

The 3-SAT Decision Problem Towards a Parallel Search Implementation Team Satisfaction

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May 4, 2013

Agenda

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Boolean Satisfiability

Boolean satisfiability is an *NP*-complete decision problem defined as:

$$SAT : \phi \rightarrow \{YES, NO\}$$

Input: Boolean formula ϕ_n on n variables.

$$\phi_5 = (x_1 \vee x_2 \vee \neg x_3) \vee \neg x_4 \wedge x_5 \wedge (\neg x_2 \vee x_3 \wedge (x_4 \wedge x_1))$$

Output: *YES* if there exists a truth assignment to the variables in ϕ_n such that it evaluates to true, *NO* otherwise.

$$\phi_n \text{ is satisfiable} \Leftrightarrow SAT(\phi_n) = YES$$

3-SAT $\in NP$

- A special case of *SAT* that fixes the format of ϕ_n .
- Each input formula is in 3-*CNF* form:
 - The conjunction (Boolean AND) of arbitrarily many clauses, where each clause is the disjunction (Boolean OR) of exactly three literals (a Boolean variable or its negation).

$$(x_1 \vee x_2 \vee \neg x_3) \wedge (\neg x_1 \vee x_2 \vee x_3) \wedge (\neg x_1 \vee x_2 \vee \neg x_3)$$

- *SAT* reduces to 3-SAT, so 3-SAT $\in NP$.

Exhaustive Search for 3-SAT

Input: 3-CNF formula ϕ_n on n variables, **Output:** YES or NO

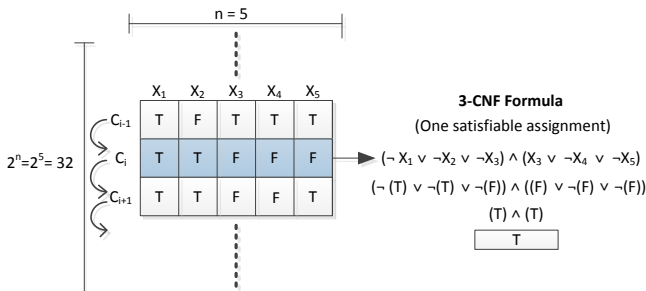
```
1:  $C \leftarrow FALSE^n$  (array of  $n$  False values, the initial configuration)
2: for  $i = 0 \rightarrow 2^n - 1$  do
3:    $SAT \leftarrow TRUE$ 
4:   for all  $clause \in \phi_n$  do
5:     if  $evaluate(clause, C) = FALSE$  then
6:        $SAT \leftarrow FALSE$ 
7:     end if
8:   end for
9:   if  $SAT = TRUE$  then return YES
10:   $C \leftarrow nextConfig(C)$ 
11: end for
12: return NO
```

Exhaustive Search for 3-SAT - A *Very Satisfiable* Example!

Input: $\phi_5 = (\neg X_1 \vee \neg X_2 \vee \neg X_3) \wedge (X_3 \vee \neg X_4 \vee \neg X_5)$

Output: Yes

Note: no early termination once a satisfiable solution is found



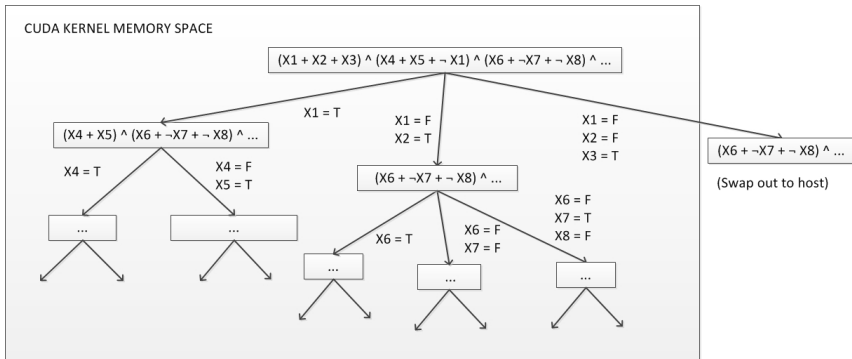
Evaluating a Clause

- Evaluating a clause depends on how ϕ_n and the variable truth assignments are stored.
 - `boolean[] variables` for variable assignments and `Literal[][3] formula` for ϕ_n .
 - A `Literal` has a variable ID and negated flag

```
for (int c = 0; c < numClauses; c++) {  
    boolean clauseValue = false;  
    for (int l = 0; l < 3 && clauseValue == false; l++) {  
        if (formula[c][l].negated == true && !variables[formula[c][l].id])  
            clauseValue = true;  
        else if (formula[c][l].negated == false && variables[formula[c][l].id])  
            clauseValue = true;  
    }  
    // Check the value of the clause now...  
}
```

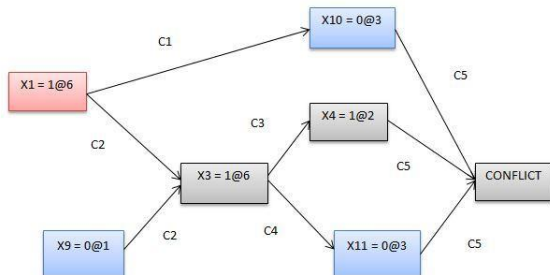
Recursive Divide and Conquer with CUDA

■ TODO: overview



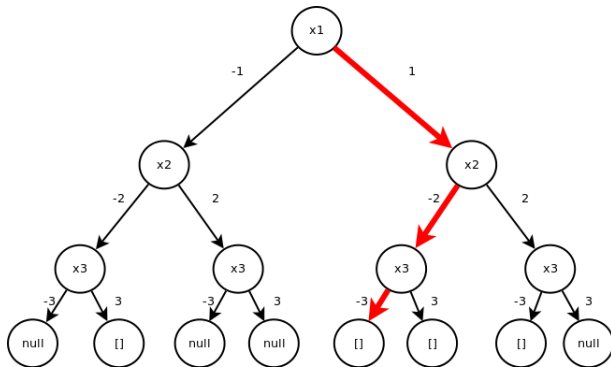
Advanced Clause Learning and Sharing with ManySAT

■ TODO: overview



Intelligent Literal Decisions and Advanced Data Structures for DPLL

■ TODO: overview



$$(x1 \wedge \sim x2 \wedge \sim x3)$$

Parallel Implementation Design Goals

Our design goals included:

- Evenly divide the configuration space among different threads
- Minimize (or remove) conflicts for shared variables

Our solution consists of:

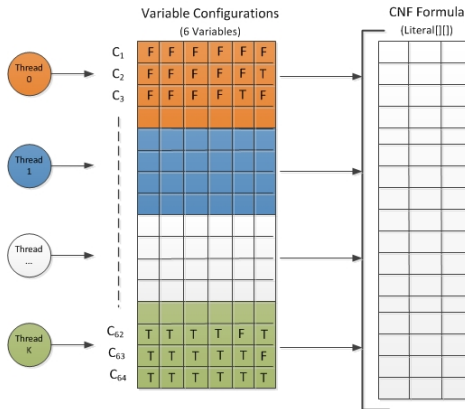


The Parallel Transformation

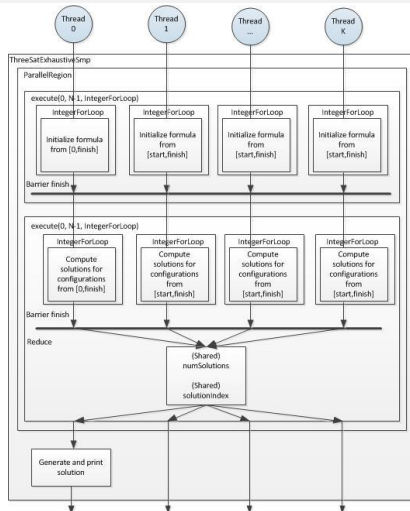
Managing variable access

Sequential Variable	Parallel Variable	Shared?
Literal[][] configuration[] numSatisfiable		

Computation Partition Strategy



Thread Synchronization

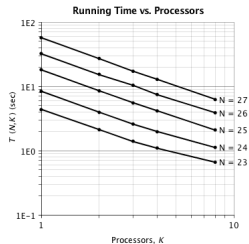
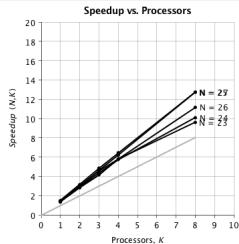
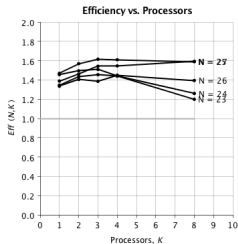
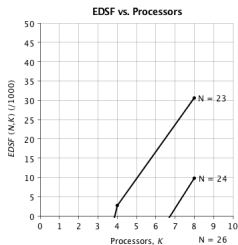


The Parallel Solver

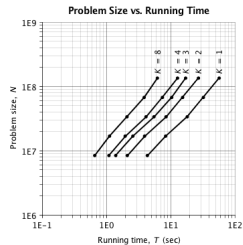
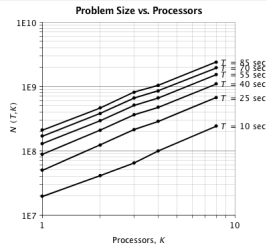
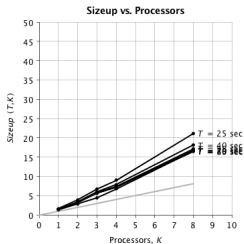
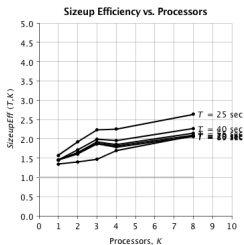
Demo time!

$$\phi_5 = (\neg X_1 \vee \neg X_2 \vee \neg X_3) \wedge (X_3 \vee \neg X_4 \vee \neg X_5)$$

Speedup Metrics (Exhaustive)



Sizeup Metrics (Exhaustive)



Performance Observations

- We achieved *superlinear* speedups and sizeups using a guided schedule with varying the number of variables
- Exhaustive 3-SAT problems have implicit unbalanced loads
 - A guided schedule yielded the best results for speedup and sizeup
 - A dynamic schedule caused a *significant* amount of overhead
- Our parallel programs achieve better performance when the number of variables is varied:
 - The problem size $N = f(N_v, N_c) = 2^{N_v} \times N_c$

Lessons Learned

- If the problem size is a function of *multiple* variables, experiments should only change one of such variables to gather valid performance data
- A guided schedule yielded the most balanced load for our computation partition strategy
- TODO
- TODO

Future Work

- Implement more advanced heuristics for literal selection
- Strive for wider splits of the configuration search space tree among multiple processes
- Experiment with different data structures to see what's the most optimal

Questions?

Fire away!