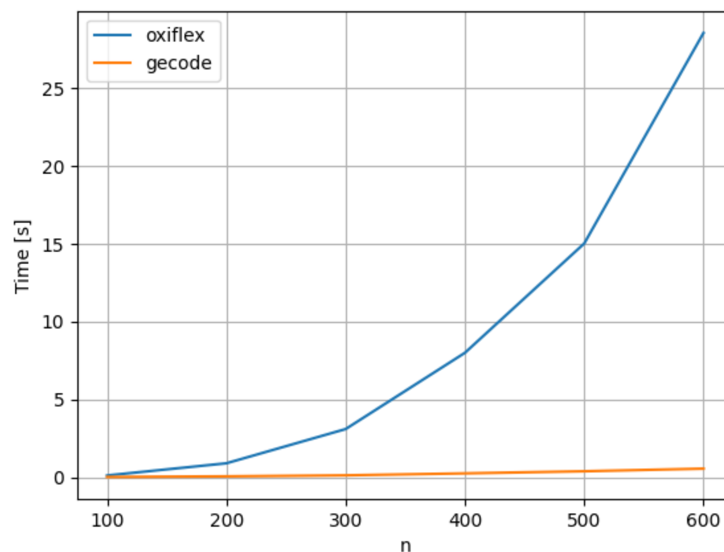

Figure 5.8: Slow Convergence Time measurements averaged over multiple runs.

6 Conclusion

6.1 Discussion

The goal of this thesis was to create a Constraint Satisfaction Problem Solver from scratch. Within this thesis we developed Oxiflex, a CSP solver from scratch written in Rust. The solver supports the CSP modeling language MiniZinc through implementing a subset of FlatZinc builtin constraints.

We started by discussing what CSPs exactly are and by writing them down formally and in the MiniZinc language. Further we especially looked at the Queens Problem as an easy to understand CSP. Next we discussed possible techniques to solve CSPs using a method called backtracking. We started by using a naive form of the algorithm and improved it further. The first improvement discussed was variable ordering with an fail early approach. That means that we choose variables to assign first, that have the most constraints. We then improved on the backtracking algorithm by adding inference. Starting with forward checking, introducing arc consistency and finally discussing AC-1 and AC-3, arc consistency enforcing algorithms.

Furthermore we gave insights into how Oxiflex works and what data structures are used to solve CSPs within Oxiflex. We discussed how the improvements like forward checking and arc consistency within Oxiflex work and what structures are in place to support them.

Finally we measured how each improvement effected both Time and number of Iterations needed for solving the N-Queens and the Slow Convergence Problems in Oxiflex. It is great to see the trade off between search and inference. As we saw in Fig. 5.7 that showed the inverse correlation between Time and number of Iterations. Although it took longer to solve, inference did reduce the number of iterations significantly. It is interesting to observe the effect that variable ordering has for the slow convergence problem. In fact it made it even possible to solve the problem at all in under 300 seconds. It can be useful to measure other things than time (like iterations) to gather insights like these.

Therefore the main takeaway for this thesis is that data structures matter. Although an algorithm performs better in theory, the right data structures have to be used to make it really go faster. Using HashMaps to hold all the data might not be the best approach if performance is the main criteria of a program. This also underlines that just using a fast programming language is not sufficient to make a program go fast.

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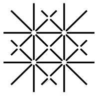

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Name Student: Gianluca Klimmer

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