Reasoning Agents aa. 2019/2020

NL2LTLf translation for restraining bolts application in BabyAI environment

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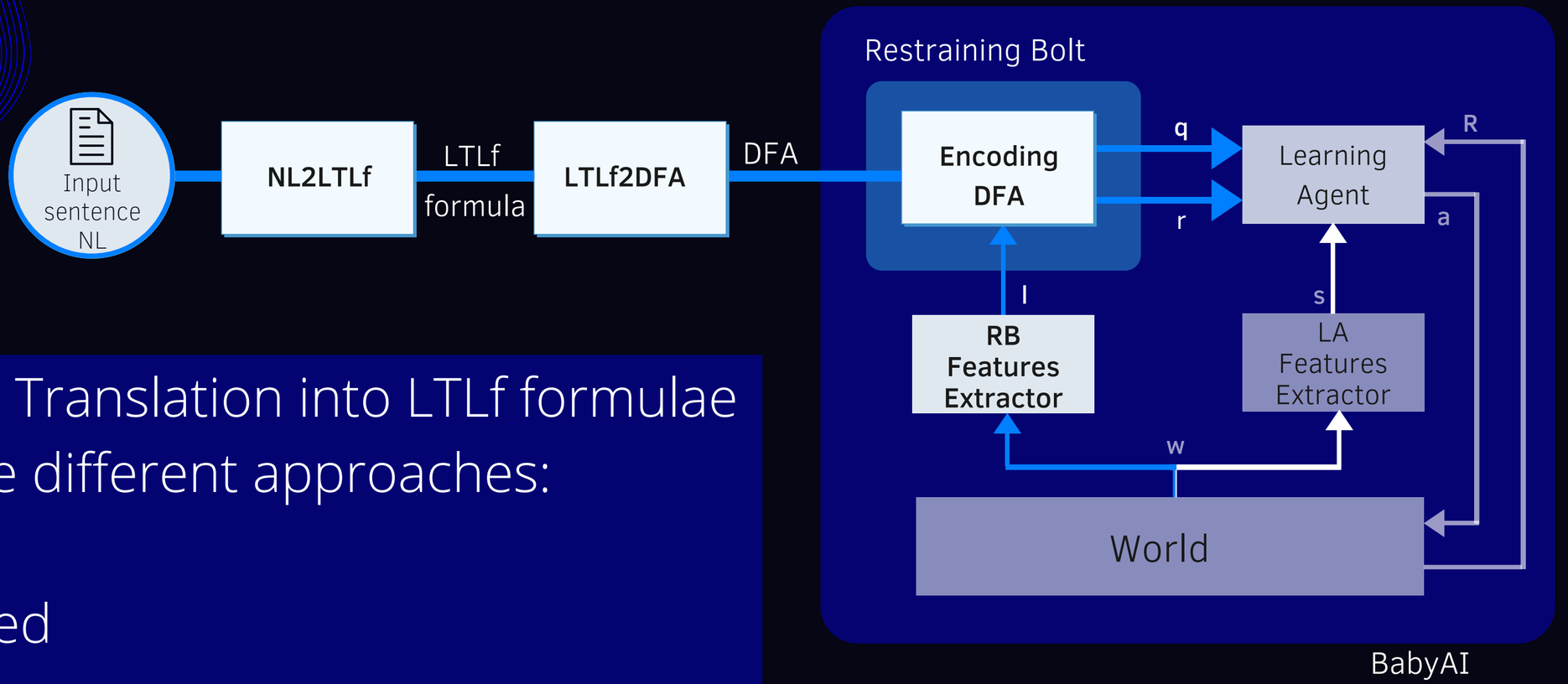
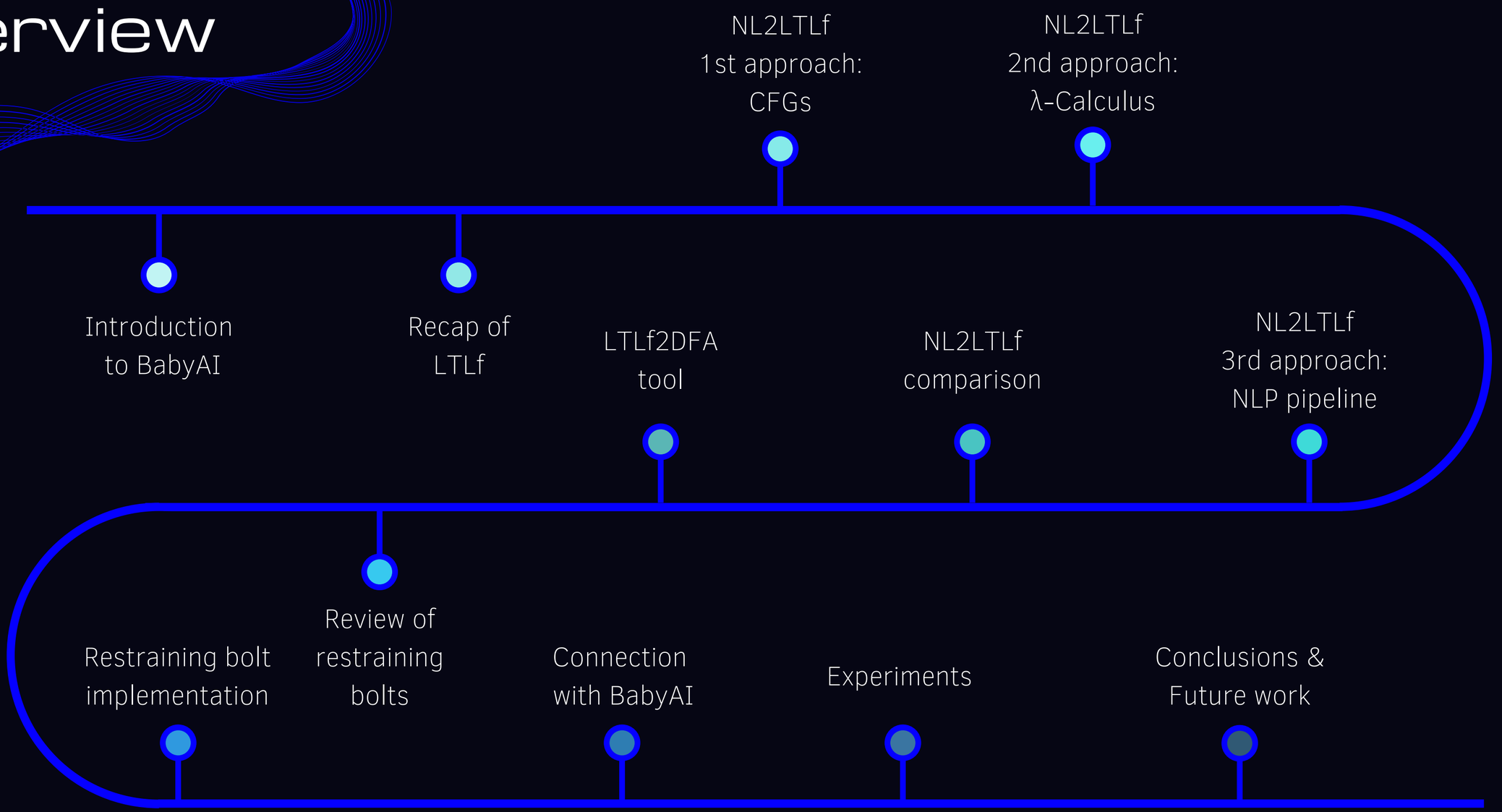
Our work



- Natural Language Translation into LTLf formulae according to three different approaches:
  - CFG Based
  - λ-Calculus Based
  - NLP Based

- Restraining Bolt implementation within BabyAI environment

Overview


NL2LTLf
1st approach:
CFGs
NL2LTLf
2nd approach:
λ-Calculus
Introduction
to BabyAI
Recap of
LTLf
LTLf2DFA
tool
NL2LTLf
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3rd approach:
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Review of
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bolts
Restraining bolt
implementation
Connection
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Experiments
Conclusions &
Future work

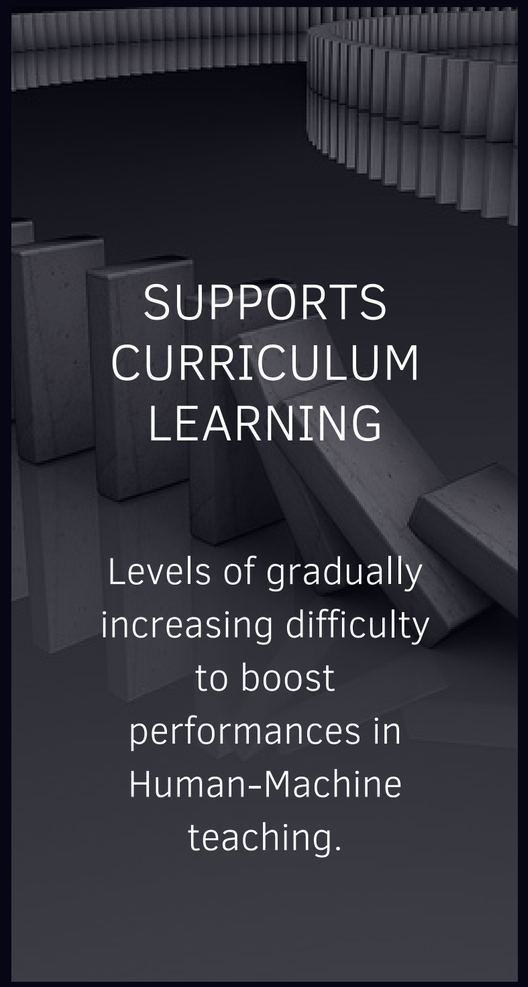
BabyAI

AN INTRODUCTION

**Description of bot functioning in Appendix 1*

POWERFUL RESEARCH PLATFORM

Facilitates research on grounded language learning as to include human in the loop.

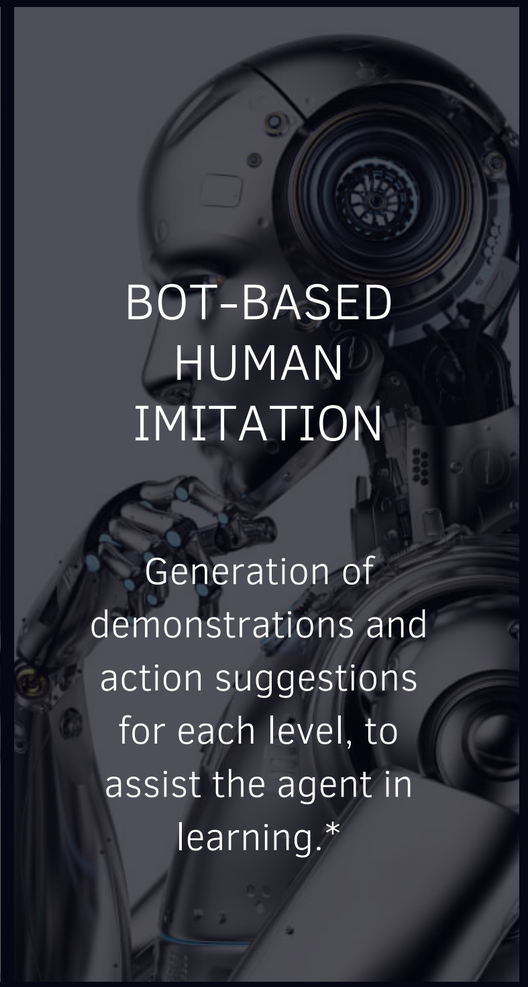


SUPPORTS CURRICULUM LEARNING

Levels of gradually increasing difficulty to boost performances in Human-Machine teaching.

SUPPORTS INTERACTIVE TEACHING

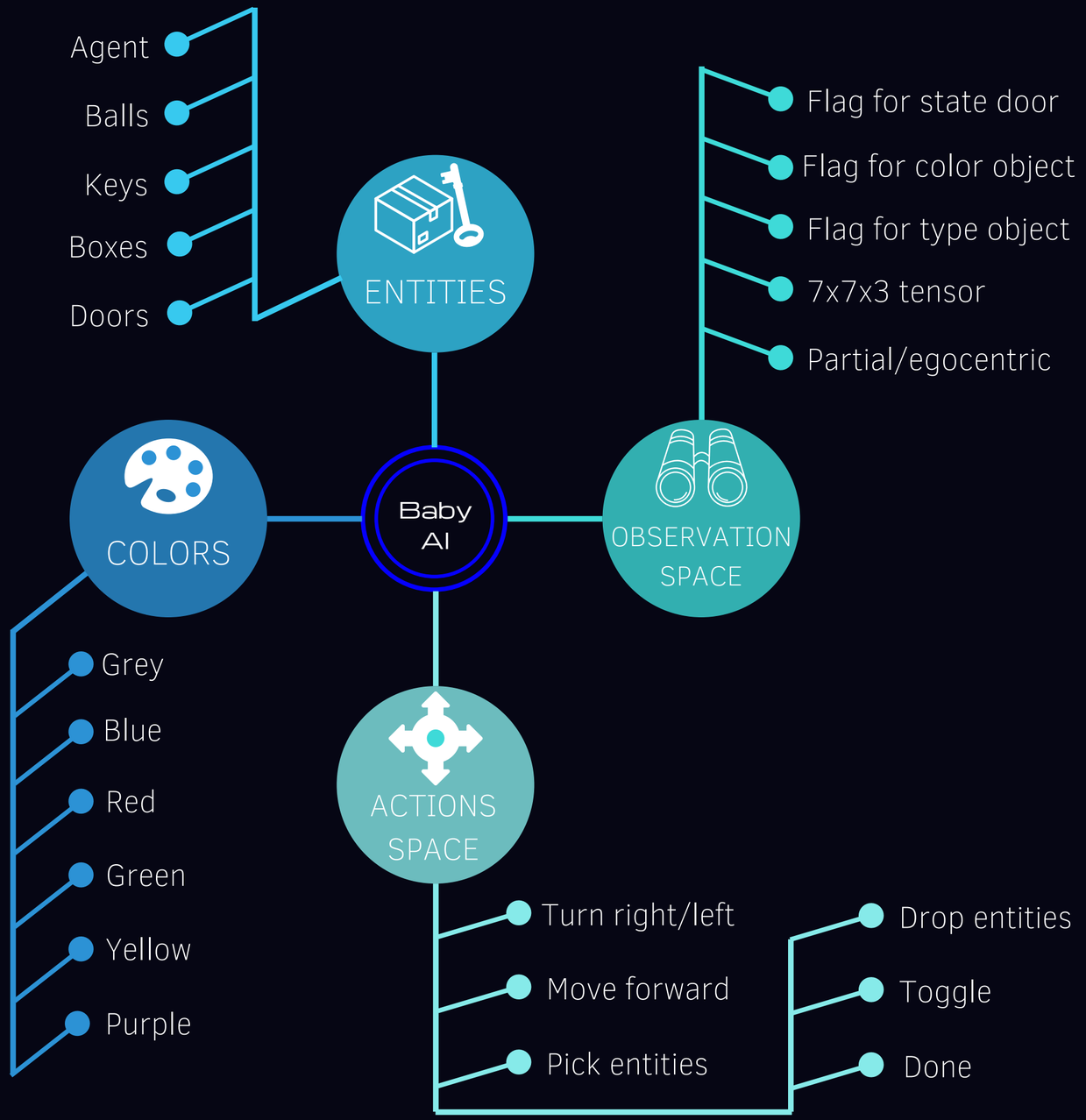
Tailored teaching based on agent's abilities currently achieved.



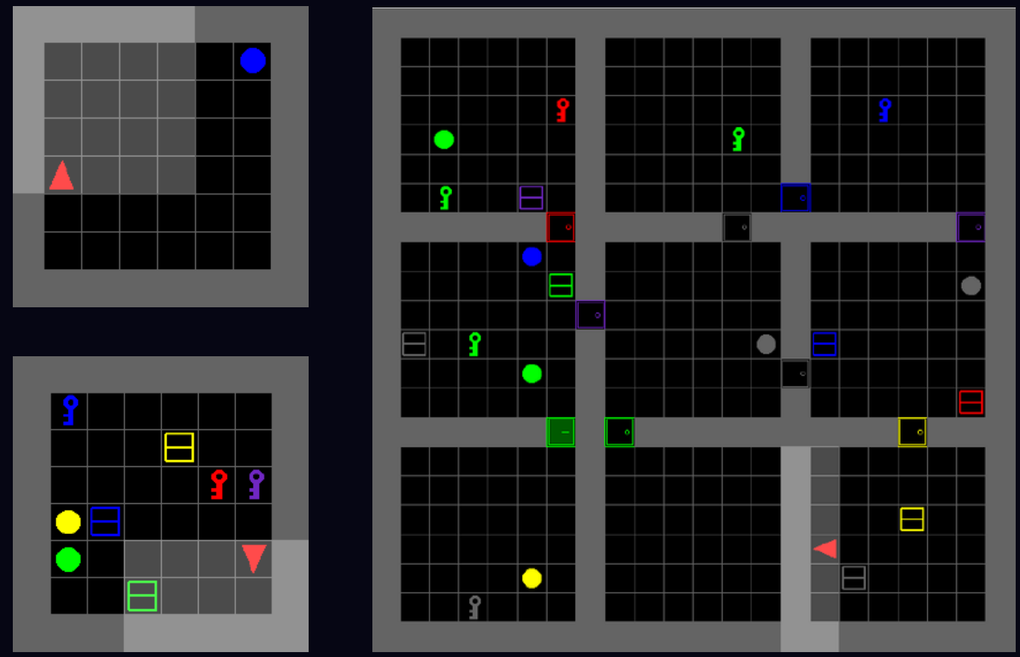
BOT-BASED HUMAN IMITATION

Generation of demonstrations and action suggestions for each level, to assist the agent in learning.*

BabyAI Structure



- NxN MINIGRID environment
- Partially observable 2D gridworld
- Support integration with OpenAI Gym



BabyAI levels with MiniGrid environment

Baby Language

- Synthetic language with **known** context-free grammar
- **Verifier** for the language: check satisfiability of the instructions w.r.t. the environment
- Not all instructions are **explicit**

BNF of the grammar of the Baby Language

⟨Sent⟩	⊨	⟨Sent1⟩ | ⟨Sent1⟩ ',' then ⟨Sent1⟩ | ⟨Sent1⟩ after you ⟨Sent1⟩
⟨Sent1⟩	⊨	⟨Clause⟩ | ⟨Clause⟩ and ⟨Clause⟩
⟨Clause⟩	⊨	go to ⟨Descr⟩ | pick up ⟨DescrNotDoor⟩ | open ⟨DescrDoor⟩ | put ⟨DescrNotDoor⟩ next to ⟨Descr⟩
⟨DescrDoor⟩	⊨	⟨Article⟩ ⟨Color⟩ door ⟨LocSpec⟩
⟨DescrBall⟩	⊨	⟨Article⟩ ⟨Color⟩ ball ⟨LocSpec⟩
⟨DescrBox⟩	⊨	⟨Article⟩ ⟨Color⟩ box ⟨LocSpec⟩
⟨DescrKey⟩	⊨	⟨Article⟩ ⟨Color⟩ key ⟨LocSpec⟩
⟨Descr⟩	⊨	⟨DescrDoor⟩ | ⟨DescrBall⟩ | ⟨DescrBox⟩ | ⟨DescrKey⟩
⟨DescrNotDoor⟩	⊨	⟨DescrBall⟩ | ⟨DescrBox⟩ | ⟨DescrKey⟩
⟨LocSpec⟩	⊨	ϵ | on your left | on your right | in front of you | behind you
⟨Color⟩	⊨	ϵ | red | green | blue | purple | yellow | grey
⟨Article⟩	⊨	the | a

Examples of instructions in Baby Language

"go to the red ball"
"put a ball next to the blue door"
"put a ball next to a purple door after you put a blue box next to a grey box and pick up the purple key"

BabyAI Levels

- Suite of 19 levels (extendable)
- Varying environment structure and difficulty of instruction
- Each level is a distribution of missions
- Each level requires a set of competencies*

Levels and their competencies

	ROOM	DISTR-BOX	DISTR	MAZE	UNBLOCK	UNLOCK	IMP-UNLOCK	GOTO	OPEN	PICKUP	PUT	LOC	SEQ
GoToObj	x												
GoToRedBallGrey	x	x											
GoToRedBall	x	x	x										
GoToLocal	x	x	x					x					
PutNextLocal	x	x	x								x		
PickupLoc	x	x	x							x		x	
GoToObjMaze	x			x									
GoTo	x	x	x	x				x					
Pickup	x	x	x	x						x			
UnblockPickup	x	x	x	x	x					x			
Open	x	x	x	x					x				
Unlock	x	x	x	x		x			x				
PutNext	x	x	x	x							x		
Synth	x	x	x	x	x	x		x	x	x	x		
SynthLoc	x	x	x	x	x	x		x	x	x	x	x	
GoToSeq	x	x	x	x				x					x
SynthSeq	x	x	x	x	x	x		x	x	x	x	x	x
GoToImpUnlock	x	x	x	x			x	x					
BossLevel	x	x	x	x	x	x	x	x	x	x	x	x	x

*Description of the competencies in Appendix 2

LTLf

- Linear Temporal Logic over **finite** traces
- Used to **express** the **goal** of the restraining bolt
- Atomic propositions model **world features**
- Temporal operators and connectives for goal **composition**
-

PL/LTL/LTLf LTL/LTLf LTLf

SYNTAX

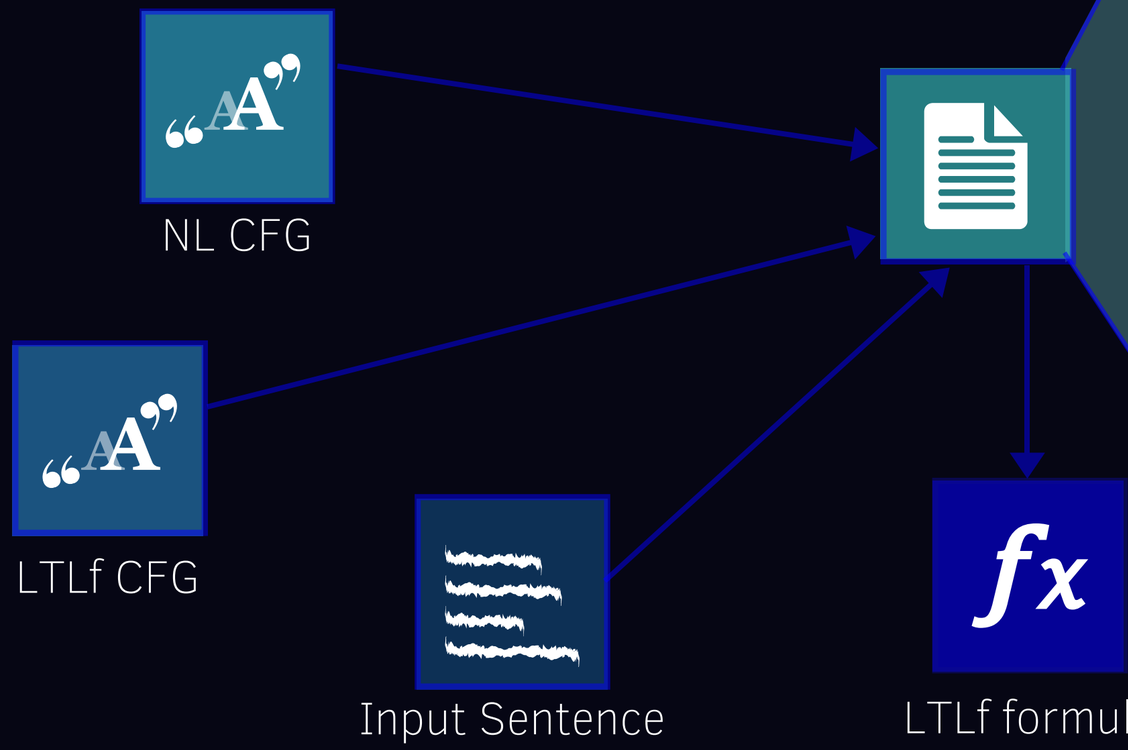
$$
\begin{array}{rcl}
\varphi, \psi \rightarrow & & \\
p & \in \Sigma & (atomic\ proposition) \\
\top & & (True) \\
\bot & & (False) \\
\neg\varphi & & (complement) \\
\varphi \wedge \psi & & (conjunction) \\
\varphi \vee \psi & & (disjunction) \\
\bigcirc\varphi & & (next) \\
\varphi \mathcal{U} \psi & & (until) \\
\Diamond\varphi & & (eventually) \\
\Box\varphi & & (always) \\
\bullet\varphi & & (weak\ next) \\
Last & & (last)
\end{array}
$$

$$
\begin{array}{rcl}
True \mathcal{U} \varphi & = & \Diamond\varphi \\
\neg\Diamond\neg\varphi & = & \Box\varphi \\
\neg\bigcirc\neg\varphi & = & \bullet\varphi \\
\neg\bigcirc True & = & Last
\end{array}
$$

$$\varphi \models A | \neg\varphi | \varphi_1 \wedge \varphi_2 | \bigcirc\varphi | \varphi_1 \mathcal{U} \varphi_2$$

CFG2LTLf

- Matches structure of parsed tree against LTLf CFG
- CGF of input sentence must be known
- CFG of LTLf must mirror structure NL CFG



CHECK CONSISTENCY

SENTENCE PREPROCESSING

PARSING WITH NL CFG

MATCHING TREE AGAINST LTLf CFG

POSTPROCESSING LTLf FORMULA

GROUNDING

CFG2LTLf (cont'd)

Input sentence: $\text{"}Pick\ up\ the\ green\ ball\ and\ put\ a\ box\ next\ to\ a\ key,\ then\ open\ the\ door.\text{"}$

LTLf (not grounded): $\Diamond((pick(green\_ball) \wedge put\_next\_to(box, key)) \wedge \Diamond open(door))$

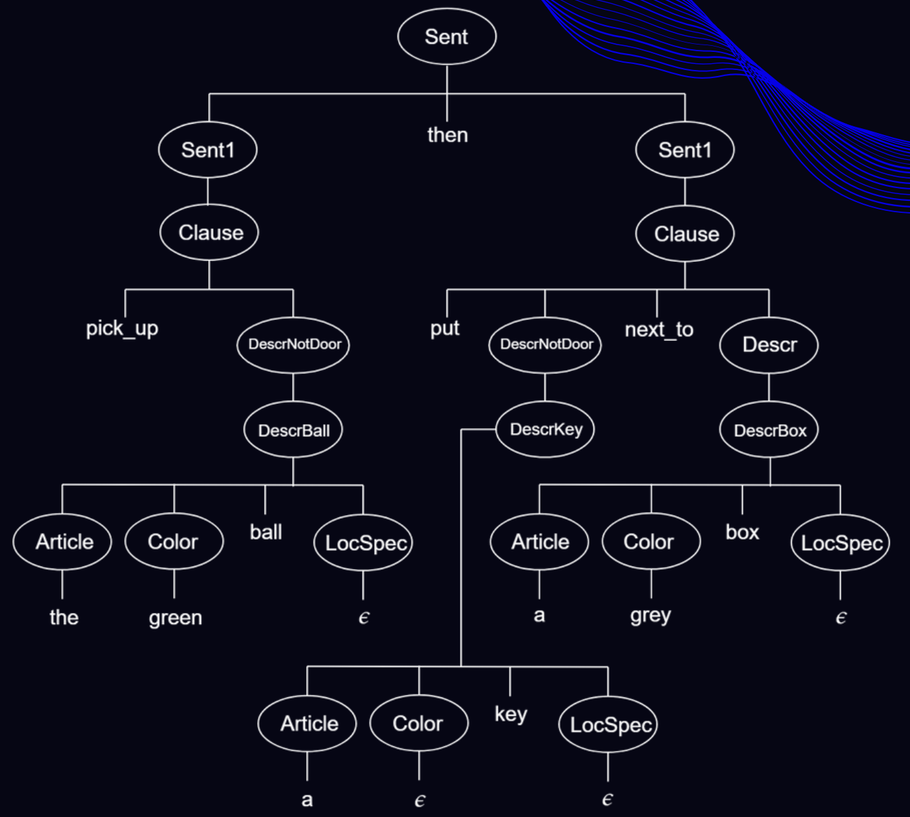
LTLf (grounded): $\Diamond((pick\_green\_ball \wedge put\_next\_to\_box\_key) \wedge \Diamond open\_door)$

⟨Sent⟩	⊨	⟨Sent1⟩ | ⟨Sent1⟩ ',' then ⟨Sent1⟩ | ⟨Sent1⟩ after you ⟨Sent1⟩
⟨Sent1⟩	⊨	⟨Clause⟩ | ⟨Clause⟩ and ⟨Clause⟩
⟨Clause⟩	⊨	go to ⟨Descr⟩ | pick up ⟨DescrNotDoor⟩ | open ⟨DescrDoor⟩ | put ⟨DescrNotDoor⟩ next to ⟨Descr⟩
⟨DescrDoor⟩	⊨	⟨Article⟩ ⟨Color⟩ door ⟨LocSpec⟩
⟨DescrBall⟩	⊨	⟨Article⟩ ⟨Color⟩ ball ⟨LocSpec⟩
⟨DescrBox⟩	⊨	⟨Article⟩ ⟨Color⟩ box ⟨LocSpec⟩
⟨DescrKey⟩	⊨	⟨Article⟩ ⟨Color⟩ key ⟨LocSpec⟩
⟨Descr⟩	⊨	⟨DescrDoor⟩ | ⟨DescrBall⟩ | ⟨DescrBox⟩ | ⟨DescrKey⟩
⟨DescrNotDoor⟩	⊨	⟨DescrBall⟩ | ⟨DescrBox⟩ | ⟨DescrKey⟩
⟨LocSpec⟩	⊨	ϵ | on your left | on your right | in front of you | behind you
⟨Color⟩	⊨	ϵ | red | green | blue | purple | yellow | grey
⟨Article⟩	⊨	the | a

NL grammar

$$
\begin{aligned}
\langle Sent\rangle &\models \langle Sent1\rangle|\Diamond(\langle Sent1\rangle \wedge \Diamond\langle Sent1\rangle)|\Diamond(\Diamond\langle Sent1\rangle \wedge \langle Sent1\rangle)\\
\langle Sent1\rangle &\models \langle Clause\rangle|(\langle Clause\rangle \wedge \langle Clause\rangle)\\
\langle Clause\rangle &\models at(\langle Descr\rangle)|pick(\langle DescrNotDoor\rangle)|open(\langle DescrDoor\rangle)|\\
&\quad put\_next\_to(\langle DescrNotDoor\rangle, \langle Descr\rangle)\\
\langle DescrDoor\rangle &\models \langle Article\rangle\langle Color\rangle door\langle LocSpec\rangle\\
\langle DescrBall\rangle &\models \langle Article\rangle\langle Color\rangle ball\langle LocSpec\rangle\\
\langle DescrBox\rangle &\models \langle Article\rangle\langle Color\rangle box\langle LocSpec\rangle\\
\langle DescrKey\rangle &\models \langle Article\rangle\langle Color\rangle key\langle LocSpec\rangle\\
\langle Descr\rangle &\models \langle DescrDoor\rangle|\langle DescrBall\rangle|\langle DescrBox\rangle|\langle DescrKey\rangle\\
\langle DescrNotDoor\rangle &\models \langle DescrBall\rangle|\langle DescrBox\rangle|\langle DescrKey\rangle\\
\langle LocSpec\rangle &\models \_onyourleft|\_onyourright|\_infrontofyou|\_behindyou|\\
\langle Color\rangle &\models red\_|green\_|blue\_|purple\_|yellow\_|grey\_|\\
\langle Article\rangle &\models \ |\ |
\end{aligned}
$$

LTLf grammar

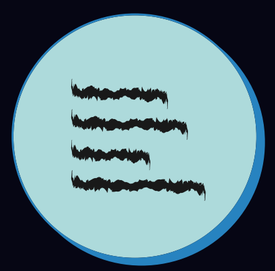


Tree corresponding to the input sentence parsed with NL CFG

λCalc2LTLf

- Inspired by [4]
- Based on Lambda Calculus
- Relies on the assumptions:
  - each word in the sentence belongs to the lexicon
  - sentences follow certain structure
- Handles semantic ambiguities
- Supports pronouns handling

REQUIRE:



Input Sentence NL

Mapping words - abstractions

BUILD DICTIONARY OF ABSTRACTIONS

SENTENCE PREPROCESSING

PARSING & ABSTRACTIONS SELECTION

β-REDUCTION

FORMULA POSTPROCESSING & GROUNDING

λCalc2LTLf (cont'd)

INPUT SENTENCE:

$$\text{"}\underline{Go\ to}\ \underline{room\ 1}\ \underline{and}\ \underline{pick\ up}\ \underline{the}\ \underline{blue\ box}.\text{"}$$

$\lambda x.at(x)$	$\lambda x.x@room\_1$	$\lambda x\lambda y.\Diamond(x \wedge \Diamond y)$	$\lambda x.pick(x)$	$\lambda x.x$	$\lambda x.x@blue\_box$
$at(room\_1)$		$\lambda x\lambda y.\Diamond(x \wedge \Diamond y)$	$\lambda x.pick(x)$		$blue\_box$
		$\lambda y.\Diamond(at(room\_1) \wedge \Diamond y)$	$pick(blue\_box)$		

not grounded: $\Diamond(at(room\_1) \wedge \Diamond pick(blue\_box))$

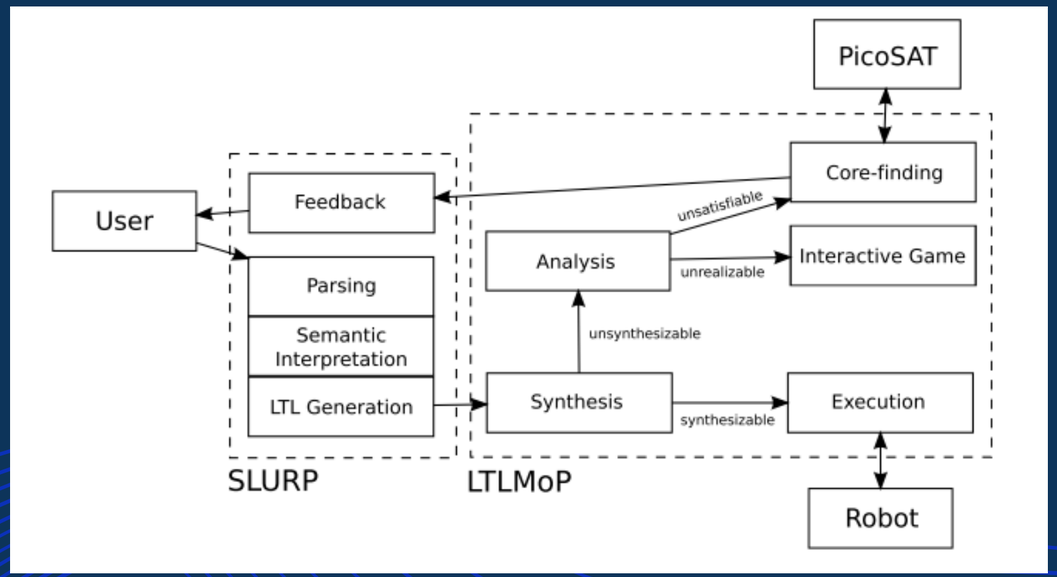
grounded: $\Diamond(at\_room\_1 \wedge \Diamond pick\_blue\_box)$

MAPPING:

Word	LT-abstraction
go to	$\lambda x.at(x)$
the	$\lambda x.x$
and	$\lambda x\lambda y.\Diamond(x \wedge \Diamond y)$
of	$\lambda x.x$
when	$\lambda x\lambda y.\Box(x \rightarrow y)$
open	$\lambda x.open(x)$
do not	$\lambda x.\neg x$
eventually	$\lambda x.\Diamond x$
pick up	$\lambda x.pick(x)$
or	$\lambda x\lambda y.x \vee y$
until	$\lambda x\lambda y.x\mathcal{U}y$
green ball	$\lambda x.x@green\_ball$
red key	$\lambda x.x@red\_key$
door	$\lambda x.x@door$

NL2LTLf with NLP

Reference paper [5]



Resources

- **Stanford CoreNLP**
- **WordNet**
- **VerbNet**

Frame **Go-02**
Subject: The Agent
Verb: Go
To: the kitchen

Frame **Go-03**
Subject: The Agent
Verb: Go
Through: the hallway

Frame **Go-04**
Subject: The Agent
Verb: Go
From: the hallway
To: the kitchen

INPUT SENTENCE | LEMMATIZATION | LTL TREE GENERATION | NLP PIPELINE | FORUMULA RECONSTRUCITON | LTL FORMULA

NL2LTLf: pt1

INPUT SENTENCE

GET THE INPUT SENTENCE IN NATURAL LANGUAGE FROM THE USER

the agent goes to room_x and picks a box or looks it

LEMMATIZATION

REDUCE INFLECTIONAL AND DERIVATIONALLY RELATED FORMS TO A COMMON BASE FORM.

Tool: StanfordLemmatizer

[the, agent, go, to, room_x, and, pick, a, box, or, look, it]

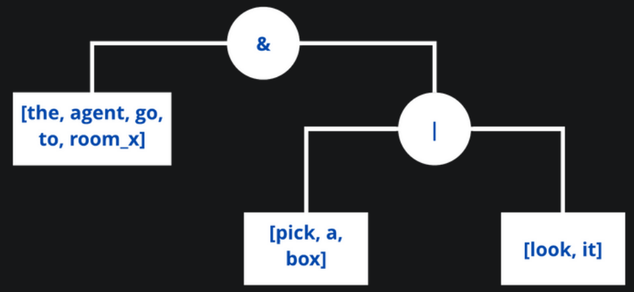
LTL TREE GENERATION

EXTRACTING LOGIC OPERATORS AND INDEPENDENT CLAUSES TO BUILD AN LTL TREE

LTL Tree:

Branching Nodes: LTL Operators

Leaves: Independent clauses



NLP Pipeline: pt1

NLP PIPELINE

POS Tagging

ASSIGNING TO EACH WORD CORRESPONDING PART OF SPEECH (POS), ACCORDING TO THE CONTEXT.

Tool: Stanford POS Tagger

1) [the/DT, agent/NN, go/VB, to/IN, room_x/NN]

2) [pick/VB, a/DT, box/NN]

3) [look/VB, it/PRP]

Null-Element Restoration

ADDING THE SUBJECT IN THE SENTENCES IN WHICH IT IS IMPLICIT.

Tool: Stanford Dependency Parser

1) already contains a subject

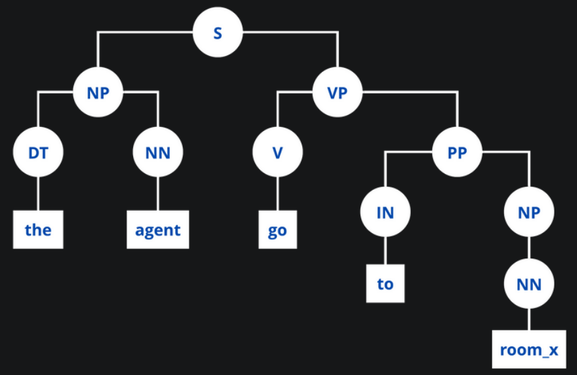
2) [the/DT, agent/NN, pick/VB, a/DT, box/NN]

3) [the/DT, agent/NN, look/VB, it/PRP]

Syntactic Parsing

BUILDING A COSTITUENCY-BASED PARSING TREE.

Tool: Stanford Syntactic Parser



NLP Pipeline: pt2

NLP PIPELINE (Cont'd)

Action Extraction

EXTRACTING THE VERB AND THEN MAPPING IT TO THE CORRESPONDING BABYAI ACTION.

Verbs:
1. **Go**
2. **Pick**
3. **Look**

→

BabyAI Actions:
1. **BabyAI.Go**
2. **BabyAI.Pick**
3. **BabyAI.See**

Semantic Interpretation

EXTRACTING THE SEMANTIC ACTORS OF THE SENTENCE FROM THE VERBNET FRAME THAT BEST MATCHES THE SYNTACTIC TREE.

1. **Sentence**
   Verbnet Class: escape-51.1
   Extracted Frame:

Frame **GO-03**
Tags**: NP V PP.destination**
Subject: agent
Verb: go
Destination: room_x

LTL Proposition

GENERATING ATOMIC FORMULAS USING PREDEFINED ACTION TEMPLATES.

Action Templates:

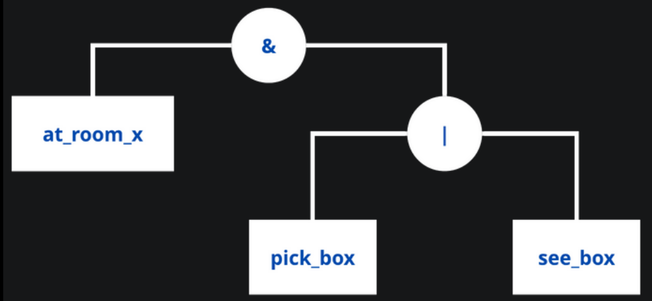
$$go(to) = \mathbf{at\_to}$$
$$pick(theme) = \mathbf{pick\_theme}$$

1.Formula: at_room_x
2.Formula: $pick\_box$
3.Formula: see_box

NL2LTLf: pt2

NLP PIPELINE

LTL TREE AFTER THE NLP PIPELINE



FORMULA RECONSTRUCTION

BOTTOM-UP FORMULA RECONSTRUCTION USING OPERATOR TEMPLATES AND CURRENT SUBTREES SUBFORMULAS.

Operator Templates:

$$AND(x, y) = \Diamond(x \wedge \Diamond y)$$
$$OR(x, y) = \Diamond x \vee \Diamond y$$
$$NOT(x) = \neg x$$

$$prop1 = pick\_box$$
$$prop2 = see\_box$$
$$OR(prop1, prop2) =$$
$$\Diamond pick\_box \vee \Diamond see\_box$$

LTL TREE GENERATION

FINAL FORMULA

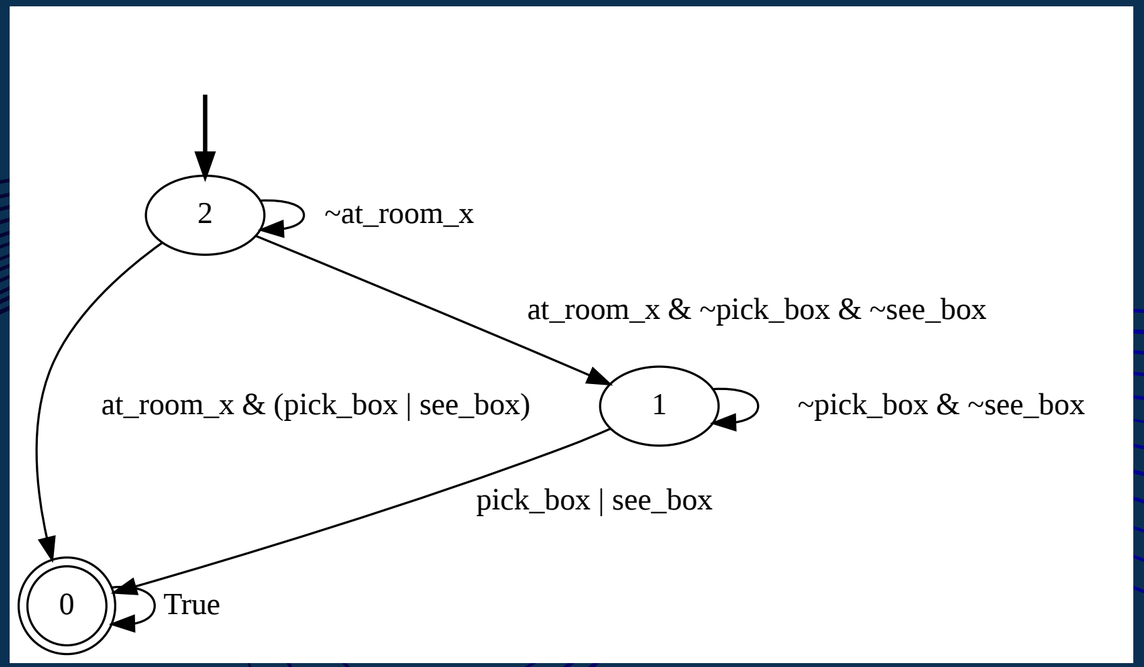
$$\Diamond(at\_room\_x \wedge$$
$$\Diamond(\Diamond pick\_box \vee \Diamond see\_box))$$

Comparison

	Independent from structure sentence	Accepts non lemmatized words	Pronouns handling	No knowledge CFG required	Autonomy	Upgradeability	Portability	Time	Overall performace
CFG Based		✗	✗	✗		✗	✓	[<6] ms	weak
λ-Calculus Based		✗	✓	✓		✓	✓	[<1] ms	average
NLP Based		✓	✓	✓		✓	✗	[1-2] s	strong

FFLOAT: From LTLf and LDLf tO AuTomata

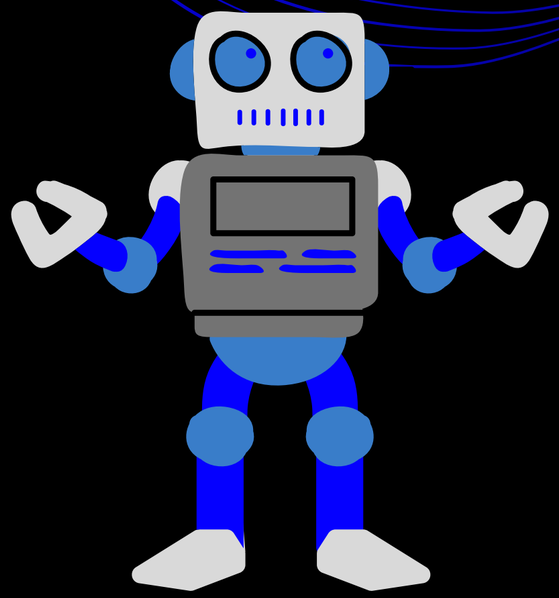
Online tool for Automata generation



LTLf Syntax

Syntax	Semantics	Example
`[A-Za-z0-9]+`	Atomic	`A,b01`
`true|false`	True	`true`
`! f`	Not	`!A`
`f1 [&|] f2`	And, Or	`A & (B | !C)`
`f1 -> f2`	Implication	`G(A -> B)`
`f1 <-> f2`	Equivalence	`F(A <-> B)`
`X f1`	Next	`X A`
`WX f1`	Weak Next	`WX A`
`f1 U f2`	Until	`A U B`
`f1 R f2`	Release	`A R B`
`F f1`	Eventually	`F A`
`G f1`	Always	`G A`

Restraining Bolt



" It is a device that restricts a droid's [agent's] actions when connected to its systems. Droid owners install restraining bolts to limit actions to a set of desired behaviors." [3]

Representations of the world

AGENT

Features

Actions

Reward

WORLD

Fluents

Restraining specification

BOLT

Example Breakout: Representations of the world

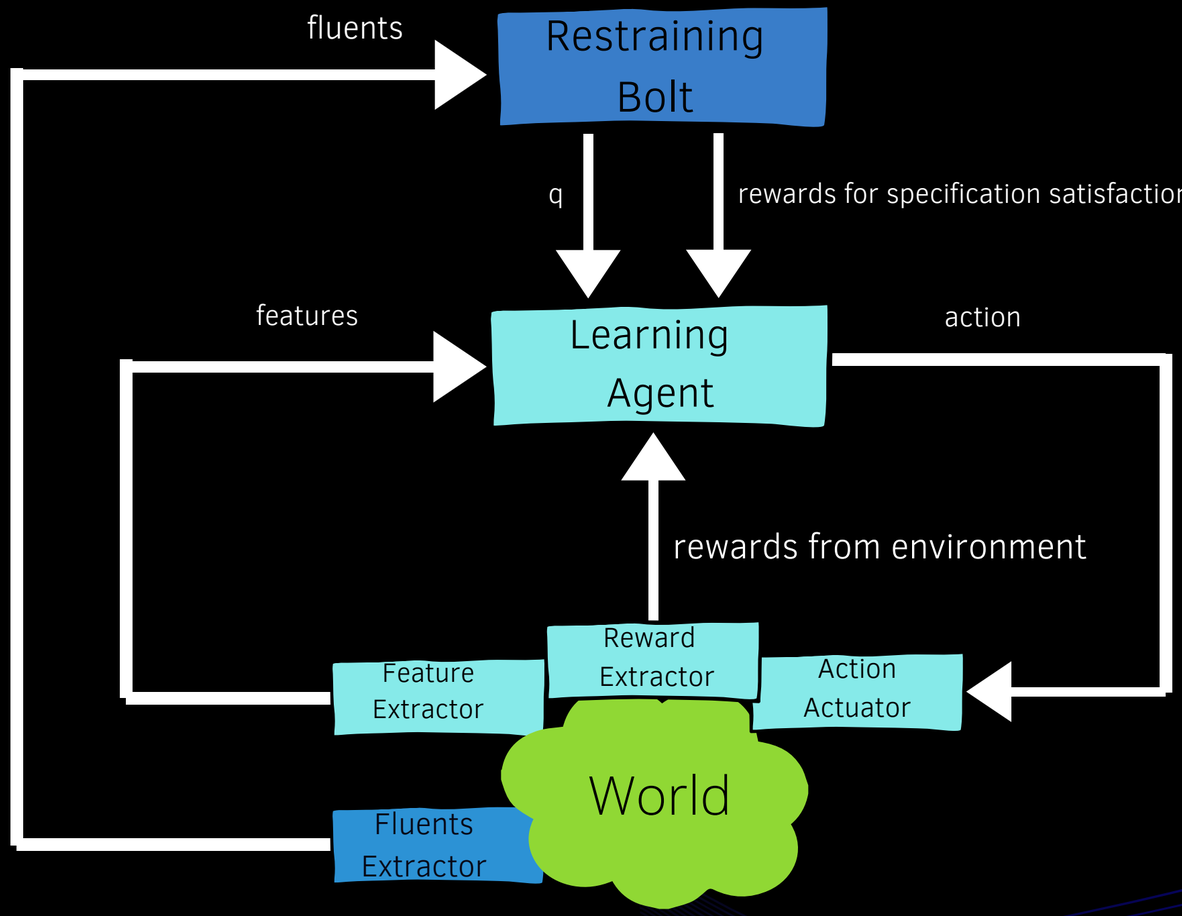
Learning Agent

- **Features:** paddle and ball positions, ball speed
- **Actions:** move the paddle (left or right)
- **Rewards:** after hitting a brick

Restraining Bolt

- **Fluents:** bricks position and status of the columns (broken or not)
- **Restraining specification:** all bricks in column i must be removed before completing the column j, with $i < j$

RL with LTLf/LDLf restraining specifications



Learning Agent: it is defined as $M = (S, A, Tr, R)$

Restraining Bolt: it is formed by *m* LTLf/LDLf formulas φ_i over the fluents *L* with associated rewards r_i it is defined as $RB = (L, \{(\varphi_i, r_i)\}_{i=1}^{m})$

Goal: The learning agent tries to learn a non-Markovian policy that maximizes the expected cumulative reward, so $p : S^* \rightarrow A$

Main differences

Classical Reinforcement Learning

The Learning Agent is an MDP (Markov Decision Process) with unknown transitions and rewards, which takes actions in order to maximize the reward. The goal is to find a policy of the form: $p : S \rightarrow A$, so given a set of features, it tells us what action to perform.

RL for non-Markovian reward decision process with LTLf/LDLf rewards

In this case, the rewards are given over sequences of configuration of the feature in MDPs, working with an MDP with non-Markovian rewards. We can overcome the problem of non-Markovian reward by:

1. Taking the formula
2. Finding the corresponding DFA
3. Combining the DFAs with MDP, so to obtain a new system in which the policy to compute is in the form $p : S^* \rightarrow A$, that can be easily solved by working with an MDP with a larger set of states.

Solution for RL with LTLf/LDLf restraining specifications

STEP 1

Transform each formula φ_i into a DFA

$$A_{\varphi_i} = (2^L, Q_i, q_{i0}, \delta_i, F_i)$$

STEP 2

Apply classical Reinforcement Learning over a new MDP

$$M' = (Q_1 \times .... \times Q_{\mathrm{m}} \times S, A, Tr', R')$$

STEP 3

The optimal policy p' learned for M' is an optimal policy of the original problem

$$R'(q_1, ..., q_m, s, a, q_1', ..., q_m', s') = \sum_{i:q_i' \in F_i} r_i + R(s, a, s')$$

Restraining Bolt Implementation: File rb.py

Class RestrainingBolt:
superclass of each Restraining Bolt

```python
class RestrainingBolt(ABC):

    def __init__(self, num_states, final_states,
                 initial_state=0, reward=1):
        self.num_states = num_states
        self.reward = reward
        self.initial_state = initial_state
        self.final_states = final_states
        self.reset()

    def reset(self):
        self.current_state = self.initial_state

    @abstractmethod
    def transition(self, world_state):
        pass

    def get_reward(self):
        if self.current_state in self.final_states:
            return self.reward
        else:
            return 0
```

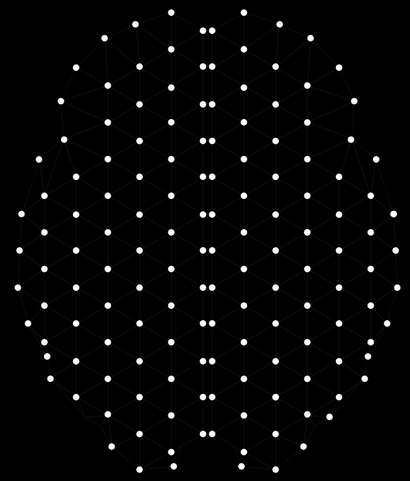
Class FluentRestrainingBolt:
allows to manage fluents of the Restraining Bolt

```python
class FluentRestrainingBolt(RestrainingBolt):
    # permette di avere tutto più automatizzato, ma è più inefficiente

    def __init__(self, num_states, final_states,
                 initial_state=0, reward=1):
        super().__init__(num_states, final_states, initial_state, reward)

    def transition(self, world_state):
        self.compute_fluents(world_state)
        self.compute_transition()

    @abstractmethod
    def compute_transition(self):
        pass

    @abstractmethod
    def compute_fluents(self, world_state):
        pass

    def reset(self):
        super().reset()
        self.current_fluents = set()
```

Class MultiBolt:
container of Restraining Bolts

```python
class MultiBolt():

    def __init__(self, bolts, same_rewards=True):
        self.bolts = bolts
        self.same_rewards = same_rewards
        self.reset()

    def reset(self):
        for bolt in self.bolts:
            bolt.reset()

    def transition(self, world_state):
        for bolt in self.bolts:
            bolt.transition(world_state)

    def get_reward(self):
        reward = 0
        for bolt in self.bolts:
            r = bolt.get_reward()
            if self.same_rewards:
                reward += r * 1/len(self.bolts)
            else:
                reward += r
        return reward

    @property
    def current_state(self):
        state = self.bolts[0].current_state
        for bolt in self.bolts[1:]:
            state += bolt.current_state * bolt.num_states
        return state
```

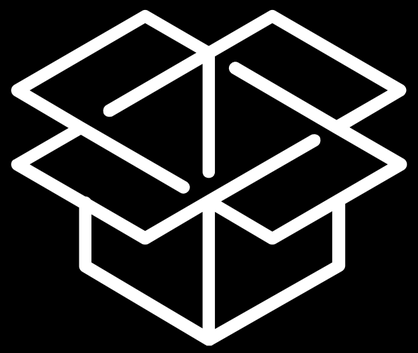
BabyAI integration

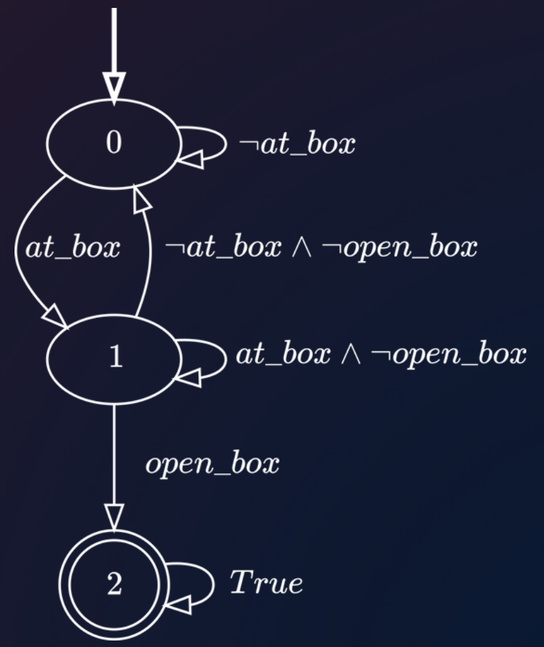


- Agent observations:
  - 7x7x3 tensors: the (partial) view of the agent inside the grid world
  - textual instruction
- During each episode parallel frames (generated by multiple Gym environments) are iterated by the PPO algorithm [10], employing an Actor Critic model.
- The Actor Critic maps the view to an embedding vector through a conditional CNN (using the textual instruction), that is mapped to a value scalar (critic) and to a distribution over actions (actor).
- We pass the observation to the bolt, perform a transition, then augment the embedding with the bolt state.
- BabyAI resets each environment when the goal of the textual instruction is reached or when a step limit is exceeded. Reward is proportional to the number of steps (0 if limit is reached, max 1). Bolts assign a reward of 1 if a final state is reached when the environment is reset.

Experiment 1

Open Box

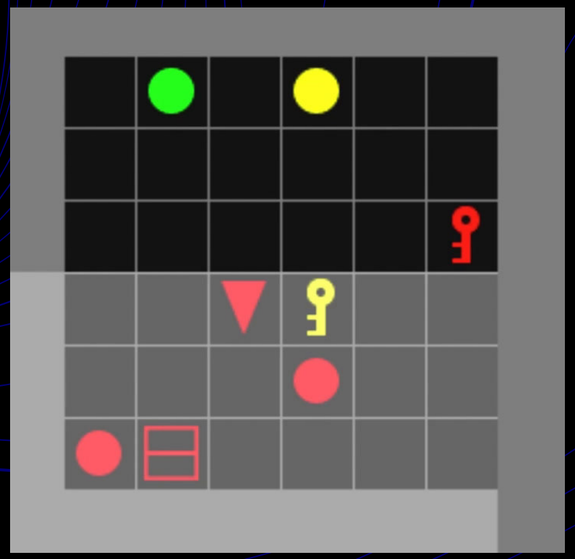


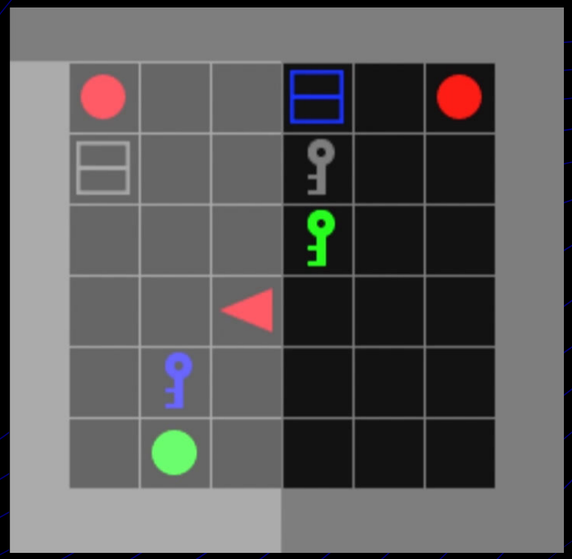
NATURAL LANGUAGE COMMAND	LTLf FORMULA	DFA
"Go to a box and immediately open it."	$\Diamond(at\_box \wedge \bigcirc open\_box)$	

Experiment 1

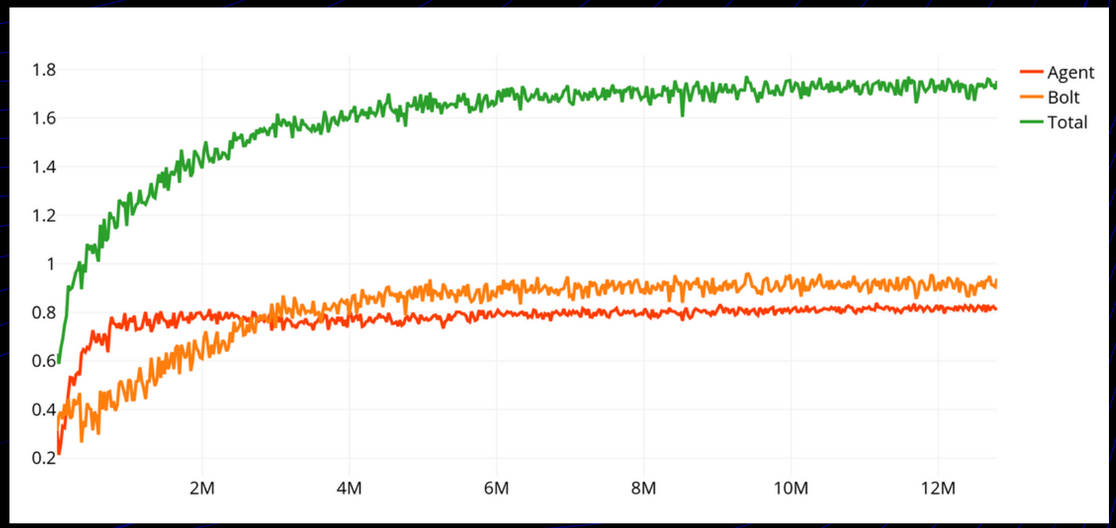
Open box

Demo





Mean Return



Vanilla agent

Goal: *Go to the red ball*

RB agent

Goal: *Go to the red ball +*
Go to a box and immediately open it

Experiment 2

Ambiguity

NATURAL LANGUAGE COMMAND

"Go to a grey ball and reach a grey key."

LTLf FORMULA 1

(sequential)

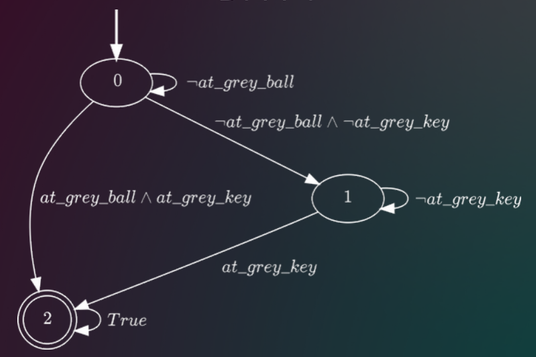
$$\Diamond(at\_grey\_ball \wedge \Diamond at\_grey\_key)$$

LTLf FORMULA 2

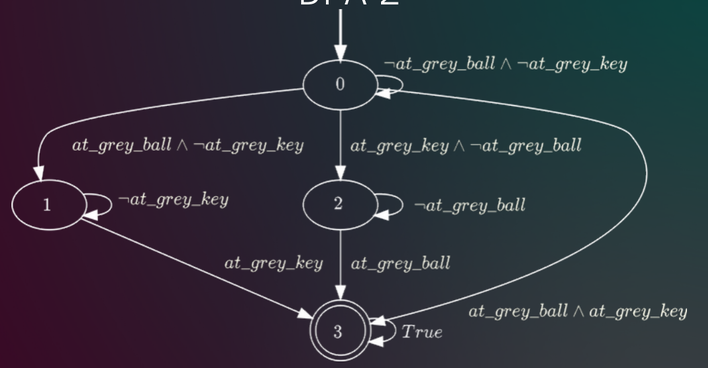
(non-sequential)

$$\Diamond at\_grey\_ball \wedge \Diamond at\_grey\_key$$

DFA 1

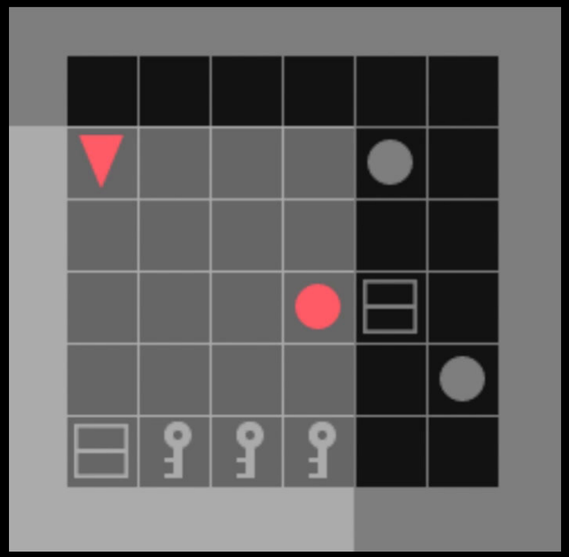


DFA 2



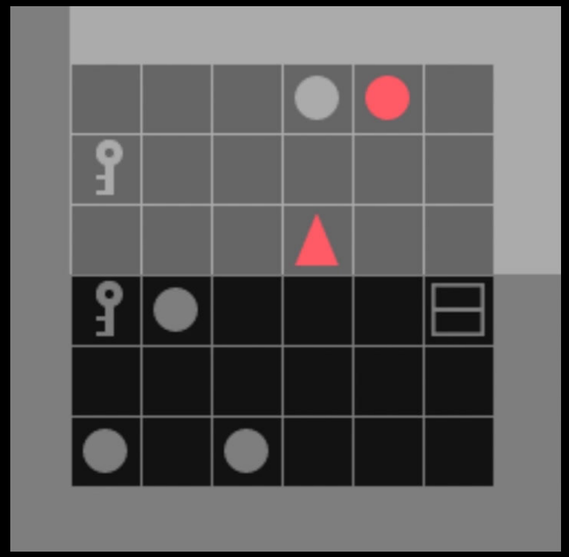
Experiment 2
Ambiguity

Demo



Vanilla agent

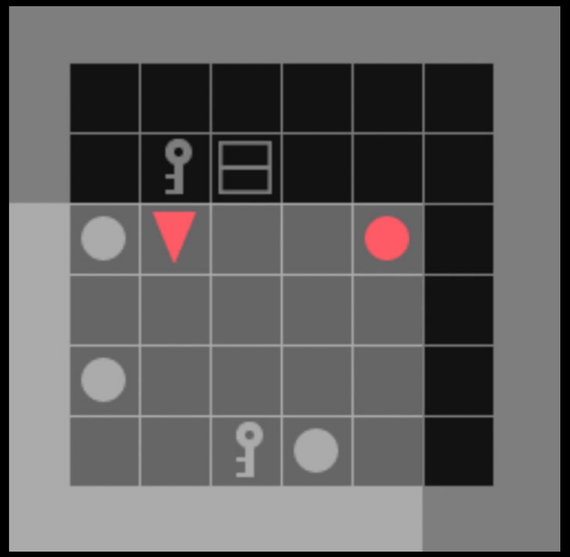
Goal: *Go to the red ball*



RB agent

(non-sequential)

Goal: Go to *the red ball* +
Go to a grey ball ***and*** *reach a grey key*



RB agent

(sequential)

Goal: *Go to the red ball* +
Go to a grey ball ***and (then)***
reach a grey key

Experiment 3

Pick and Place

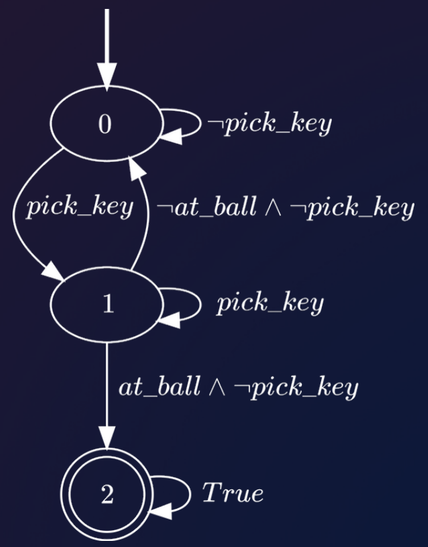
NATURAL LANGUAGE COMMAND

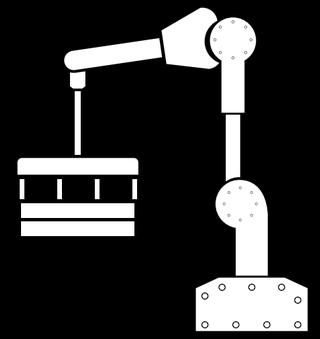
"Pick a key and keep it until you reach a box, then drop it."

LTLf FORMULA

$$\Diamond(pick\_key \wedge \bigcirc(pick\_key\, \mathcal{U}\, at\_box) \wedge \bigcirc\neg pick\_key)$$

DFA

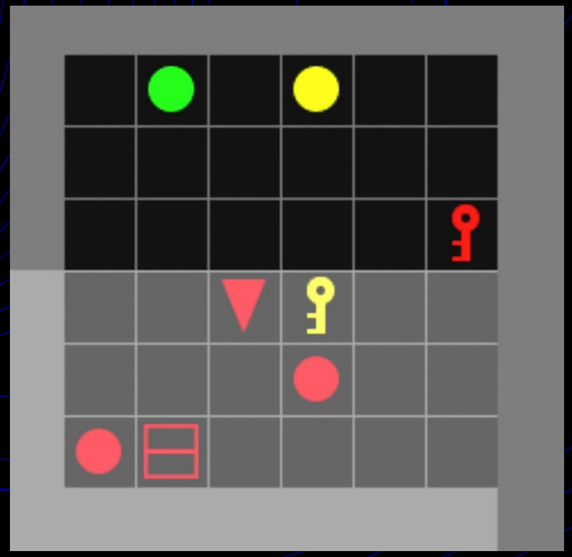


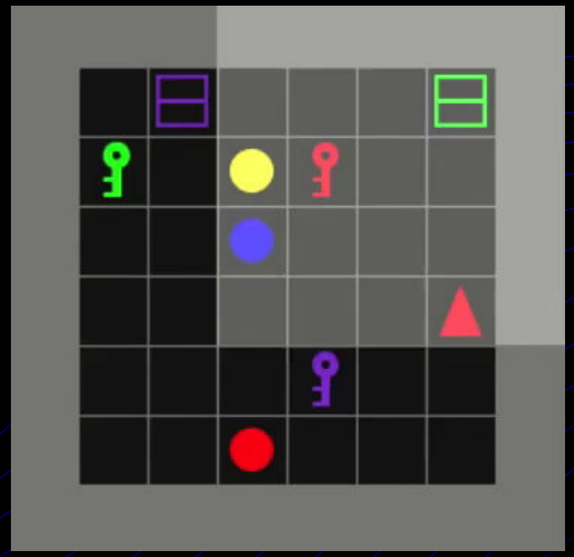


Experiment 3

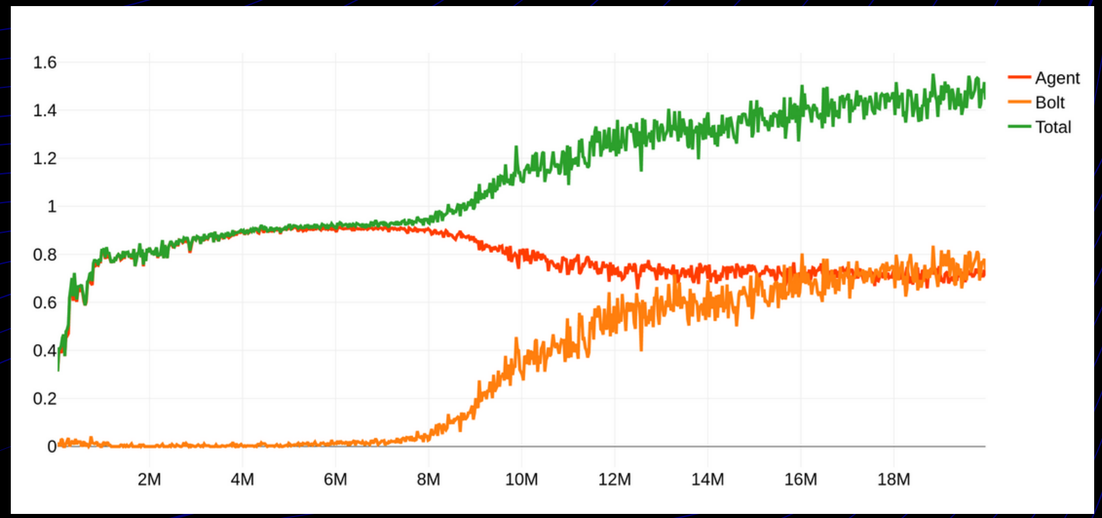
Pick and Place

Demo





Mean Return



Vanilla agent

Goal: *Go to the red ball*

RB agent

Goal: *Go to the red ball +*

Pick a key and keep it until you reach a box, then drop it

Conclusions

LANGUAGE TRANSLATION

We developed a modular system able to translate a sentence in NL into an LTLf formula using three different approaches.

RESTRAINING BOLTS INTEGRATION IN BABYAI

We explored the way in which the restraining bolts can be connected with the BabyAI platform and we validated the work with several experiments, obtaining interesting results.

Future work

ROBUSTNESS OF LANGUAGE TRANSLATION

Implementing a Deep Word Sense Disambiguation system to detect the correct verb sense and make the frame extraction easier and more flexible.

END-TO-END PIPELINE

Composing the translator, the automata tool and the Fluent Restraining Bolt, an end-to-end architecture is achievable. The only requirement is the set of fluents and the mapping between world states and fluents.

AUTOMATIC FLUENT DETECTION

The explicit mapping between world states and fluents could be delegated to a visual relation classifier. This is useful in continous domains such as robotics, where the mapping is difficult to implement. More interestingly, this component would decouple a bolt not only from an underlying learning agent, but from an underlying environment too.

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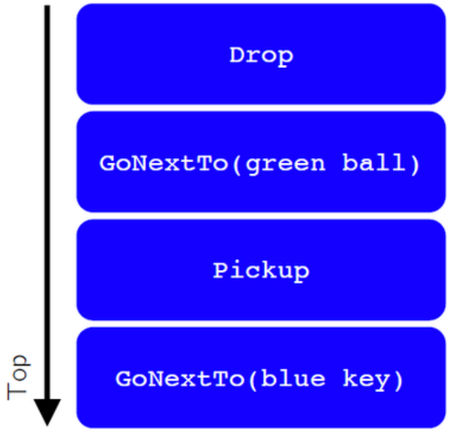
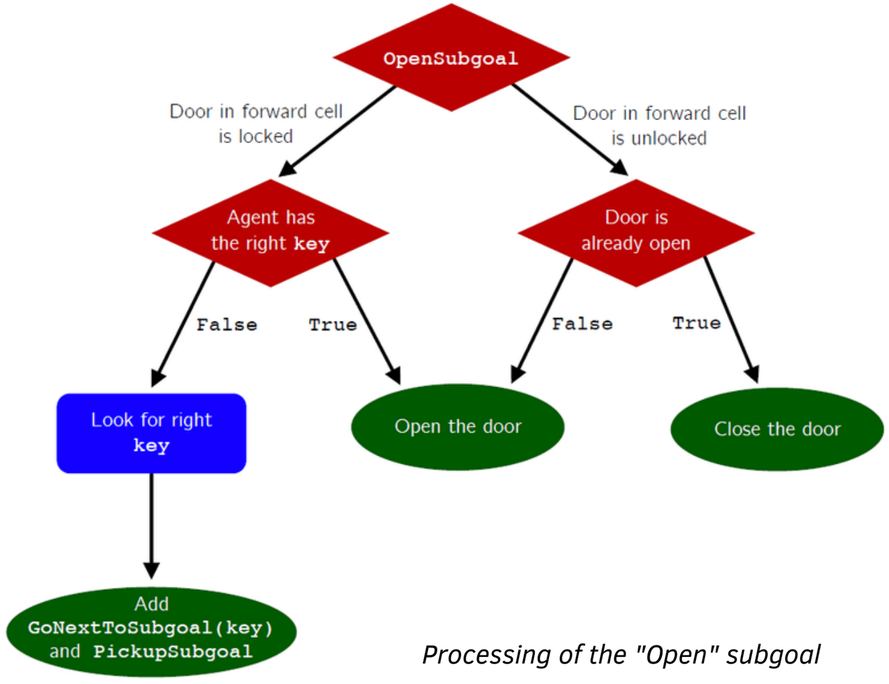
The BOT

- Simulates a human teacher by helping the agent during learning
- Direct access to a tree representation of instructions
- Uses a stack machine with possibly recursive subgoals
- Implements the shortest path search routine



Initial stack state of the instruction "put the blue key next to the green ball"



Processing of the "Open" subgoal

Implemented subgoals:

- Open: open a door that is in front of the agent
- Close: close a door that is in front of the agent
- Pickup: execute pickup action
- Drop: execute drop action
- GoNextTO: go next to an opject matching a given description or next to a cell at a given position
- Explore: uncover unseen parts of the environment

Competencies of levels

- **Room Navigation (ROOM)**: navigate a 6x6 room.
- **Ignoring Distracting Boxes (DISTR-BOX)**: navigate the environment even when there are multiple distracting grey box objects in it.
- **Ignoring Distractors (DISTR)**: same as DISTR-BOX, but distractor objects can be boxes, keys or balls of any color.
- **Maze Navigation (MAZE)**: navigate a 3x3 maze of 6x6 rooms, randomly inter-connected by doors.
- **Unblocking the Way (UNBLOCK)**: navigate the environment even when it requires moving objects out of the way.
- **Unlocking Doors (UNLOCK)**: to be able to find the key and unlock the door if the instructions requires this explicitly.
- **Guessing to Unlock Doors (IMP-UNLOCK)**: to solve levels that require unlocking a door, even if this is not explicitly stated in the instruction.
- **Go To Instructions (GOTO)**: understand "go to" instructions.
- **Open Instructions (OPEN)**: understand "open" instructions.
- **Pickup Instructions (PICKUP)**: understand "pick up" instructions.
- **Put Instructions (PUT)**: understand "put" instructions.
- **Location Language (LOC)**: understand instructions where objects are referred to by relative location as well as their shape and color.
- **Sequences of Commands (SEQ)**: understand composite instructions requiring an agent to execute a sequence of instruction clauses.

Markovian Decision Processes

Appendix 3

Markov Decision Process (MDP)

- It contains a set of states *S*, a set of actions *A*, a transition function $Tr : S \times A \to Prob(S)$, that returns for every state *s* and action *a*, a probability distribution over the next state, and a reward function $R : S \times A \times S \to \mathbb{R}$ that specifies the reward received by the agent when transitioning from state *s* to state *s'* by applying action *a*.
- The solution of an MDP is a function called *policy*, assigning an action to each state. The value of a policy *p* at state *s* is the expected sum of rewards when starting at state *s* and selecting actions based on *p*.
- Reinforcement Learning is the task of learning a possibly optimal policy, from an initial state s_0, on an MDP where only *S* and *A* are known, while *Tr* and *R* are not.

Non Markovian Reward Decision Process (NMRDP)

- It is a tuple $M = (S, A, Tr, \hat{R})$, where *S*, *A*, *Tr* are as in an MDP, but the reward $\hat{R}$ is a real-valued function over finite state-action sequences (known as traces) as: $\hat{R} : (S \times A)^* \to \mathbb{R}$
- The policy is also non-Markovian $\hat{p} : S^* \to A$
- It is possible to specify $\hat{R}$ implicitly, using a set of pairs $\{(\varphi_i, r_i)\}_{i=1}^{m}$, with φ_i an LTLf formula selecting the traces to reward and r_i the reward assigned to those traces, where the atomic propositions, so the fluents, of φ_i, correspond to boolean features or boolean propositions.

RB Theory: Lemmas and Thorem

Appendix 4

Lemma 4

RL with LTLf/LDLf restraining specifications $M_{ag}^{rb} = (M_{ag}, RB)$with $M_{ag} = (S, A, Tr_{ag}, R_{ag})$ and $RB = (L, \{(\varphi_i, r_i)\}_{i=1}^{m})$ can be reduced to RL over the NMRDP $M_{ag}^{n} = (S \times L, A, Tr_{ag}^{rb}, \{(\varphi_i, r_i)\}_{i=1}^{m})) \cup \{(\varphi_s, R_{ag}(s, a, s'))\}_{s \in S, a \in A, s' \in S})$, by restricting the policy to learn to have the form $\hat{p} : (Q_1 \times ... \times Q_m \times S)^* \rightarrow A$.

Lemma 5

RL with LTLf/LDLf restraining specifications $M_{ag}^{rb} = (M_{ag}, RB)$ with $M_{ag} = (S, A, Tr_{ag}, R_{ag})$ and $RB = (L, \{(\varphi_i, r_i)\}_{i=1}^{m})$ can be reduced to RL over the MDP $M_{ag}^{'} = (S^{'}, A, Tr_{ag}^{'}, R_{ag}^{'})$, by restricting the policy to learn to have the form $(Q_1 \times ... \times Q_n \times S) \rightarrow A$.

Theorem 6

RL with LTLf/LDLf restraining specifications $M_{ag}^{rb} = (M_{ag}, RB)$ with $M_{ag} = (S, A, Tr_{ag}, R_{ag})$ and $RB = (L, \{(\varphi_i, r_i)\}_{i=1}^{m})$ can be reduced to RL over the MDP $M_{ag}^{q} = (Q_1 \times ... \times Q_m \times S, A, Tr_{ag}^{''}, R_{ag}^{''})$, and optimal policies$p_{ag}^{new}$ for M_{ag}^{rb} can be obtained by learning corresponding optimal policies for M_{ag}^{q}.

Multibolt

Appendix 5

- We can express the goals of Examples 1 and 3 in an alternative way by employing multiple bolts that act simultaneously, one for each natural language command.
- In our implementation we embed multiple bolts in a single container class called Multibolt. In this way the interaction with the BabyAI code is minimal, since a Multibolt exposes the interface of a normal Restraining Bolt.
- The reward of a multibolt is the sum of the rewards of the contained bolts.
- The state of a multibolt is computed from the states of the contained bolts like in TaskExecutor from RLGames [3].

Example 1

"Go at a box."

$$\Diamond at\_box$$

+

"When you are at a box open the box."

$$\Box(at\_box \rightarrow \bigcirc open\_box)$$

Example 3

"Pick a key and keep it until you reach a box."

$$\Diamond(pick\_key \wedge \bigcirc(pick\_key\, \mathcal{U}\, at\_box))$$

+

"When you are at a box drop the key."

$$\Box(at\_key \rightarrow \bigcirc \neg pick\_key)$$