

Planning with Temporal Logic April 25, 2016



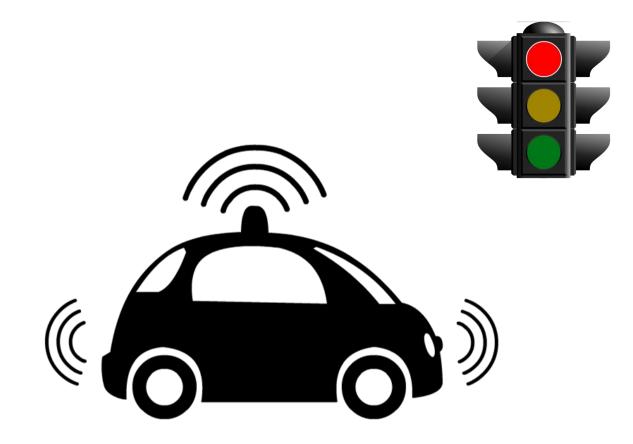
• Consider a self-driving car...

 Regardless of our destination, we also want to make sure we always follow the rules of the road.





Motivation





Motivation





- Modeling temporally-extended goals with linear temporal logic (LTL)
- Modeling preferences between alternative plans



Outline

- Introduction to Linear Temporal Logic
 - -Why use Linear Temporal Logic?
 - -Linear Temporal Logic Operators
 - -Example LTL Problems
 - Applications to Planning
 - Planning with Preferences
 - -Expressing Preferences
 - -Planning in LPP



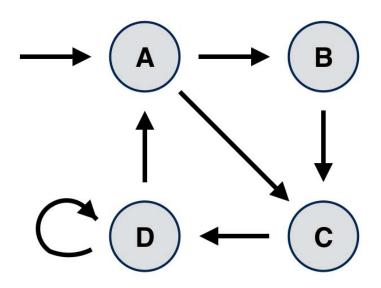
Linear Temporal Logic

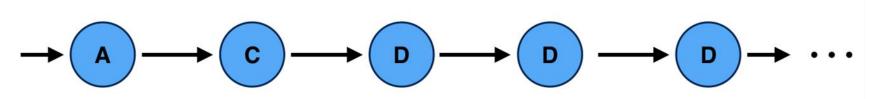


 Formalism for specifying properties of systems that vary with time



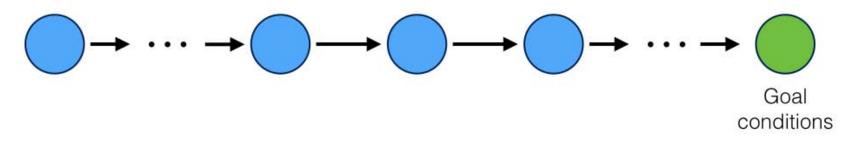
 Systems proceed through a sequence of discrete states







 Previously our planning algorithms have used propositional logic to specify goals dealing with a single state at a single point in time



•Temporal logic allows these goals to be specified over a sequence of states

$$\bigcirc \rightarrow \cdots \rightarrow \bigcirc \rightarrow \bigcirc \rightarrow \cdots \rightarrow \bigcirc \rightarrow \cdots$$

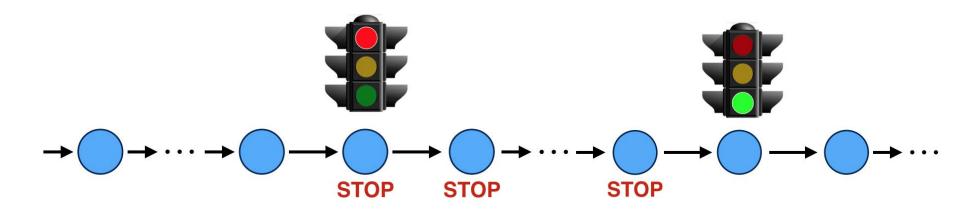
Goal conditions over a set of states



Why Temporal Logic?

• What if the problem requires a condition to:

Be met until another condition is met... For example: red implies (stop until green)

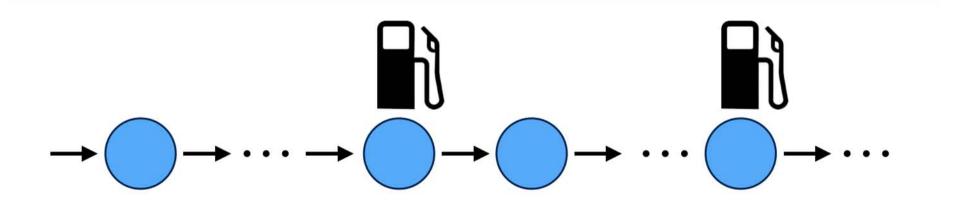




Why Temporal Logic?

• What if the problem requires a condition to:

Always eventually be met
For example, always have some point in the future when you visit a gas station





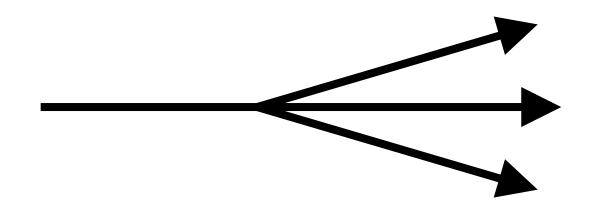
Branching vs linear time

- Linear time
 - Models physical time
 - At each time instant, <u>only one</u> of the future behaviors is considered
 - We can reason about always



Branching vs linear time

- Branching time
 - At each time instant, <u>all possible</u> future behaviors are considered
 - Time may split into alternate courses
 - We can reason about **possibilities**



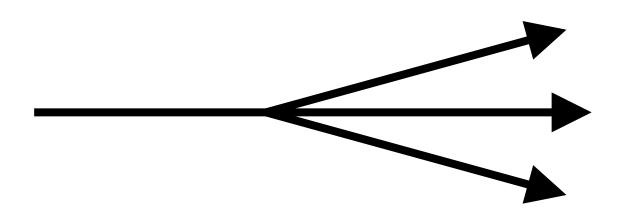


Temporal Logic

Branching vs linear time

• Linear time

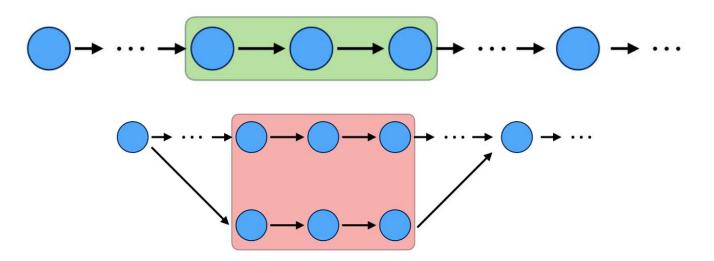
• Branching time





Linear Temporal Logic

- Linear Temporal Logic (LTL) involves:
 - Linear time model
 - Infinite sequences of states
 - $\rightarrow \bigcirc \rightarrow \cdots \rightarrow \bigcirc \rightarrow \bigcirc \rightarrow \bigcirc \rightarrow \cdot$
 - Forward-looking conditions
- Cannot express properties over a set of different paths



Applications of Temporal Logic

Temporal logic is used in:

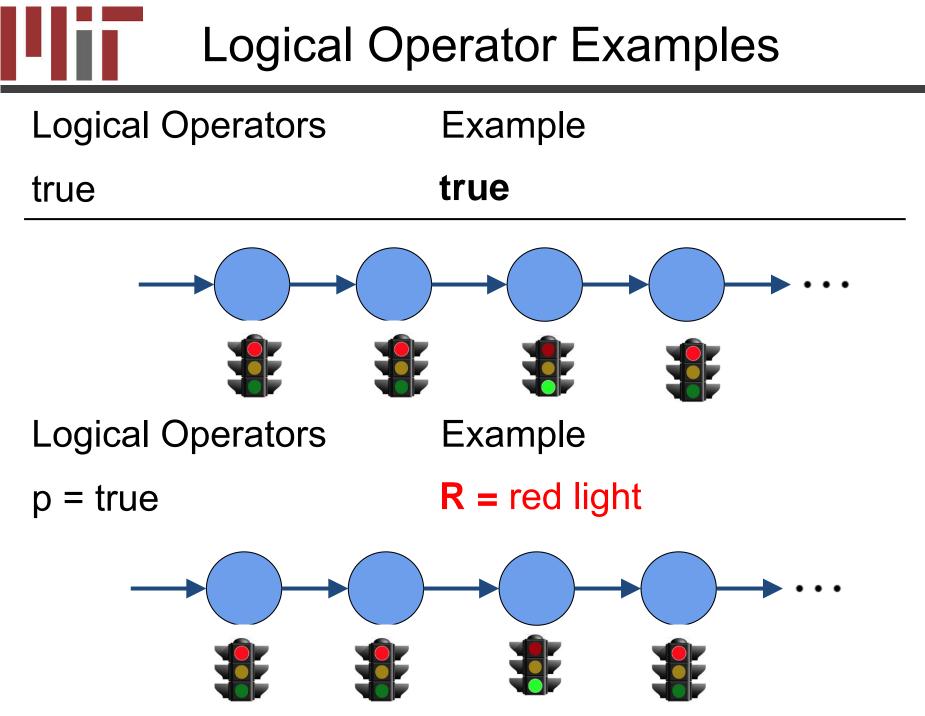
 Verification and Model Checking
 Safety and Maintenance
 Planning

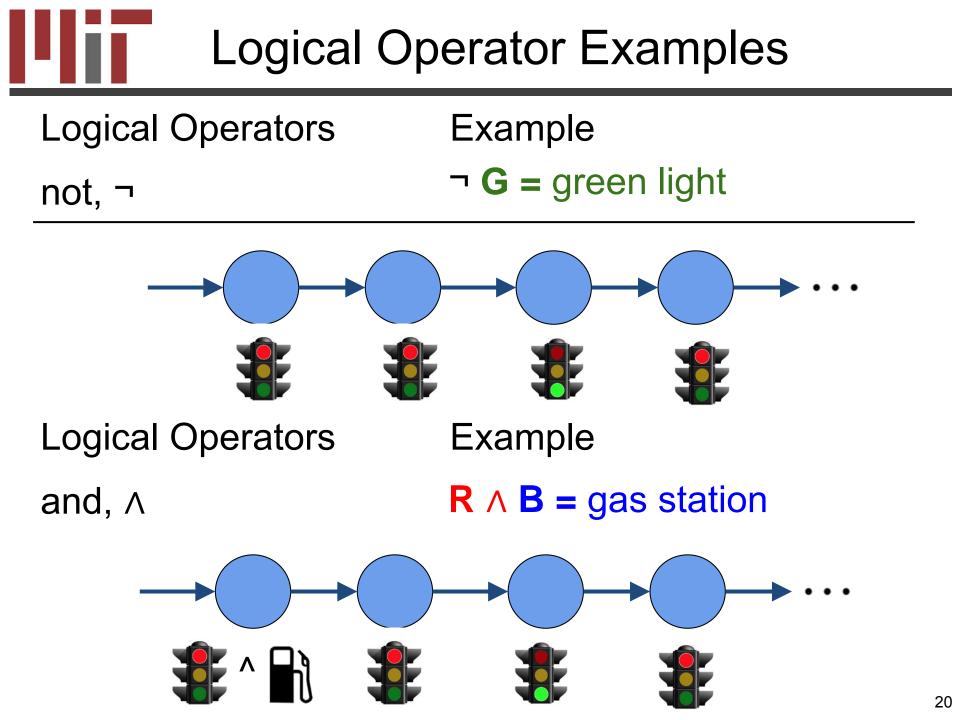


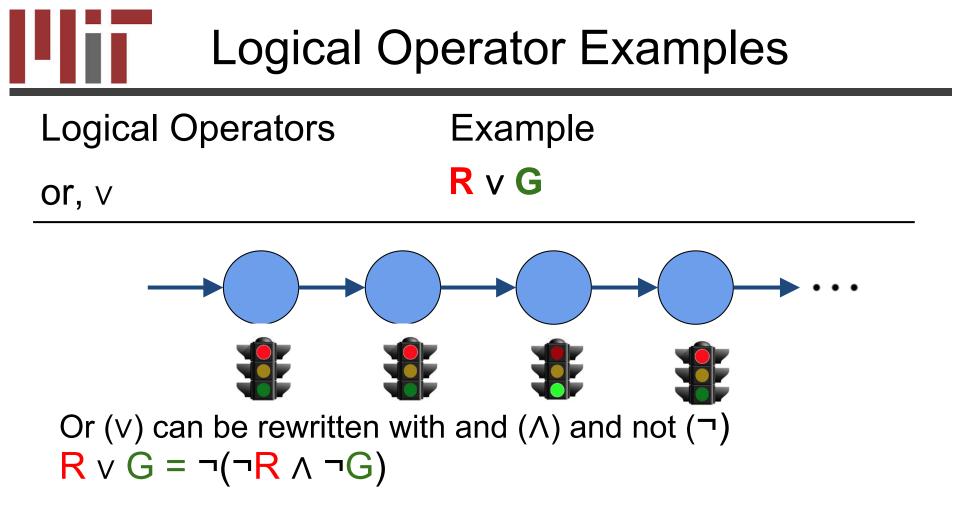
LTL formula f := true | p_i | $f_i \wedge f_j$ | $\neg f_i$ | X f_i | $f_i \cup f_j$

An LTL formula is built from:

- 1. Propositional variables: p, ρ, φ, ω etc. Can be True or False
- 2. Logical Operators: \neg , V, \land , \rightarrow , \leftrightarrow , True, False $-\neg = not$
 - -v = or
 - $-\Lambda$ = and
 - \rightarrow = implies
 - $-\leftrightarrow$ = if and only if
 - -True, False







Similar process can be done for implies and iff, but we won't be explaining them due to time constraints



LTL formula f := true | p_i | $f_i \wedge f_j$ | $\neg f_i$ | X f_i | $f_i \cup f_j$

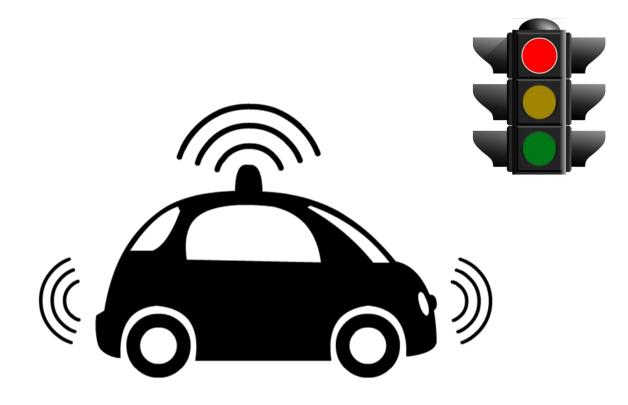
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 - -v = or
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 - $-\leftrightarrow$ = if and only if
 - -True, False

3.Temporal Operators



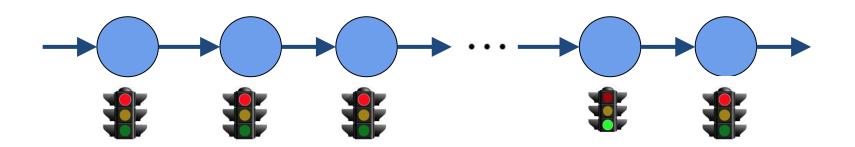
What are some useful operators we may want to describe our car?





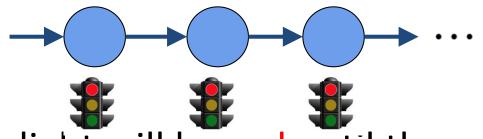
Temporal Operators

- The next light to be green
 The ingut win be required in the ingut win be required in the series of the series
- The I 🔹 : wi 🏖 ver 🕸 ally 🏖 some point in the future, turn green

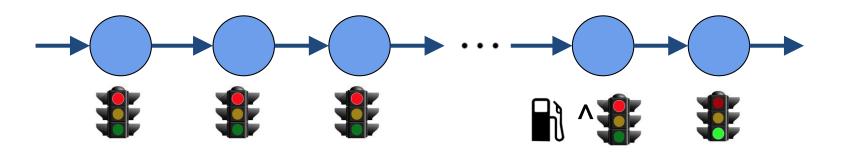


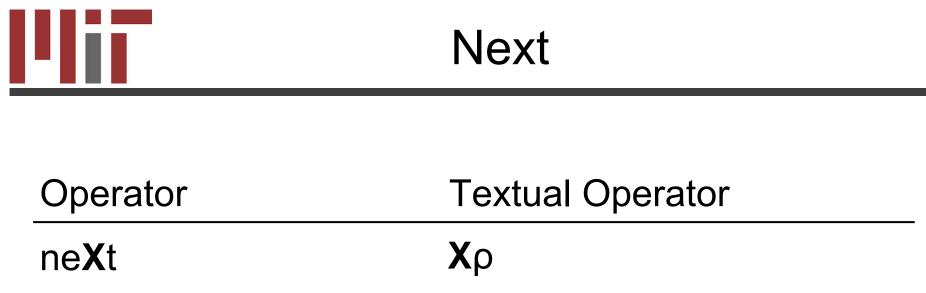


• The light will **always** be **red**

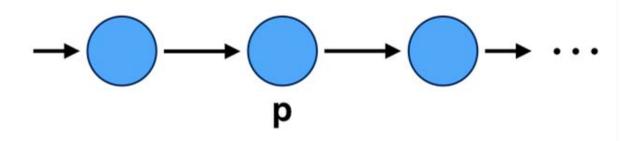


 The light will be red until the car gets gas and the state after it's released, the light can be whatever





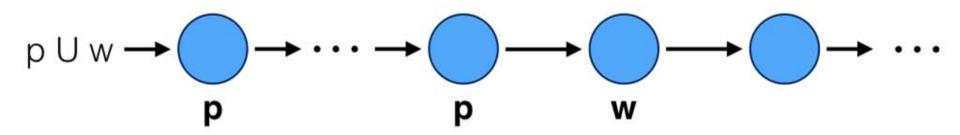
Definition: Variable p must be true in the next state





Operator Textual Operator Until ρUω

Definition: Variable ρ must remain true up until the state where variable ω becomes true, at which point ρ becomes unconstrained

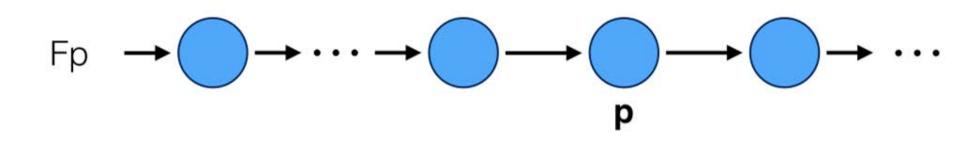


Note that ω is required to become true in some future state



OperatorTextual OperatorFuture/EventuallyFρ

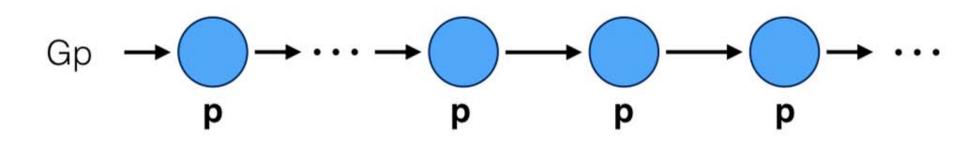
Definition: Variable p must become true in some future state





Operator	Textual Operator
Globally	G ρ

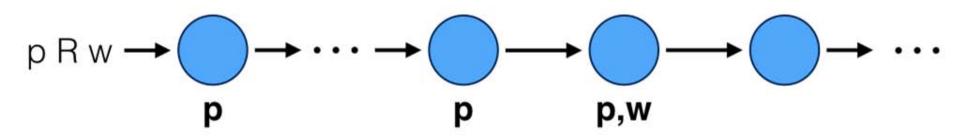
Definition: Variable p must be true in all future states





OperatorTextual OperatorReleaseρRω

Definition: Variable ρ must be true up until and including the state where ω becomes true, after which ω is unconstrained. If ρ is not true in any future state, then ω is true in all future states

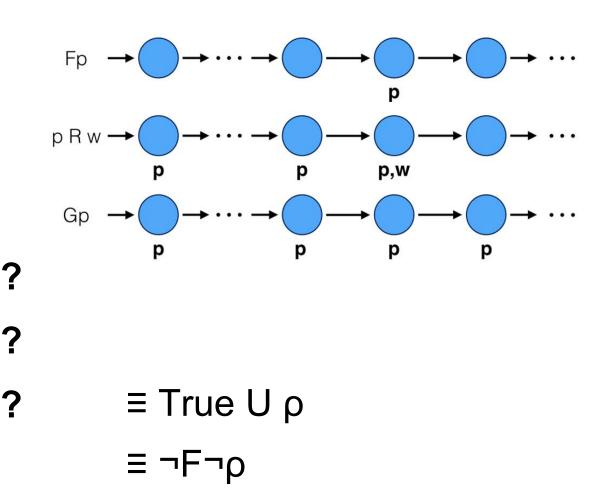


Different from **U** in that both ρ and ω are true in one state



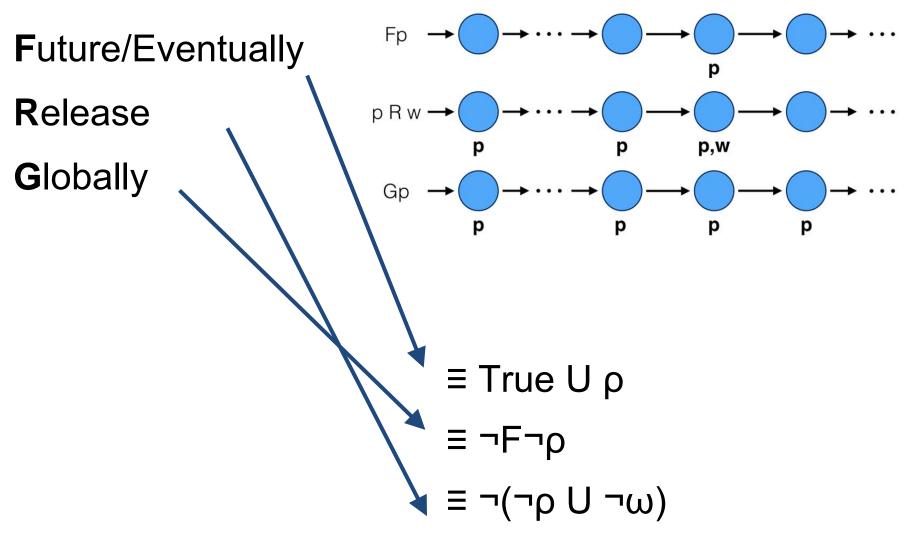
Which describe the other?

Future/Eventually Release Globally



≡ ¬(¬ρ U ¬ω)

Which describe the other?



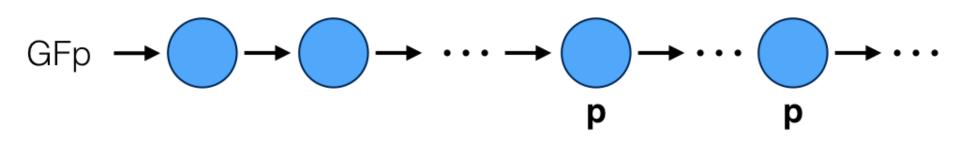
Temporal Operators (Recap)

Operator	Textual Operator	
ne X t	Χρ	
U ntil	ρ U ω	
Future/Eventually	F ρ	≡ True U ρ
G lobally	G ρ	≡ ¬F¬ρ
Release	ρ R ω	≡ ¬(¬ρ U ¬ω)

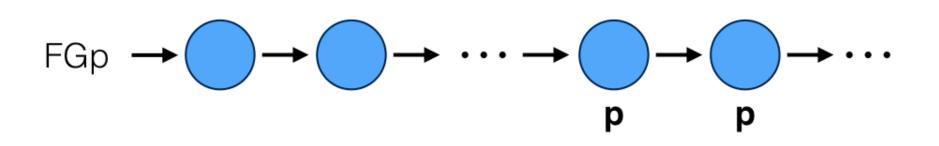


Combination of Operators

Infinitely Often



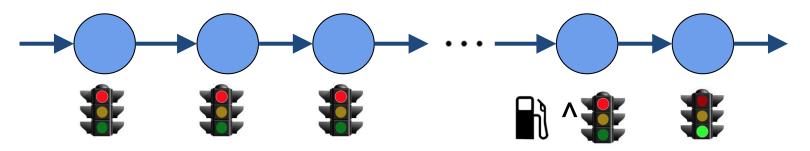
Eventually Forever





Example Problem

What are some true statements about this LTL formation?



- XR
- **F**G
- RUG
- (**RU**G)∧(**F**G)∧(**XR**)

Expressing Temporal Logic in PDDL

PDDL3 Goal Description

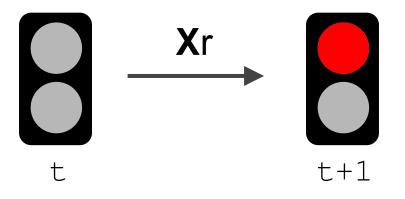
- <GD> ::= (at end <GD>)
 - | (always <GD>)
 - (sometime <GD>)
 - | (within <num> <GD>)
 - | (at-most-once <GD>)
 - (sometime-after <GD> <GD>)
 - (sometime-before <GD> <GD>)
 - (always-within <num> <GD> <GD>)
 - (hold-during <num> <num> <GD> | ...



Operator		PDDL3
ne X t	Χρ	(within 1 $ ho$)
U ntil	ρ U ω	(always-until $\rho \omega$)
Future	ρ F ω	(sometime-after $ ho \omega$)
Globally	G ρ	(always $ ho$)
Release	ρ R ω	(or (always ω) (always-until $\omega \rho$))

Expressing Temporal Logic in PDDL

•The traffic light will turn red in the next state



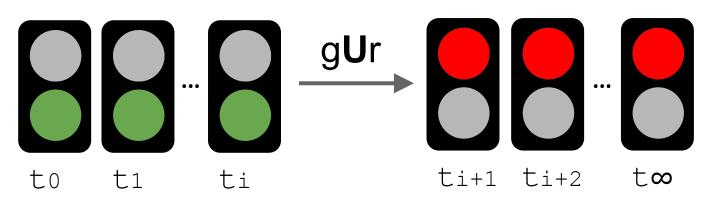
(:goal (within 1 (turn red)))

Command Syntax

(within <num> <GD>)
(within <num> φ) would mean that φ must hold within
<num> happenings

Expressing Temporal Logic in PDDL

 The traffic light will be green until it turns red at which point it will be red forever (g U r) ∧ (r → Gr)



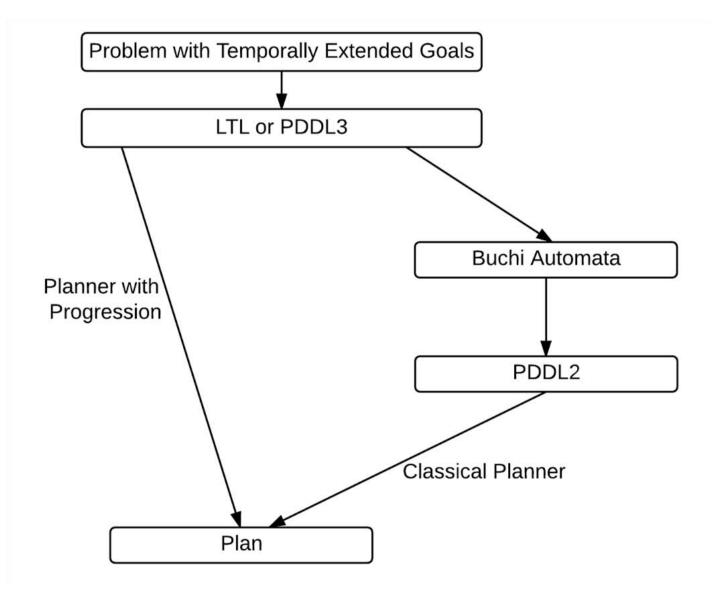
(:goal

(and

(always-until (turn green) (turn
red))
 (implies (turn red) (always (turn red)))
))



Application to Planning





Büchi Automata - *extension of finite automaton to infinite inputs (words)*

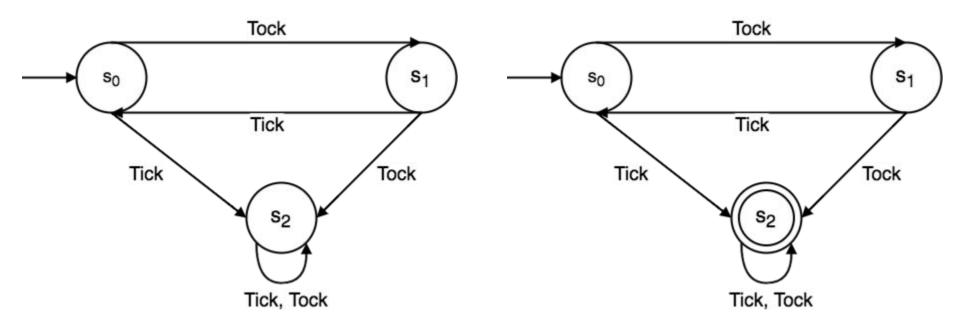
- A Büchi automaton is 5-tuple <S, s_0 , T, F, Σ >
 - S is a finite set of states
- $s_0 \in S$ is an initial state
- $T \subseteq S \times \Sigma \rightarrow S$ is a transition relation
- $F \subseteq S$ is a set of accepting states
- Σ is a finite set of symbols ('alphabet')

An infinite sequence of states is accepted iff it visits the <u>accepting state(s) infinitely often</u>



Example Büchi Automata

Example: Model a clock



Accepted words:

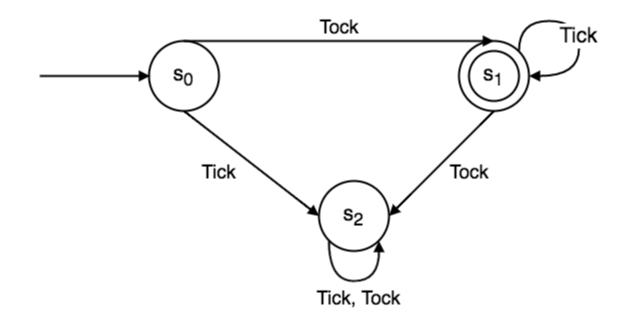
TickTockTockTickTockTickTickTock...

TockTickTockTickTickTockTockTickTock...



Example Büchi Automata

Example: Model a clock



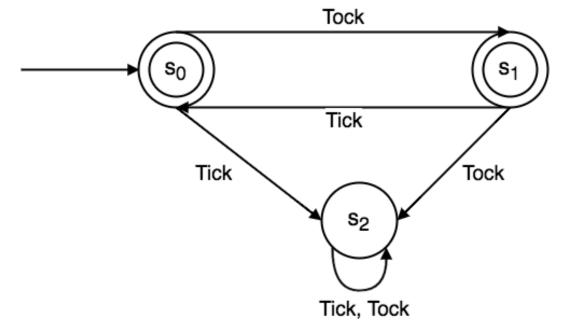
Accepted words:

TockTickTickTickTickTickTick...



Example Büchi Automata

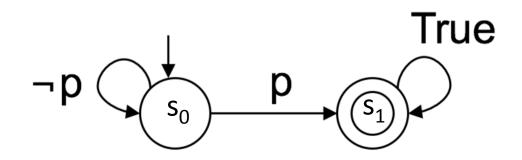
Example: Model a clock



Accepted words:

TockTickTockTickTockTickTockTick...

LTL to Büchi Automata



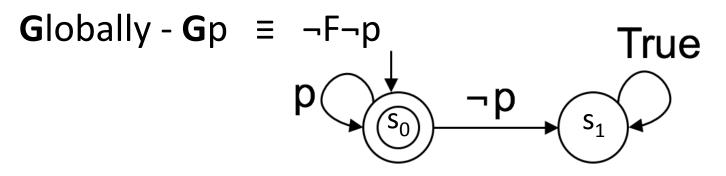
neXt? Future/Eventually? Globally?

<u>|||iī</u>

LTL to Büchi Automata

Future - Fp = True U p True $\neg p \xrightarrow{\downarrow} s_0 p \xrightarrow{s_1} s_1$

Accepted word: $\neg p \neg p \neg p p p \neg p \dots$ Sequence of states: $s_0 s_0 s_0 s_1 s_1 s_1 \dots$



Accepted word: p p p p p ...Sequence of states: $s_0 s_0 s_0 s_0 s_0 ...$



LTL to Büchi Algorithm

N – Node object

N.curr – LTL formulas to be processed N.old – LTL formulas already processed N.next – LTL formulas to be processed in next node N.incoming – Incoming transitions from predecessor nodes N_s – List of processed Nodes

N_i – Arbitrary node from N_s

expand (N,N_s)

```
if N.curr is empty
```

```
if N.curr = N<sub>i</sub>.curr
```

Append N.curr to N_i.curr

else

```
Append N to N_s
Create new node N_{new} with N_{new}-curr = N.next
expand (N_{new}, N_s)
```

else

Remove an LTL formula f from N.curr and append to N.old Perform **Progression** on f Call **expand** on result of **Progression**

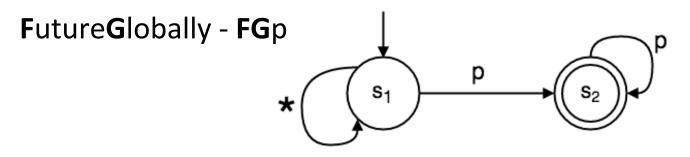
The result of this algorithm is a generalized Buchi automata which is then transformed into a simple Buchi automata.

Progression Algorithm

```
progress(f,N, \Delta t = 1) #\Delta t is time between successive states
     if f contains no temporal qualities:
           if N.curr entails f:
                       f' = True
           else
                       f' = False
     if f = f_1 \wedge f_2:
           progress(f_1, N, \Delta t) \Lambda progress(f_2, N, \Delta t)
     if f = \mathbf{X}f_1:
           N.next.append(f_1)
     if f = f_1 U_{[a,b]} f_2:
                                               #[a,b] is a time interval that could be infinite
           if b < a:
                 f' = False
           else if 0 \in [a,b]:
                       progress(f_2, N, \Delta t) V (progress(f_1, N, \Delta t) \Lambda N.next.append(f_1 U_{[a,b] - \Delta t}
           f))
           else
                       progress(f_1, N, \Delta t) \Lambda N.next.append(f_1 U_{fa,bl-\Delta t} f)
```

Büchi Automata to PDDL2

Büchi states are not equivalent to PDDL2 states. Consider:



Two ways to transform temporally extended goals to PDDL2:

- Create new actions that encapsulate the allowable transitions in each state
- Introduce derived predicates
 - Do not depend on the actions
 - Used to determine which state the planner is in
 - Goal of the planner is to move from initial state to any accepting state



Planning with Preferences



Classical Planning Problem

problem := (S, s_0, A, G)

S - set of states s₀ - initial state A - set of operators G - set of goal states **Preference-based Planning Problem**

problem := (S, s_0, A, G, R)

R is a partial or total relation expressing preferences (\leq) between plans

Preferences express properties of the plan that are desired but not required

Preference Expression Languages

- Quantitative assign numeric values to plans to compare them
 - Markov Decision Processes (MDP's)
 - Find preferred policy using a reward function over conditional plans
 - PDDL3
 - Preferences expressed through reward function based on satisfying/violating logical formulas on the plan
- Qualitative relations compare plans based on properties of the plans that need not be numeric
 - Ranked Knowledge Bases
 - Plan properties are ranked with preferred formulas ranked higher
 - Temporally Extended Preferences
 - Use LTL to express plan properties that are then ranked

Quantitative languages imply total comparibility while qualitative languages may allow incomparability



Syntax for modeling preferences: (preference [name] <GD>) - label for fluents that represent preferences

is-violated -function that returns the number of times the
preference was not satisfied in the plan

Example:

Traffic light is green until it turns red
 (preference gUr
 (always-until(turn green) (turn
red)))
Plan tries to not violate any preferred fluents
 (metric minimize (is-violated gUr))



- LPP is a quantitative language to express temporal preferences for planning
 - Preferences between different temporal goals can be expressed along with the strength of preference
 - i.e. Goal A is preferred twice as much as Goal B
- LPP is an extension of an older language PP
- Preference formulas in LPP are constructed hierarchically

See Bienvenu, Meghyn, Christian Fritz, and Sheila A. McIlraith. "Planning with Qualitative Temporal Preferences." KR 6 (2006): 134-144.



Basic Desire Formula (BDFs)

express temporally extended propositions

- At some point, will cook
 - $b_1 = \mathbf{F}(\text{cook})$
- At some point, will order takeout
 - b₂=F(orderTakeout)
- At some point, will eat spaghetti

• At some point, will eat pizza

 $- b_4 = \mathbf{F}(eatPizza)$



Atomic Preference Formulas (APFs) express preferences between BDFs

- In this example, weights associated with each BDF define preferences
 - -Lower weight is preferred
- Prefer to cook over ordering takeout
 a₁=b₁[0.2]≫b₂[0.4]
- Prefer eating spaghetti over eating pizza
 − a₂=b₃[0.3]≫b₄[0.9]



General Preference Formulas (GPFs) allow conjunctions or disjunctions of APFs or qualification of BDFs with conditionals

- Satisfy the most preferred option among the APFs (satisfy APF with lowest weight) $-g_1=a_1 \mid a_2$
- Choose the most preferred option that satisfies both APFs (minimize the maximum weight across both APFs)

 $-g_2 = a_1 \& a_2$



Aggregated Preferences Formulas (APFs) define the order in which preferences should be relaxed

• Prefer that if both g_1 and g_2 from previous slide can't be met, that g_2 from previous slide is met

 $-g_1 \wedge g_2 \preccurlyeq g_2 \preccurlyeq g_1$

 Situations that aren't distinguished any other way can be sorted lexicographically (alphabetically)



- Basic Desire Formula (BDF)
 - -Express temporally extended propositions
- Atomic Preference Formula (APF)
 - -Express preferences between BDFs
- General Preference Formula (GPF)
 - Allow conjunctions or disjunctions of APFs or qualification of BDFs with conditionals
- Aggregated Preference Formula (APF)
 - Define the order in which preferences should be relaxed



References

Gerevini, A., and D. Long. *Plan constraints and preferences in PDDL3: The language of the fifth international planning competition. University of Brescia.* Italy, Tech. Rep, 2005.

- Patrizini, Fabio, et al. "Computing infinite plans for LTL goals using a classical planner." *Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence; july 16-22, 2011; Barcelona. Menlo Park, California: AAAI Press; 2011. p. 2003-2008.*. Association for the Advancement of Artificial Intelligence (AAAI), 2011.
- Baier, Jorge A., and Sheila A. McIlraith. "Planning with Temporally Extended Goals Using Heuristic Search." *ICAPS*. 2006.
- Bacchus, Fahiem, and Froduald Kabanza. "Planning for temporally extended goals." *Annals of Mathematics and Artificial Intelligence* 22.1-2 (1998): 5-27.
- Baier, Jorge A., and Sheila A. McIlraith. "Planning with first-order temporally extended goals using heuristic search." *Proceedings of the National Conference on Artificial Intelligence*. Vol. 21. No. 1. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 2006.

Baier, Jorge A., and Sheila A. McIlraith. "Planning with preferences." AI Magazine 29.4 (2009): 25.

- Bienvenu, Meghyn, Christian Fritz, and Sheila A. McIlraith. "Planning with Qualitative Temporal Preferences." *KR* 6 (2006): 134-144.
- Gerth, Rob, et al. "Simple on-the-fly automatic verification of linear temporal logic." *Protocol Specification, Testing and Verification XV*. Springer US, 1996. 3-18.



Appendix



- PPLAN
 - implemented by Meghyn Bienvenu, Christian Fritz, and Sheila A. McIlraith
- Solves planning problems with preferences expressed in LPP via bounded best-first search forward chaining planner
 - use of *progression* efficiently evaluates how well partial plans satisfy Φ (a general preference formula)
 - use of admissible *evaluation function* ensures best-first search is optimal



- Forward Chaining Planner Forward chaining starts with the available data and uses inference rules to extract more data (from an end user, for example) until a goal is reached.
- A situation s is a *history* of the primitive actions a ∈ A performed from an initial situation S0.



- Purpose of progression:
 - take in a situation and temporal logic formula (TLF)
 - evaluates the TLF with respect to the state of the situation
 - generates a new formula representing those aspects of the TLF that remain to be satisfied in subsequent situations.
- Weight of general preference formula with respect to a situation is equal to progressed preference formula with respect to final situation



- Evaluation Function
 - has optimistic and pessimistic weights to provide best and worst weights on a successor with respect to Φ.
 - the optimistic weight is non-decreases and does not over-estimate the actual weight
 - this allows PPLAN to define an optimal search algorithm



PPLAN Algorithm

optW = optimistic weight (Assumes all unfulfilled preferences
 are fulfilled)

pessW = pessimistic weight (Assumes all unfulfilled

preferences are not fulfilled)

Algorithm

L = list of nodes sorted by optW, then pessW, then length

while L is not empty
Remove first node from L
If goal is achieved and optW = pessW
return partial plan, optW
Perform Progression
Add new nodes to L and sort



PPLAN

- PPLAN is implemented with a
 - –general preference formula fΦ they define is admissible and when used in best first search, the search is optimal
 - -the best first search searches through the partial plans based on their weights
 - -for full details see paper "Planning with Qualitative Temporal Preferences" by Fritz, Christian, Sheila A. McIlraith, and Meghyn Bienvenu.



Additional Examples were taken from the youtube videos of NOC15 July-Oct CS12 : https://www.youtube.com/watch?v=W5Q0DL 9plns



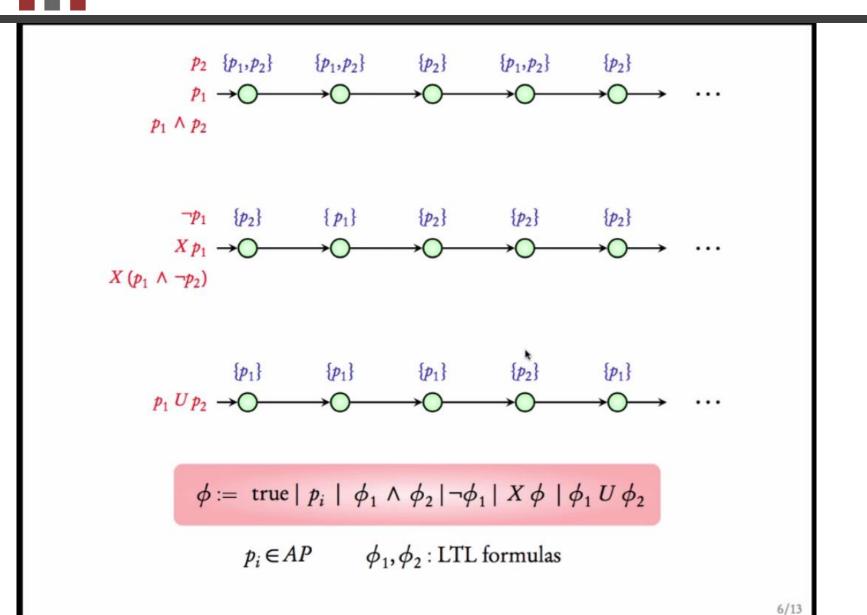
Example Formulations

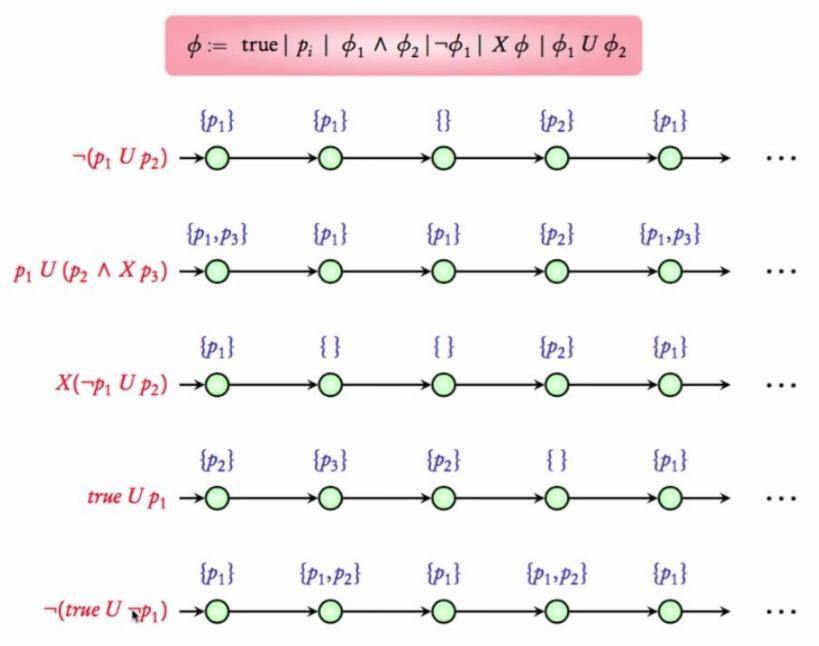
- Traffic light is red: r
- Traffic light is green: g
- The traffic light will turn red in the next state – Xr
- The traffic light will be green until it turns red but it may not ever turn red

 $-(g U r) \vee Gg$ (Weak Until)

- The traffic light will be green until it turns red
 at which point it will be red forever
 - (g U r) \land (r \rightarrow Gr)

Additional Examples





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16.412J / 6.834J Cognitive Robotics Spring 2016

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