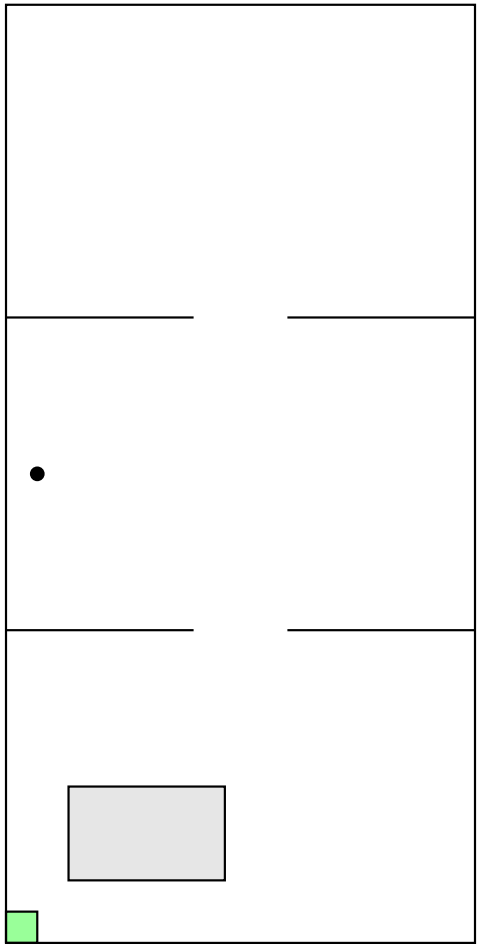
Robot Motion Planning

F. Barbosa, K. Grover, J. Křetínský, J. Tumova

Motion Planning Problem



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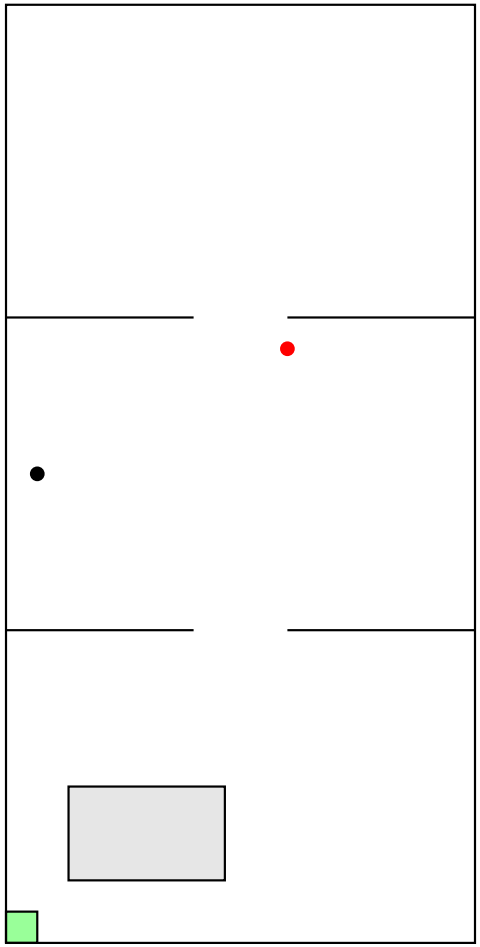

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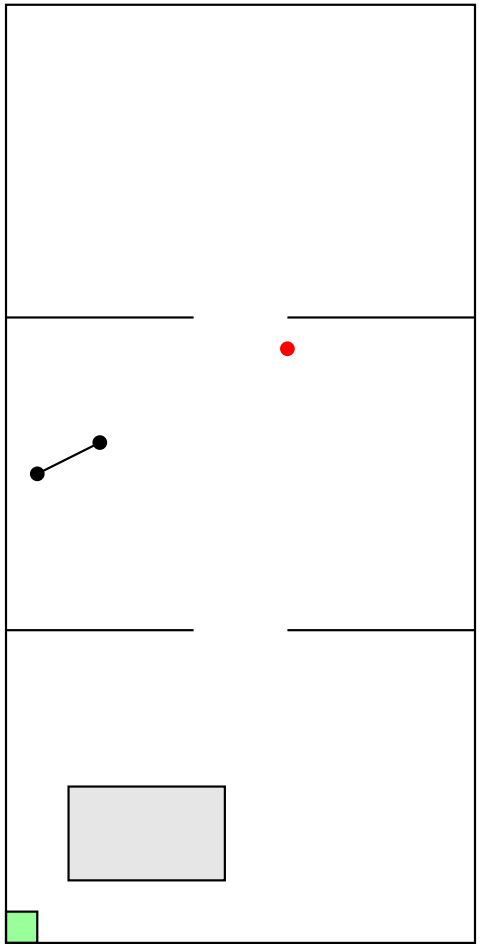

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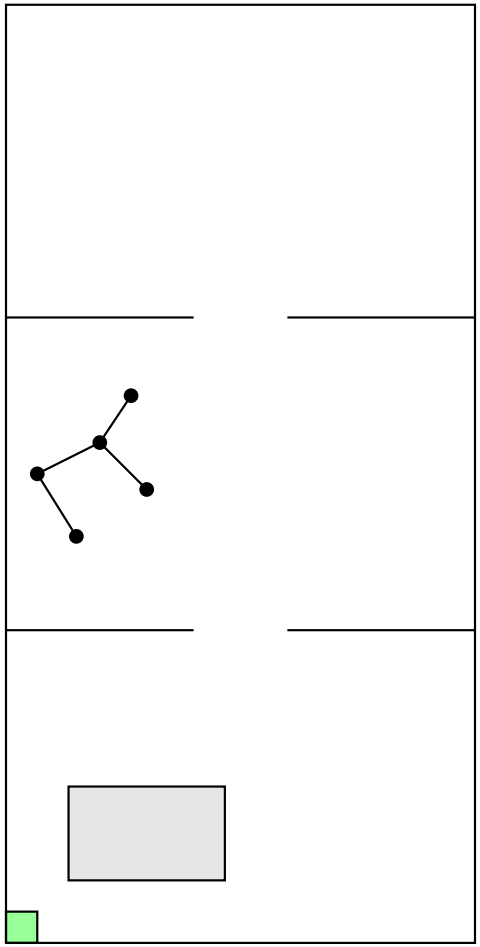

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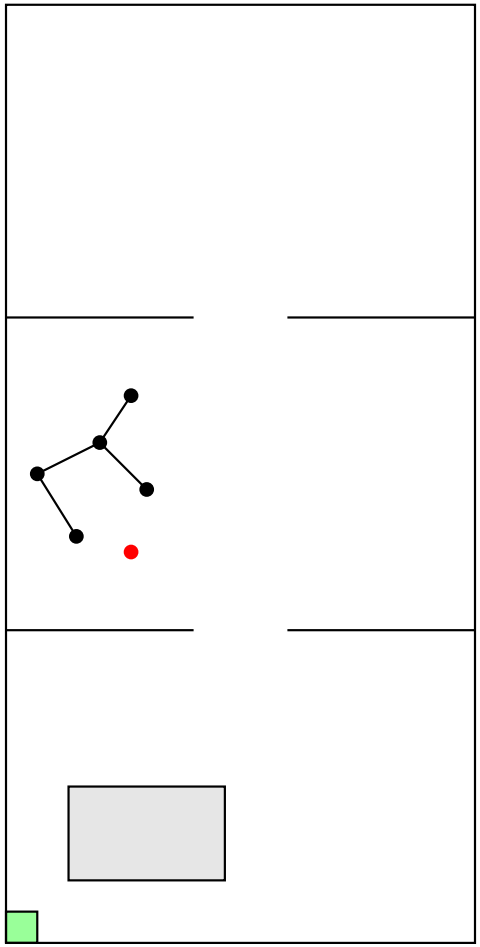

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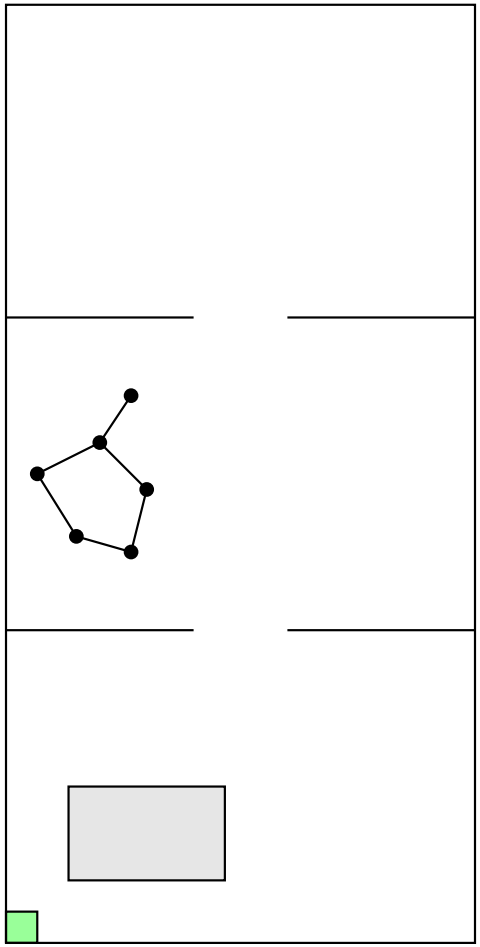

Jan's vision

- Want a robot that can move around on its own and figure out the stuff it has to do.

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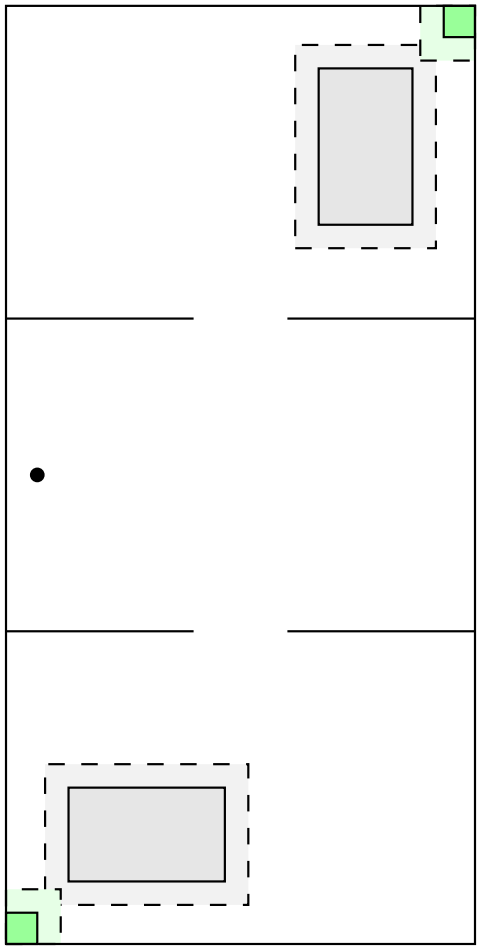
  LTL or a subclass of LTL.
  Given a labeling of the environment. Find a path that satisfies a given LTL formula.

LTL Motion Planning



Specification: $GF(r_1 \wedge b) \wedge GF(r_2 \wedge b)$

Solution

- Build an abstraction of the system.
- Construct the product automaton with the property automaton (ldba).
- Find a path in the abstraction.
- Lift this path to the original system.

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For e.g: The bin was close to the table in first room so try to look close to the table in the other room to find the bin.

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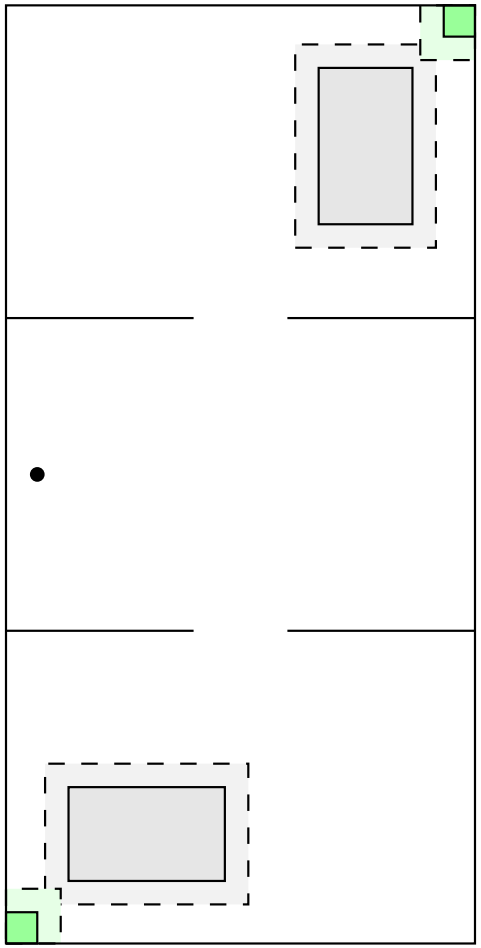
- Have 'maybe' and 'maybe not' transitions in the abstraction.
- Whenever you see a transition, add similar 'maybe' transitions in the abstraction as well.
- What does similar mean here?
  $(r_1, t) \to (r_1, b) \implies (r_2, t) \to (r_2, b)$.
  - Compute domain of changes: Set of APs changing in a transition.
    $DOC = \{t, b\}$, $(s_1 \oplus s_2)$
  - Add transitions $s_1' \to s_2'$ where s_1' and s_2' are states which agree with s_1 and s_2 on DOC respectively.

Algorithm



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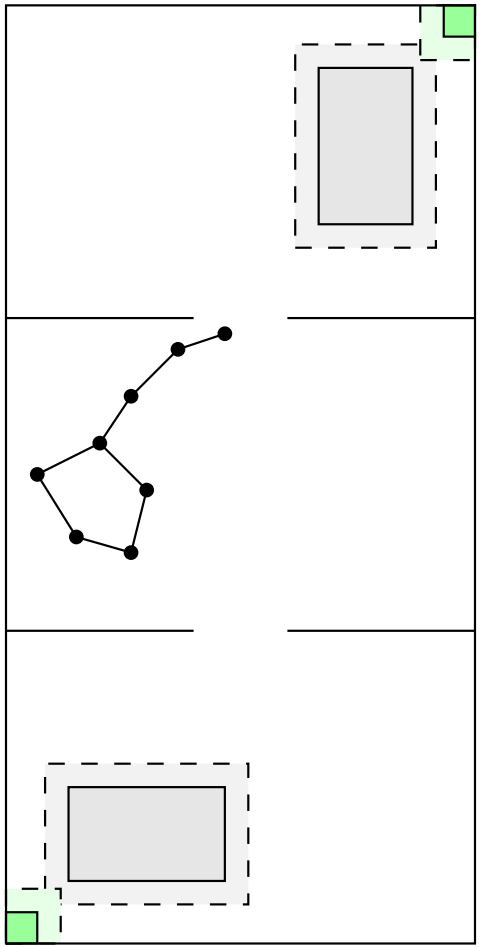

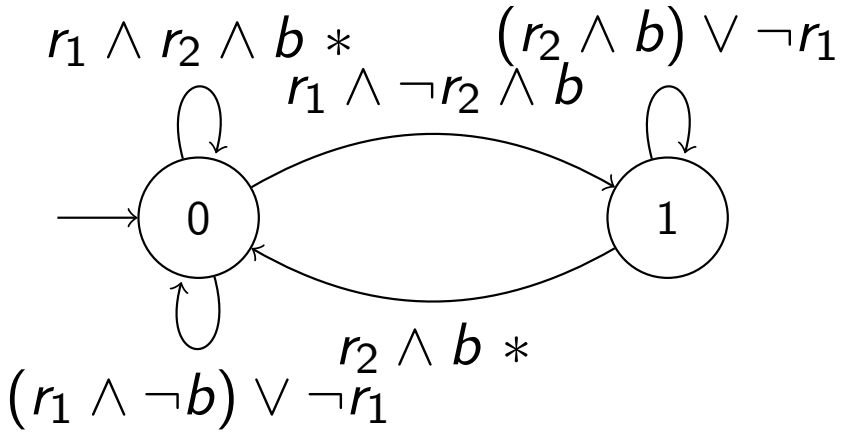
$r_1 \wedge r_2 \wedge b *$
$(r_2 \wedge b) \vee \neg r_1$
$r_1 \wedge \neg r_2 \wedge b$
0
1
$r_2 \wedge b *$
$(r_1 \wedge \neg b) \vee \neg r_1$

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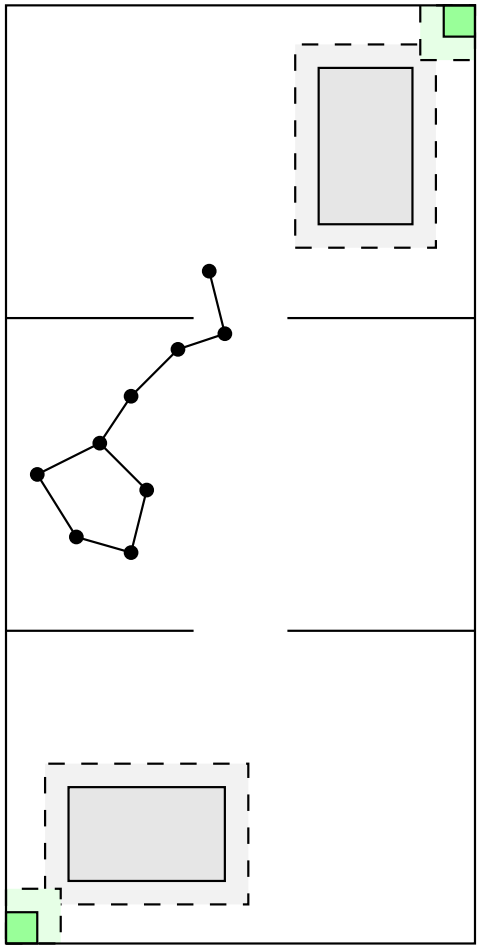

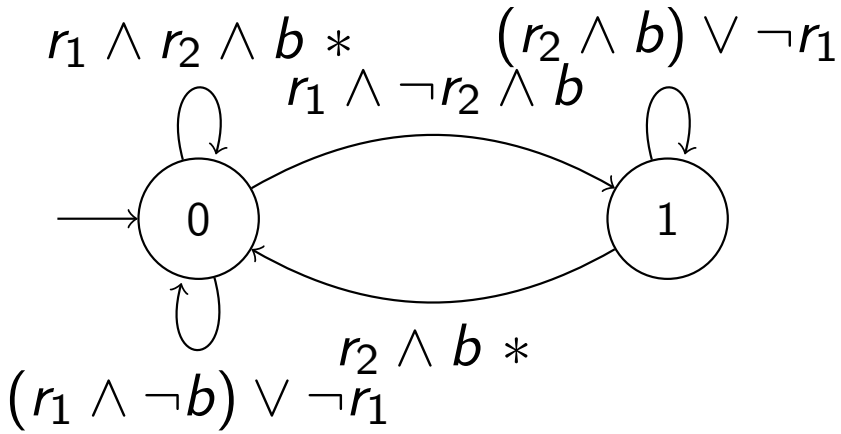
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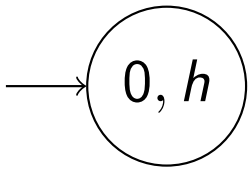
$0, h$

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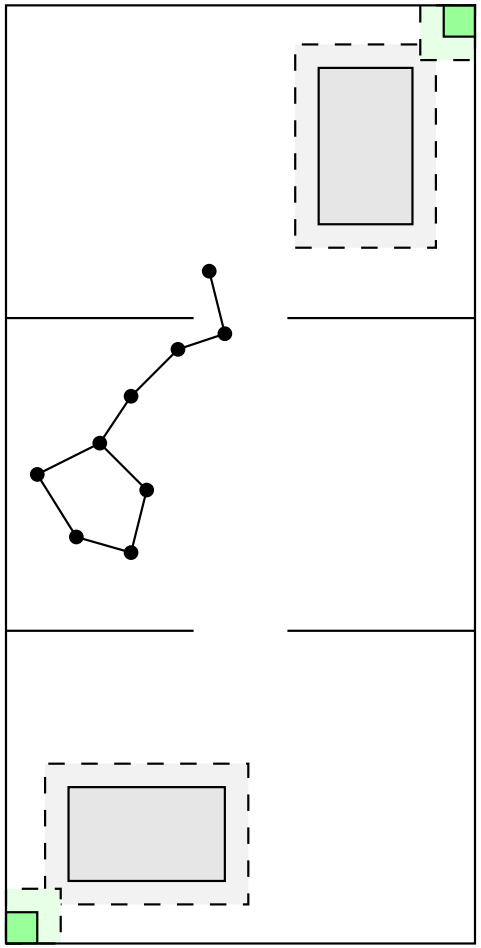

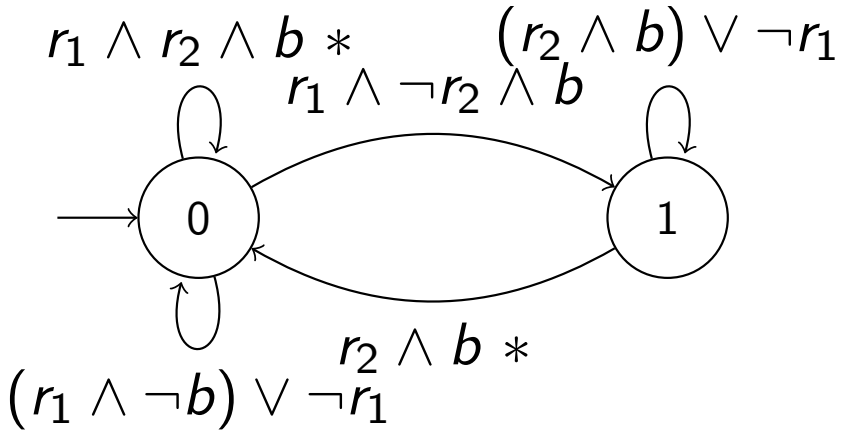
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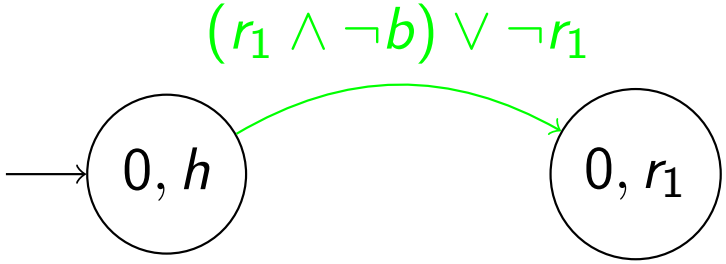
$(r_1 \wedge \neg b) \vee \neg r_1$
$0, h$
$0, r_1$

Learn

- Sample a transition s_1 to s_2.

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- Add similar transitions.

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- Sample a transition s_1 to s_2.
- Add similar transitions.
- If s_1 has been visited 50 times, all the 'maybe' transitions gets converted to 'maybe not' transitions.

Ask

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- Look at the accepting 'maybe' transitions and get a list of sets of states $reach[n]$, such that $reach[i]$ will have all the states in *visitedStates* that can reach an accepting transition in i steps. First try to sample transitions from $reach[1] \rightarrow reach[0]$, then from $reach[2] \rightarrow reach[1]$ and so on.

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- Can we do full LTL? or LTL $\setminus\{X\}$.
- What kind of filters can we use to learn useful similar transitions?
- Make implementation faster.
- Figure out the best thresholds.
- Still very hard because we have to compete with very efficient algorithm.

After this project

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- Figure out atomic propositions as it goes on to make learning better (not the ones in the property).