

Implementing a Constraint Solver: A Case Study

Emmanuel Hebrard

Cork Constraint Computation Centre & University College Cork

Road-map

- Goal
- Blueprint
- Data Structures
- Propagation
- Search
- Code Optimization
- Competition



Road-map

- Goal
- Blueprint
- Data Structures
- Propagation
- Search
- Code Optimization
- Competition



Goal



Goal

- “Constraint Programming represents one of the closest approaches computer science has yet made to the Holy Grail of programming: the user states the problem, the computer solves it.” [E. Freuder]



Goal

- “Constraint Programming represents one of the closest approaches computer science has yet made to the Holy Grail of programming: the user states the problem, the computer solves it.” [E. Freuder]
- ...if given enough time!



Does Mistral achieve this goal?



Does Mistral achieve this goal?

- Library in C++



Does Mistral achieve this goal?

- Library in C++
- Developed during my PhD
 - Ilog Solver is not open source
 - Good substitutes (Gecode, Choco and others) did not exist yet



Does Mistral achieve this goal?

- Library in C++
- Developed during my PhD
 - Ilog Solver is not open source
 - Good substitutes (Gecode, Choco and others) did not exist yet
- Under GNU General Public License



Does Mistral achieve this goal?

- Library in C++
- Developed during my PhD
 - Ilog Solver is not open source
 - Good substitutes (Gecode, Choco and others) did not exist yet
- Under GNU General Public License
- Why Mistral?
 - because **M**istral **I**S a **T**errific **R**ecursive **A**cronym for a **L**ibrary.



Does Mistral achieve this goal?

- Library in C++
- Developed during my PhD
 - Ilog Solver is not open source
 - Good substitutes (Gecode, Choco and others) did not exist yet
- Under GNU General Public License
- Why Mistral?
 - because **M**istral **I**S a **T**errific **R**ecursive **A**cronym for a **L**ibrary.



Model: Golomb ruler

```
int main(int argc, char *argv[])
{
    // input
    int nbMarks = (argc > 1 ? atoi(argv[1]) : 8);
    int rulerSize = ( 2 << (nbMarks-1) );

    // declare model and variables
    CSP model;
    VarArray mark(nbMarks, 0, rulerSize-1);
    VarArray distance(nbMarks*(nbMarks-1)/2, 1, rulerSize-1);

    // post constraints
    int i, j, k=0;
    for(i=1; i<nbMarks; ++i) {
        model.add( mark[i-1] < mark[i] );
        for(j=0; j<i; ++j)
            model.add( mark[i] == (mark[j] + distance[k++]) );
    }
    model.add( BoundAllDifferent(distance) );

    // post objective function
    model.add( Minimise( Max(mark) ) );

    // solve
    Solver s( model, mark );
    s.setVerbosity(1);
    s.solve();

    // print search statistics
    s.printStatistics( cout, (Solver::NDS | Solver::RUNTIME) );
    cout << endl;
}
```

Model: Golomb ruler

```
int main(int argc, char *argv[])
// input
int nbMarks = (argc > 1 ? atoi(argv[1]) : 8);
int rulerSize = ( 2 << (nbMarks-1) );

CSP model;
VarArray mark(nbMarks, 0, rulerSize-1);
VarArray distance(nbMarks*(nbMarks-1)/2, 1, rulerSize-1);

// post constraints
int i, j, k=0;
for(i=1; i<nbMarks; ++i) {
    model.add( mark[i-1] < mark[i] );
    for(j=0; j<i; ++j)
        model.add( mark[i] == (mark[j] + distance[k++]) );
}
model.add( BoundAllDifferent(distance) );

// post objective function
model.add( Minimise( Max(mark) ) );

// solve
Solver s( model, mark );
s.setVerbosity(1);
s.solve();

// print search statistics
s.printStatistics( cout, (Solver::NDS | Solver::RUNTIME) );
cout << endl;
}
```

Model: Golomb ruler

```
int main(int argc, char *argv[])
{
    // input
    int nbMarks = (argc > 1 ? atoi(argv[1]) : 8);
    int rulerSize = ( 2 << (nbMarks-1) );

    // declare model and variables
    CSP model;
    VarArray mark(nbMarks, 0, rulerSize-1);
    VarArray distance(nbMarks*(nbMarks-1)/2, 1, rulerSize-1);

    for(i=1; i<nbMarks; ++i) {
        model.add( mark[i-1] < mark[i] );
        for(j=0; j<i; ++ j)
            model.add( mark[i] == (mark[j] + distance[k++]) );
    }
    model.add( BoundAllDifferent(distance) );

    // post objective function
    model.add( Minimise( Max(mark) ) );

    // solve
    Solver s( model, mark );
    s.setVerbosity(1);
    s.solve();

    // print search statistics
    s.printStatistics( cout, (Solver::NDS | Solver::RUNTIME) );
    cout << endl;
}
```

Model: Golomb ruler

```
int main(int argc, char *argv[])
{
    // input
    int nbMarks = (argc > 1 ? atoi(argv[1]) : 8);
    int rulerSize = ( 2 << (nbMarks-1) );

    // declare model and variables

    // post constraints
    int i, j, k=0;
    for(i=1; i<nbMarks; ++i) {
        model.add( mark[i-1] < mark[i] );
        for(j=0; j<i; ++j)
            model.add( mark[i] == (mark[j] + distance[k++]) );
    }
    model.add( BoundAllDifferent(distance) );

    // solve
    Solver s( model, mark );
    s.setVerbosity(1);
    s.solve();

    // print search statistics
    s.printStatistics( cout, (Solver::NDS | Solver::RUNTIME) );
    cout << endl;
}
```


Model: Golomb ruler

```
int main(int argc, char *argv[])
{
    // input
    int nbMarks = (argc > 1 ? atoi(argv[1]) : 8);
    int rulerSize = ( 2 << (nbMarks-1) );

    // declare model and variables
    CSP model;
    VarArray mark(nbMarks, 0, rulerSize-1);
    VarArray distance(nbMarks*(nbMarks-1)/2, 1, rulerSize-1);

    // post constraints
    int i, j, k=0;
    for(i=1; i<nbMarks; ++i) {
        model.add( mark[i-1] < mark[i] );
        for(j=0; j<i; ++ j)
            model.add( mark[i] == (mark[j] + distance[k++]) );
    }
```

```
// post objective function
model.add( Minimise( Max(mark) ) );
```

```
.....
s.setVerbosity(1);
s.solve();

// print search statistics
s.printStatistics( cout, (Solver::NDS | Solver::RUNTIME) );
cout << endl;
}
```

Model: Golomb ruler

```
int main(int argc, char *argv[])
{
    // input
    int nbMarks = (argc > 1 ? atoi(argv[1]) : 8);
    int rulerSize = ( 2 << (nbMarks-1) );

    // declare model and variables
    CSP model;
    VarArray mark(nbMarks, 0, rulerSize-1);
    VarArray distance(nbMarks*(nbMarks-1)/2, 1, rulerSize-1);

    // post constraints
    int i, j, k=0;
    for(i=1; i<nbMarks; ++i) {
        model.add( mark[i-1] < mark[i] );
        for(j=0; j<i; ++ j)
            model.add( mark[i] == (mark[j] + distance[k++]) );
    }
    model.add( BoundAllDifferent(distance) );

    // solve
    Solver s( model, mark );
    s.setVerbosity(1);
    s.solve();

    cout << endl;
}
```

Message:

Message:

- Efficient implementation
 - Details do matter

Message:

- Efficient implementation
 - Details do matter
- Modeling choices
 - Automatic choices of the best representation/algorithm
 - ✓ Variable (Constant, Boolean, Interval, Bitset, List, ...)
 - ✓ Constraints (Specific algorithm, Decomposition, Generic algorithms, ...)
 - ✓ Heuristics
 - Automatic rewriting?

Message:

- Efficient implementation
 - Details do matter
- Modeling choices
 - Automatic choices of the best representation/algorithm
 - ✓ Variable (Constant, Boolean, Interval, Bitset, List, ...)
 - ✓ Constraints (Specific algorithm, Decomposition, Generic algorithms, ...)
 - ✓ Heuristics
 - Automatic rewriting?
- Robustness
 - Worst case principle

Road-map

- Goal
- Blueprint
- Data Structures
- Propagation
- Search
- Code Optimization
- Competition



A little bit of structure

Search

- Search algorithms
- Heuristics

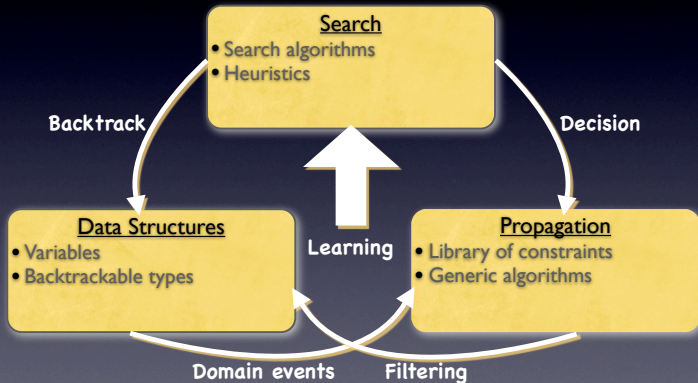
Data Structures

- Variables
- Backtrackable types

Propagation

- Library of constraints
- Generic algorithms

A little bit of structure



Road-map

- Goal
- Blueprint
- Data Structures
 - Variables (Backtracks)
- Propagation
- Search
- Code Optimization
- Competition



Backtrackable Data-Structures

- Copying/Trailing
 - See Shulte's papers and PhD Thesis
 - Copying
 - ✓ Easier to implement data structures
 - ✓ Easier to implement search strategies
 - ✓ Easier to parallelize
 - Trailing
 - ✓ Do only necessary work
 - ✓ Memory efficient



Copying



Trailing

Domain as a Bitset

- One 32 bits word for every value in $[\min(D)..\max(D)]$

X in
 $\{0,1,2,5,7,18,19,21\}$

1	1	1	0	0	1	0	1
---	---	---	---	---	---	---	---

0	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---

0	0	1	1	0	1	0	0
---	---	---	---	---	---	---	---

Domain as a Bitset

- One 32 bits word for every value in $[\min(D)..\max(D)]$
- For every word, we allocate as many word as values in that word:
 - $O((\max - \min + 1) + 32 * |D|)$ bits

X in
 $\{0,1,2,5,7,18,19,21\}$

1	1	1	0	0	1	0	1

0	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---

0	0	1	1	0	1	0	0

Domain as a Bitset

- One 32 bits word for every value in $[\min(D)..\max(D)]$
- For every word, we allocate as many word as values in that word:
 - $O((\max - \min + 1) + 32 * |D|)$ bits

X in
 $\{0, 1, 2, 5, 7, 18, 19, 21\}$

1	1	1	0	0	1	0	1

0	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---

0	0	1	1	0	1	0	0

Allocated statically

Domain as a Bitset



X in $\{0, 1, 2, 5, 7, 18, 19, 21\}$

Domain as a Bitset

1 1 1 0 0 1 0 1

0 0 0 0 0 0 0 0

0 0 1 1 0 1 0 0

$X \text{ in } \{0, 1, 2, 5, 7, 18, 19, 21\}$

Domain as a Bitset

decision 1



$\{0,5,7,18,19,21\}$

11100101

00000000

00110100

X in $\{0,1,2,5,7,18,19,21\}$

Domain as a Bitset

decision 1 $\rightarrow$ {0,5,7,18,19,21} wl

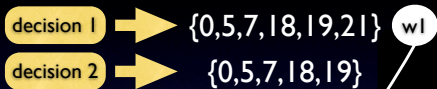
1	1	1	0	0	1	0	1
1	0	0	0	0	1	0	1

0	0	0	0	0	0	0	0
---	---	---	---	---	---	---	---

0	0	1	1	0	1	0	0
---	---	---	---	---	---	---	---

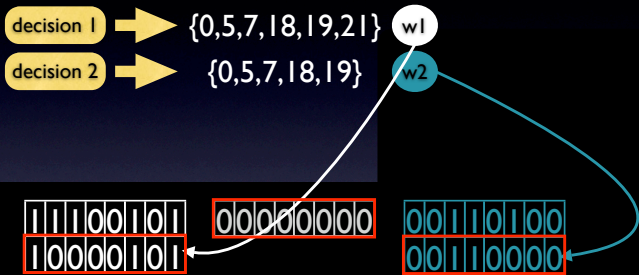
X in {0,1,2,5,7,18,19,21}

Domain as a Bitset



X in {0,1,2,5,7,18,19,21}

Domain as a Bitset

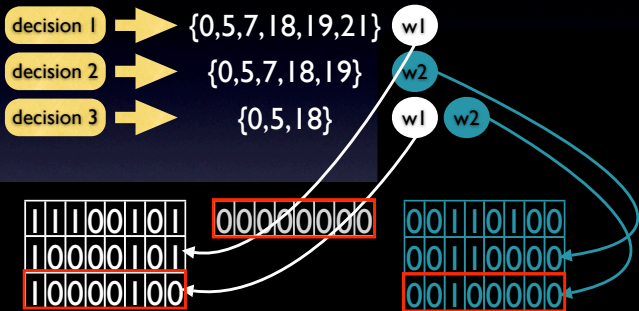


X in {0,1,2,5,7,18,19,21}

Domain as a Bitset

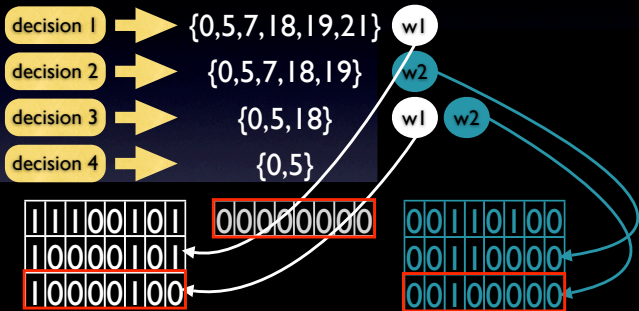


Domain as a Bitset



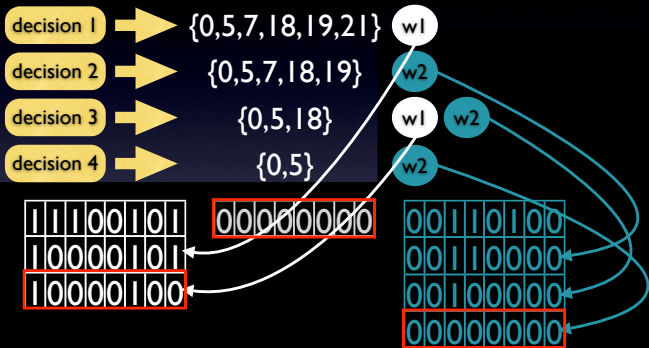
X in {0,1,2,5,7,18,19,21}

Domain as a Bitset



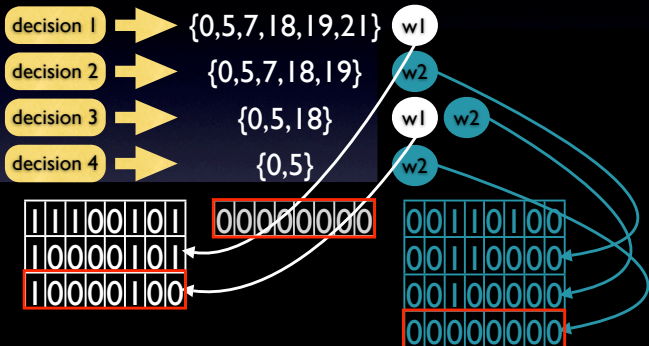
X in {0,1,2,5,7,18,19,21}

Domain as a Bitset



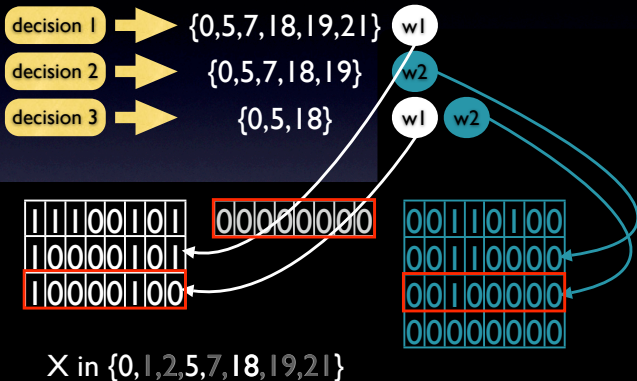
X in {0,1,2,5,7,18,19,21}

Domain as a Bitset

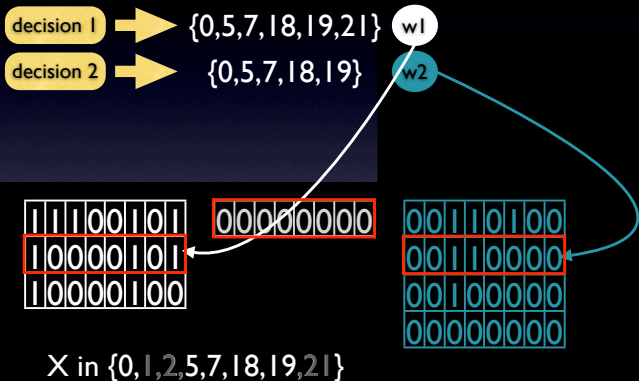


X in {0,1,2,5,7,18,19,21}

Domain as a Bitset



Domain as a Bitset



Domain as a List

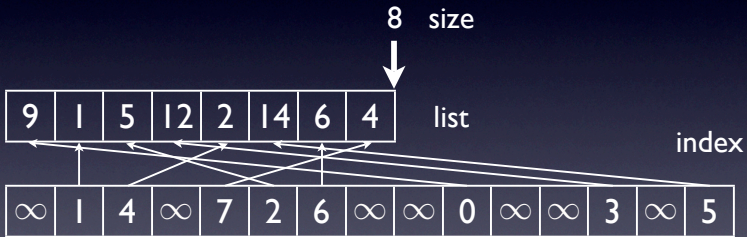
Domain as a List

9	1	5	12	2	14	6	4	list
---	---	---	----	---	----	---	---	------

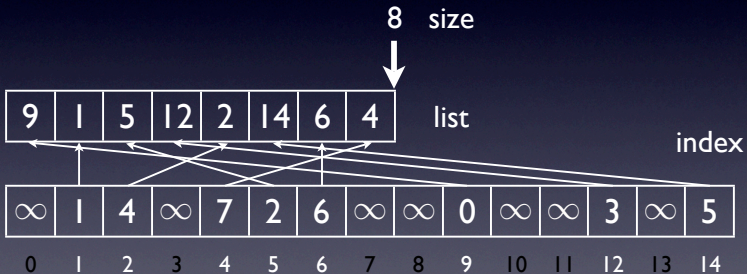
Domain as a List



Domain as a List

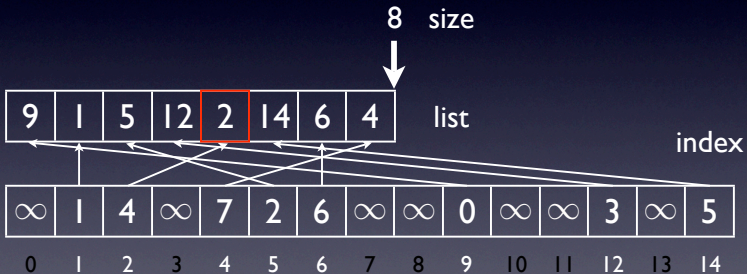


Domain as a List



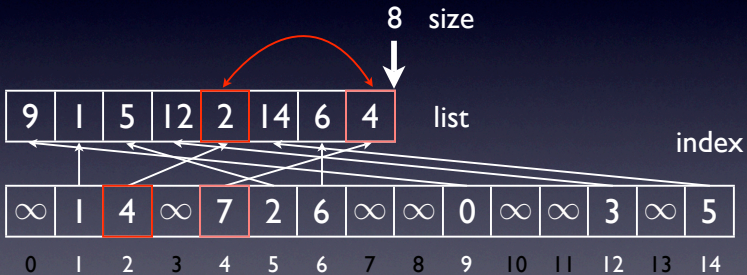
membership: $index[v] < size$

Domain as a List



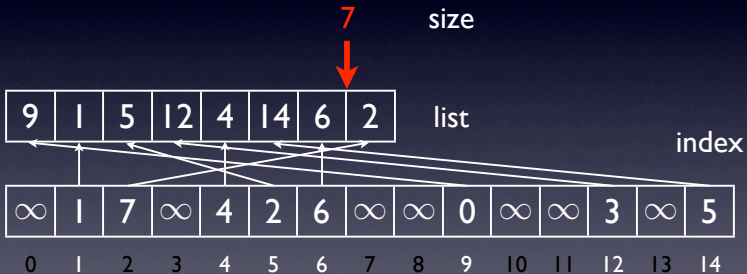
membership: $index[v] < size$

Domain as a List

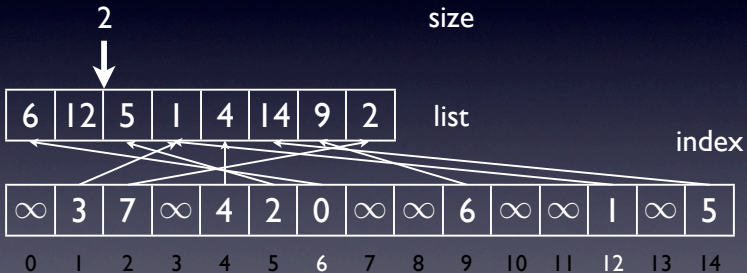


membership: $index[v] < size$

Domain as a List

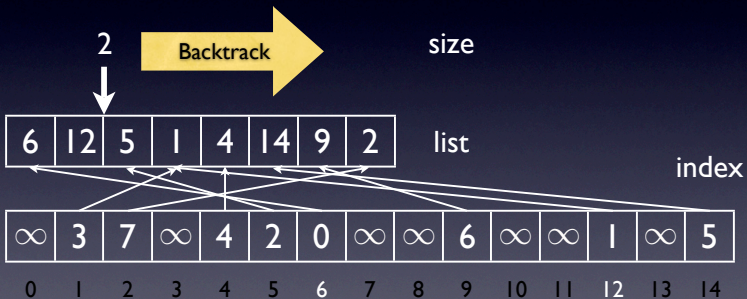


Domain as a List

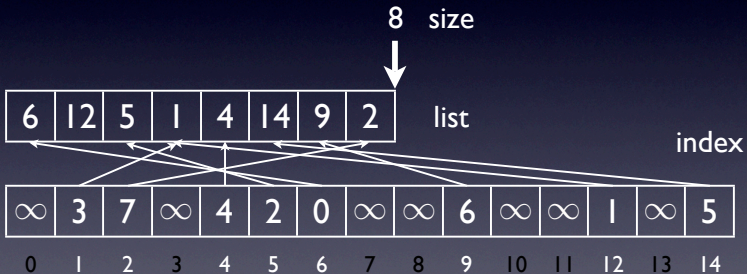


membership: $index[v] < size$

Domain as a List



Domain as a List



membership: $index[v] < size$

Pigeon holes



Pigeon holes

- Domain as a Bitset:
 - ✓ Space complexity in $O(\max - \min)$
 - ✓ Restore up to 32 values at a time
 - ✓ 600,000 Bts/second



Pigeon holes

- Domain as a Bitset:

- ✓ Space complexity in $O(\text{max-min})$
- ✓ Restore up to 32 values at a time
- ✓ 600,000 Bts/second

- Domain as a List:

- ✓ Similar space complexity
- ✓ Restore any number of values in one operation
- ✓ 900,000 Bts/second
- ✓ However, operations are much slower on the list (interval reasoning, set operations)



Road-map

- Goal
- Blueprint
- Data Structures
- Propagation
 - Nested predicates
 - GAC valid v allowed
- Search
- Code Optimization
- Competition



Constraint Propagation

- Variable/Constraint Queue
- Specific Propagators
- Nested Predicates
- Generic AC algorithms
 - Binary: AC3Bitset
 - Tight: GAC2001Allowed
 - Loose: GAC3rValid

Pruning:



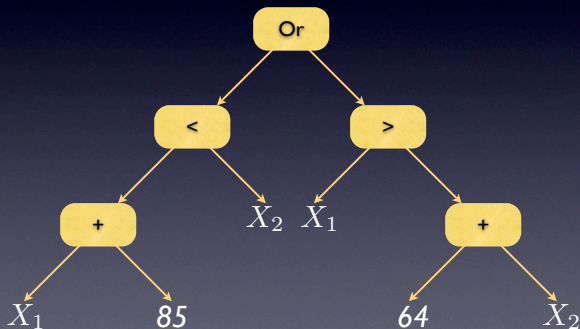
Nested Predicates

Example: open-shop scheduling:

```
<predicate name="P0">  
  <parameters>int X0 int X1 int X2 int X3 int X4 int X5</parameters>  
  <expression>  
    <functional>or(le(add(X0,X1),X2),le(add(X3,X4),X5))</functional>  
  </expression>  
</predicate>  
  
<constraint name="C0" arity="2" scope="V0 V1" reference="P0">  
  <parameters>V0 85 V1 V1 64 V0</parameters>  
</constraint>
```

Nested Predicates: Decomposition

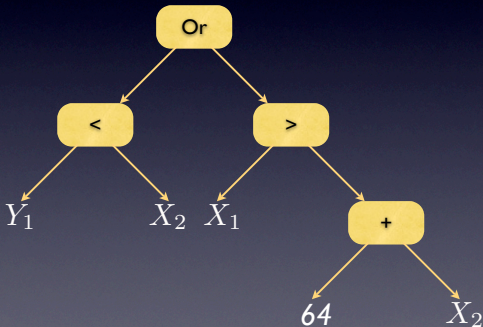
Example: open-shop scheduling:



Nested Predicates: Decomposition

Example: open-shop scheduling:

$$Y_1 = X_1 + 85$$

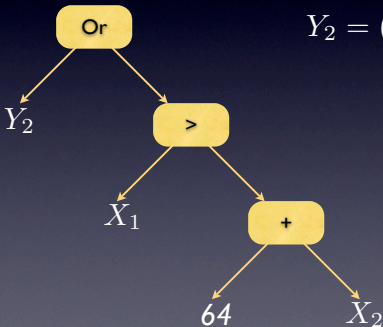


Nested Predicates: Decomposition

Example: open-shop scheduling:

$$Y_1 = X_1 + 85$$

$$Y_2 = (Y_1 < X_2)$$



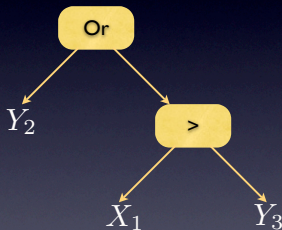
Nested Predicates: Decomposition

Example: open-shop scheduling:

$$Y_1 = X_1 + 85$$

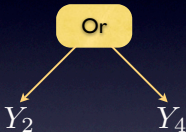
$$Y_2 = (Y_1 < X_2)$$

$$Y_3 = X_2 + 64$$



Nested Predicates: Decomposition

Example: open-shop scheduling:



$$Y_1 = X_1 + 85$$

$$Y_2 = (Y_1 < X_2)$$

$$Y_3 = X_2 + 64$$

$$Y_4 = (Y_3 < X_1)$$

Nested Predicates: Decomposition

Example: open-shop scheduling:

$$Y_1 = X_1 + 85$$

$$Y_2 = (Y_1 < X_2)$$

$$Y_3 = X_2 + 64$$

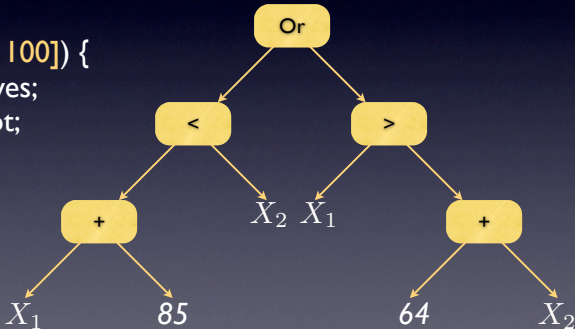
$$Y_4 = (Y_3 < X_1)$$

$$(Y_2 \vee Y_4)$$

Nested Predicates: GAC-Checker

Example: open-shop scheduling:

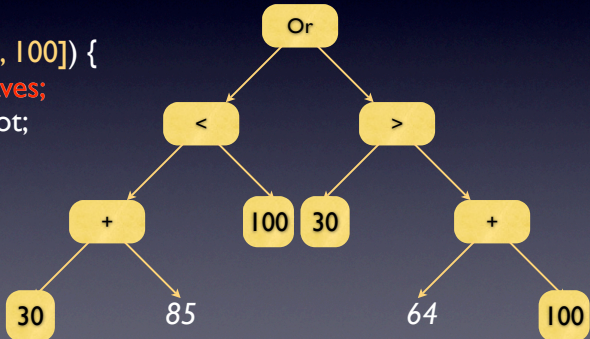
check $[30, 100]$ {
 assign leaves;
 query root;
}



Nested Predicates: GAC-Checker

Example: open-shop scheduling:

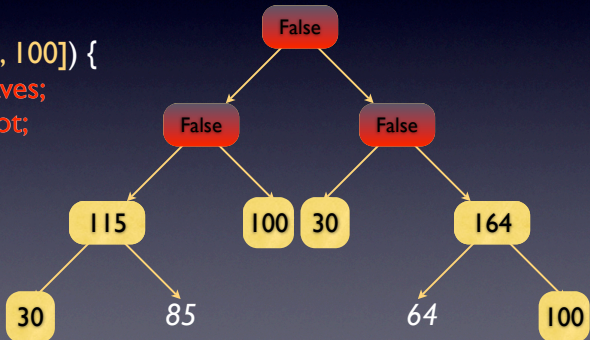
check ([30, 100]) {
 assign leaves;
 query root;
}



Nested Predicates: GAC-Checker

Example: open-shop scheduling:

check ([30, 100]) {
 assign leaves;
 query root;
}



Golomb ruler / FAPP

Instance:

Decomposition

GAC-Checker

Golomb ruler / FAPP

Instance:	Golomb Ruler
Decomposition	128 nodes 0.18 seconds
GAC-Checker	87 nodes 38.22 seconds

Golomb ruler / FAPP

Instance:	Golomb Ruler	FAPP
Decomposition	128 nodes 0.18 seconds	60181 nodes 55.18 seconds
GAC-Checker	87 nodes 38.22 seconds	374 nodes 1.18 seconds

Making the Right Choice

Making the Right Choice

Feature	GAC	Decomp	OSP
---------	-----	--------	-----

Making the Right Choice

Feature	GAC	Decomp	OSP
Constraint Arity	-	+	binary

Making the Right Choice

Feature	GAC	Decomp	OSP
Constraint Arity	-	+	binary
Ratio node/leaves	+	-	5/2

Making the Right Choice

Feature	GAC	Decomp	OSP
Constraint Arity	-	+	binary
Ratio node/leaves	+	-	5/2
Domain continuity	-	+	no holes

Making the Right Choice

Feature	GAC	Decomp	OSP
Constraint Arity	-	+	binary
Ratio node/leaves	+	-	5/2
Domain continuity	-	+	no holes
Cartesian product cardinality	-	+	>60,000

Making the Right Choice

Feature	GAC	Decomp	OSP
Constraint Arity	-	+	binary
Ratio node/leaves	+	-	5/2
Domain continuity	-	+	no holes
Cartesian product cardinality	-	+	>60,000
Boolean domains	-	+	no

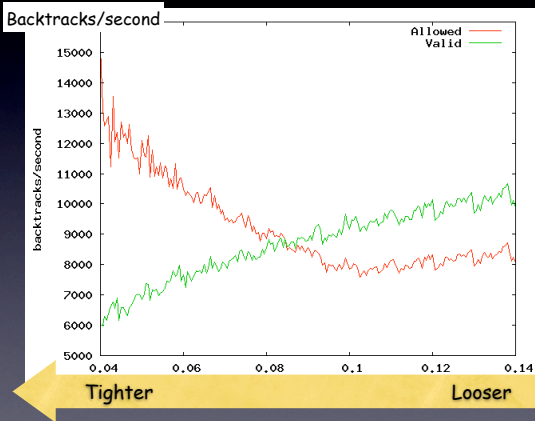
Making the Right Choice

Feature	GAC	Decomp	OSP
Constraint Arity	-	+	binary
Ratio node/leaves	+	-	5/2
Domain continuity	-	+	no holes
Cartesian product cardinality	-	+	>60,000
Boolean domains	-	+	no
Total number of constraints	+	-	small

Making the Right Choice

Feature	GAC	Decomp	OSP
Constraint Arity	-	+	binary
Ratio node/leaves	Decomposition!	-	5/2
Domain continuity		+	no holes
Cartesian product cardinality	-	+	>60,000
Boolean domains	-	+	no
Total number of constraints	+	-	small

GAC Allowed v. GAC Valid



Road-map

- Goal
- Blueprint
- Data Structures
- Propagation
- Search
 - Heuristics
- Code Optimization
- Competition



Search Strategies

- Depth-first, Breadth-first, LDS,...
- Branching Choices
 - Domain Splitting
 - Arbitrary Constraint
- Variable/Value Ordering
 - “Learning” heuristics
 - ✓ Weighted Degree, Impact



Weighted Heuristics

- The best general purpose orderings are based on some kind of learning (or weighting)
 - Weighted Degree [Boussemart, Hemery, Lecoutre, Sais 2004]
 - Impact [Refalo 2004]
- A “Weighter” can subscribe for different types of event
 - Weighted degree: **failures**
 - Impact: **Decisions, success, failures**
- This architecture allows easy development of variations around these models
 - Why isn't **Impact/Weighted Degree** any good?

Road-map

- Goal
- Blueprint
- Data Structures
- Propagation
- Search
- Code Optimization
- Competition



Optimisation: Binary Extensional

- Standard algorithms:
 - AC3-bitset, Variable queue (fifo), revision condition
- Profiling, what does take time?
 - Propagation:..... 68%
 - "&" operation:..... 25.9%
 - Domain iteration:..... 20.6%
 - AC3 (queuing/dequeuing):..... 11.4%
 - Revision condition + virtual call:.. 10.0%
 - Data structure modification:..... 19%
 - Domain modification:..... 19.0%
 - Search:..... 12%
 - Trailing:..... 9.7%
 - Variable choice + Branching:..... 2.2%

Intersection on Bitsets (25%)

```
bool VariableList::wordIntersect(const MistralSet& s) const  
{  
    return values.wordIntersect(s);  
}
```



```
inline bool MistralSet::wordIntersect(const MistralSet& s) const  
{  
    return ( table[neg_words] & s.table[neg_words] ) ;  
}
```


Values Iteration (20%)



Values Iteration (20%)

- Random binary CSP



Values Iteration (20%)

- Random binary CSP
- Domain as a Bitset:
 - 6,500 Bts/second



Values Iteration (20%)

- Random binary CSP
- Domain as a Bitset:
 - 6,500 Bts/second
- Domain as a List (hybrid bitset/list):
 - 10,000 Bts/second
 - Values are stored contiguously in an array
 - The order does not matter



Road-map

- Goal
- Blueprint
- Data Structures
- Propagation
- Search
- Code Optimization
- Competition



Quick Comparison

(#instances)



Abscon

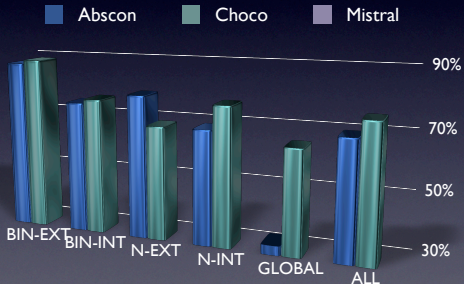


Choco

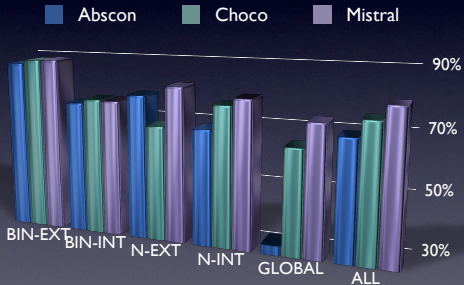


Mistral

Quick Comparison (#instances)



Quick Comparison (#instances)



Quick Comparison

(cpu time)



Abscon



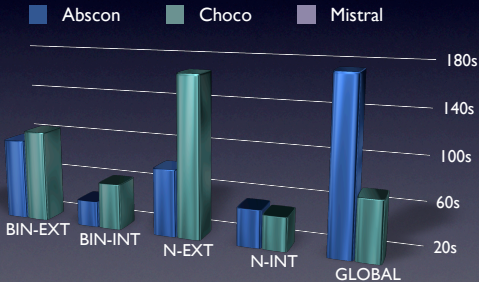
Choco



Mistral

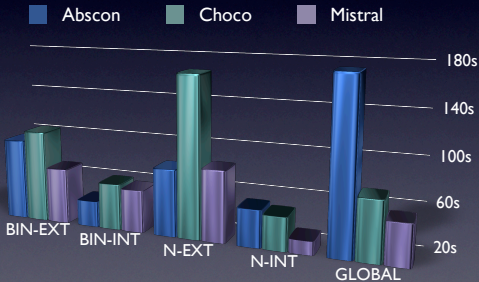
Quick Comparison

(cpu time)

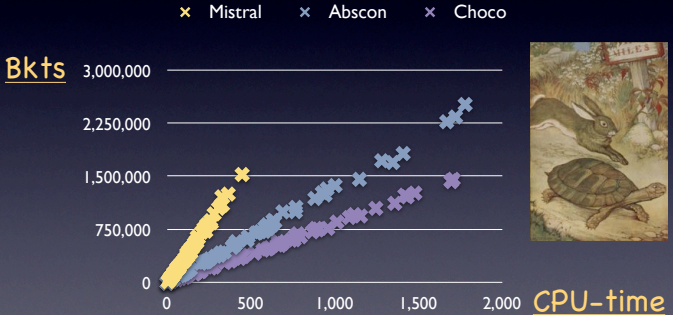


Quick Comparison

(cpu time)

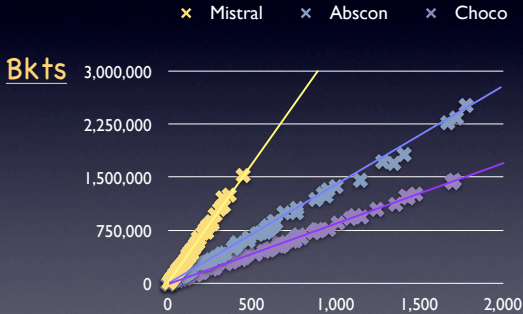


Backtracks v CPU-time



rand-2-40-19-443-230-* and frb40-19

Backtracks v CPU-time



rand-2-40-19-443-230-* and frb40-19

Conclusion



Conclusion

- Implementing a constraint solver may appear like a daunting task



Conclusion

- Implementing a constraint solver may appear like a daunting task
 - It is so.



Conclusion

- Implementing a constraint solver may appear like a daunting task
 - It is so.
 - But you'll learn a lot!



Conclusion

- Implementing a constraint solver may appear like a daunting task
 - It is so.
 - But you'll learn a lot!
- Adaptability



Conclusion

- Implementing a constraint solver may appear like a daunting task
 - It is so.
 - But you'll learn a lot!
- Adaptability
- Attention to details



Conclusion

- Implementing a constraint solver may appear like a daunting task
 - It is so.
 - But you'll learn a lot!
- Adaptability
- Attention to details
- Robustness



Conclusion

- Implementing a constraint solver may appear like a daunting task
 - It is so.
 - But you'll learn a lot!
- Adaptability
- Attention to details
- Robustness
 - Weaknesses are always more obvious to a user than strengths

