Tools to learn and work with planning models

1. Misc: modern toolbox
2. MACQ: time series > models
3. L2P: natural language > models

Misc Planning Utilities

```
$ pip install planutils
$ planutils setup
$ planutils activate

  Entering planutils environment...

(planutils) $ lama d.pddl p.pddl

Package not installed!
  Download & install? [Y/n] Y
lama will be installed.

About to install the following
 packages: downward (36M), lama (20K)

  Proceed? [Y/n] Y

Installing downward...
INFO:    Downloading shub image
 45.84 MiB / 45.84 MiB
 [==========] 100.00% 7.30 MiB/s 6s

Finished installing downward (size: 46M)

Installing lama...
Finished installing lama (size: 20K)

Successfully installed lama!

Original command: lama d.pddl p.pddl
  Re-run command? [Y/n] Y

INFO     Running translator.
...
```

planutils

- Package manager and docker for planning tech
- Dozens of planners, all pre-compiled
- Ability to spin up lightweight local server
- Available via Dockerhub
  - The most common entry point

README Apache-2.0 license

Planning as a service (PaaS) provides an extendable API to deploy planners online in local or cloud servers. The service provides a queue manager to control a set of workers, which can easily be extended with one of several planners available in PLANUTILS.

Getting Started

Docker Build & Launch

1. Get sources

```
git clone https://github.com/AI-Planning/plannin
cd planning-as-a-service/server
```

solver.planning.domains

- Hosted on servers in Melbourne University
- Limited resource access to several planners
  - 500Mb & 30s
- Configured to host field's most commonly used planning systems
- Built on the planutils package
- Also an open source project
  - Used by organizations for internal planner hosting

editor.planning.domains

- Online editor for PDDL
- Import access to hundreds of benchmarks
- Solver access to solver.planning.domains
- Cloud session functionality (complete with read-only links)
- Plugin functionality with catalogue of custom built plugins from the planning community

PDDL Editor

File Session Import

domain.pddl

po2.pddl

ains

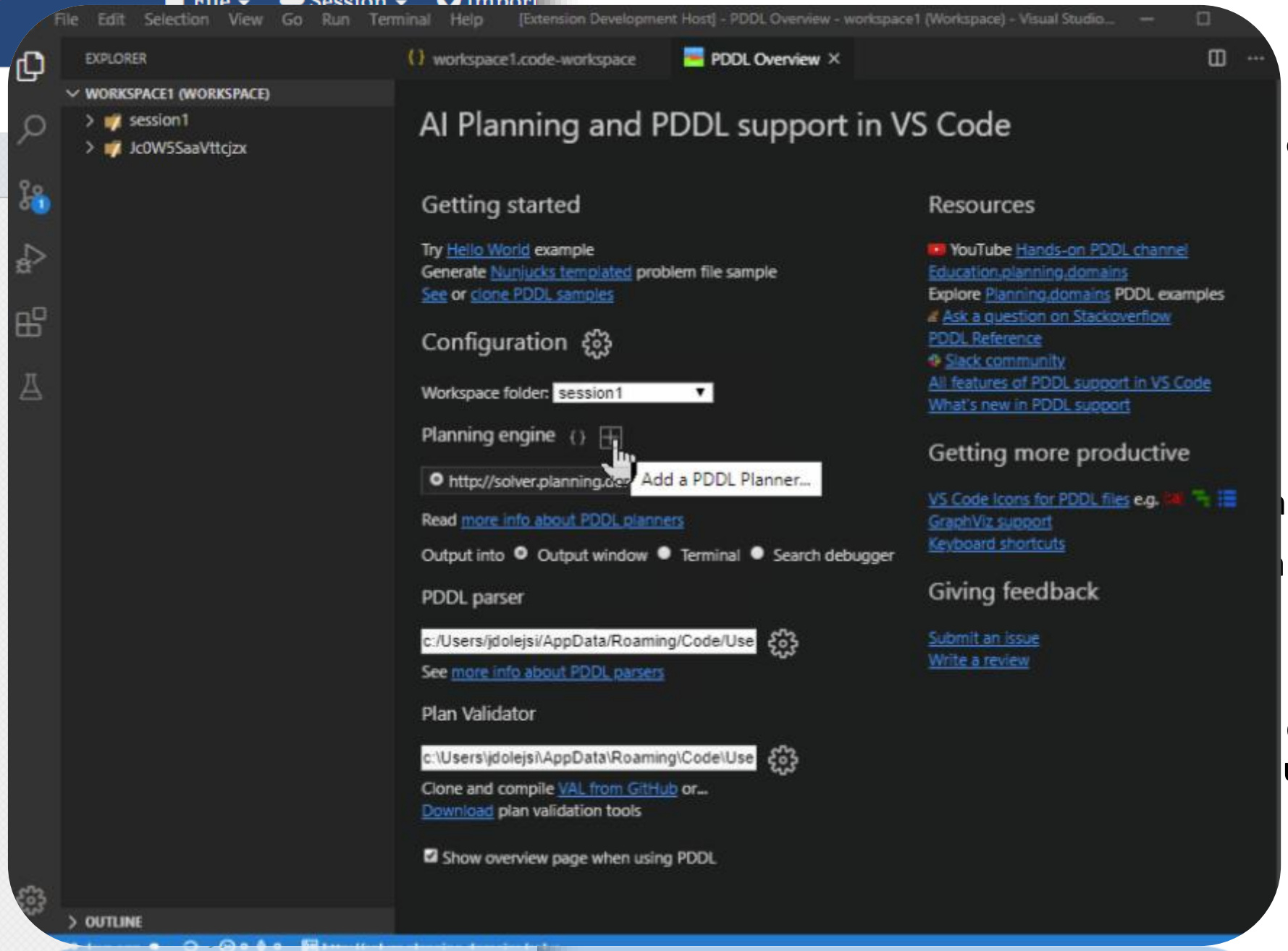
arks

ins

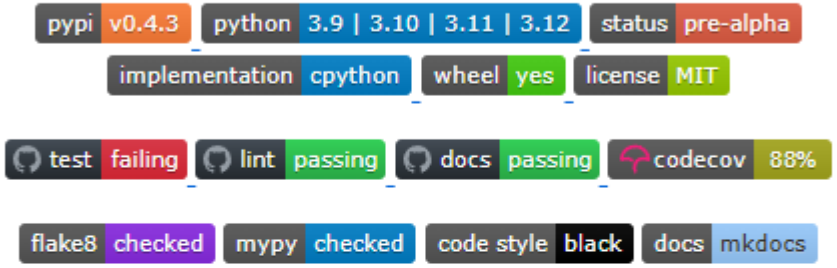
with

custom

unity



pddl



`pddl` aims to be an unquestionable and complete parser for PDDL 3.1.

Install

- from PyPI:

```
pip install pddl
```

Example parsing:

```
from pddl import parse_domain, parse_problem
domain = parse_domain('d.pddl')
problem = parse_problem('p.pddl')
```

pddl

- Python library for parsing and processing PDDL
- Rich flexibility in PDDL features
- Growing list of auxiliary libraries that leverage it (state maintenance, compilations, etc).

MACQ:
The Model
Acquisition Toolkit

What is Model Acquisition?

Input: State Trace Data

Output: PDDL Action Model

```
(define (domain BLOCKS)
  (:requirements :strips)
  (:predicates (on ?x ?y)
               (ontable ?x)
               (clear ?x)
               (handempty)
               (holding ?x)
               )

  (:action pick-up
           :parameters (?x)
           :precondition (and (clear ?x) (ontable ?x)
              (handempty))
           :effect
           (and (not (ontable ?x))
            (not (clear ?x))
            (not (handempty))
            (holding ?x)))

  (:action put-down
           :parameters (?x)
           :precondition (holding ?x)
           :effect
           (and (not (holding ?x))
            (clear ?x)
            (handempty)
            (ontable ?x)))
```

Research in Model Acquisition + Motivations

Showing all 43 papers.

Insights

Learning First-Order Symbolic Representations for Planning from the Structure of the State Space *by Bonet, Blai, and Hector Geffner*. ECAI (2020)

Learning Planning Operators by Observation and Practice *by Xuemei Wang*. AIPS (1994)

Online Learning of Action Models for PDDL Planning *by Leonardo Lamanna, Alessandro Saetti, Luciano Serafini, Alfonso Gerevini, Paolo Traverso* . IJCAI (2021)

etc...

Still need a centralized API for:

Trace generation and visualization.

Converting traces into a format that varying model acquisition techniques will recognize.

Testing different model acquisition techniques on the fly.

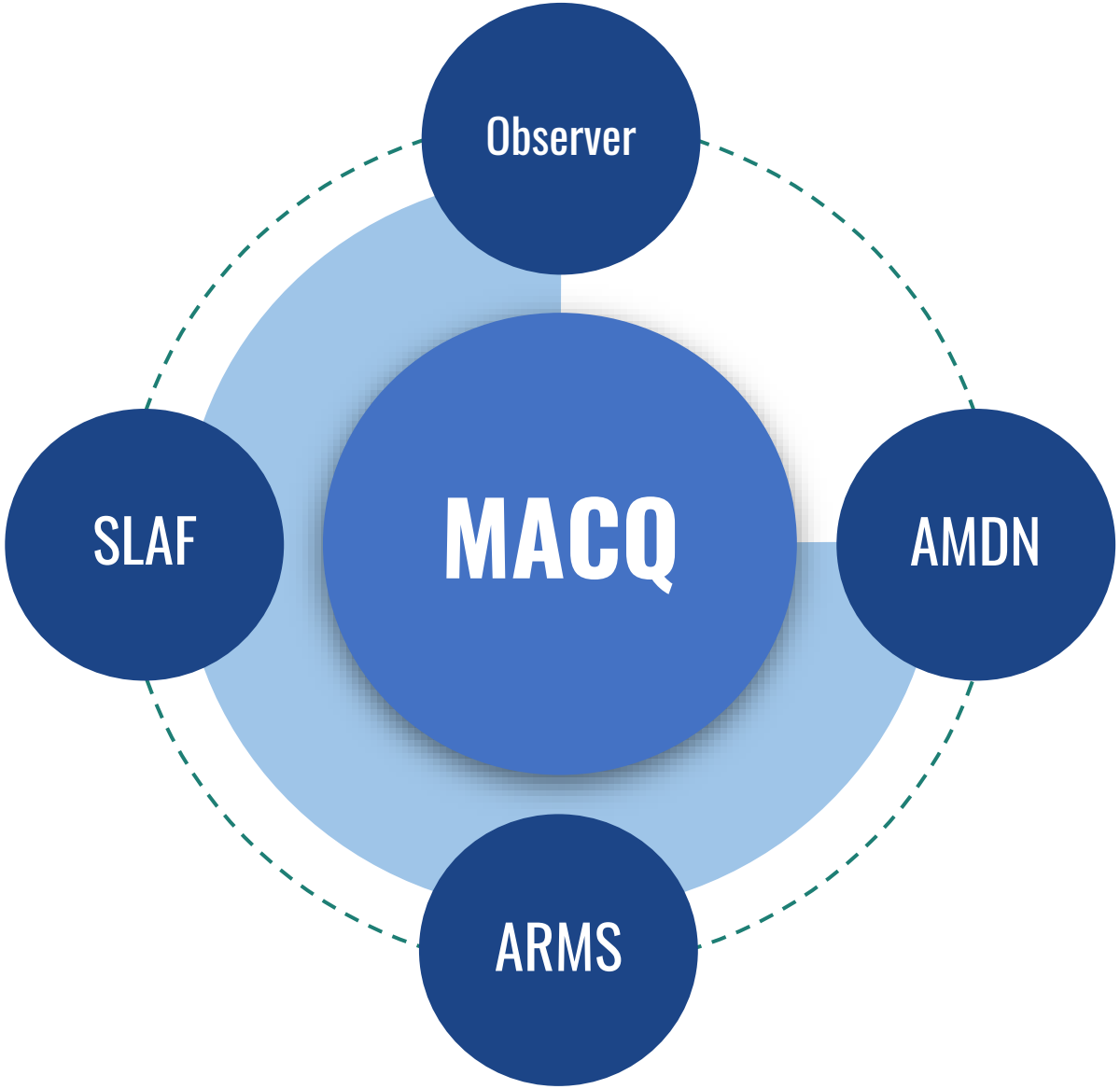
Introducing MACQ

State Trace Data	Trace Generation	Tokenization	Model Acquisition

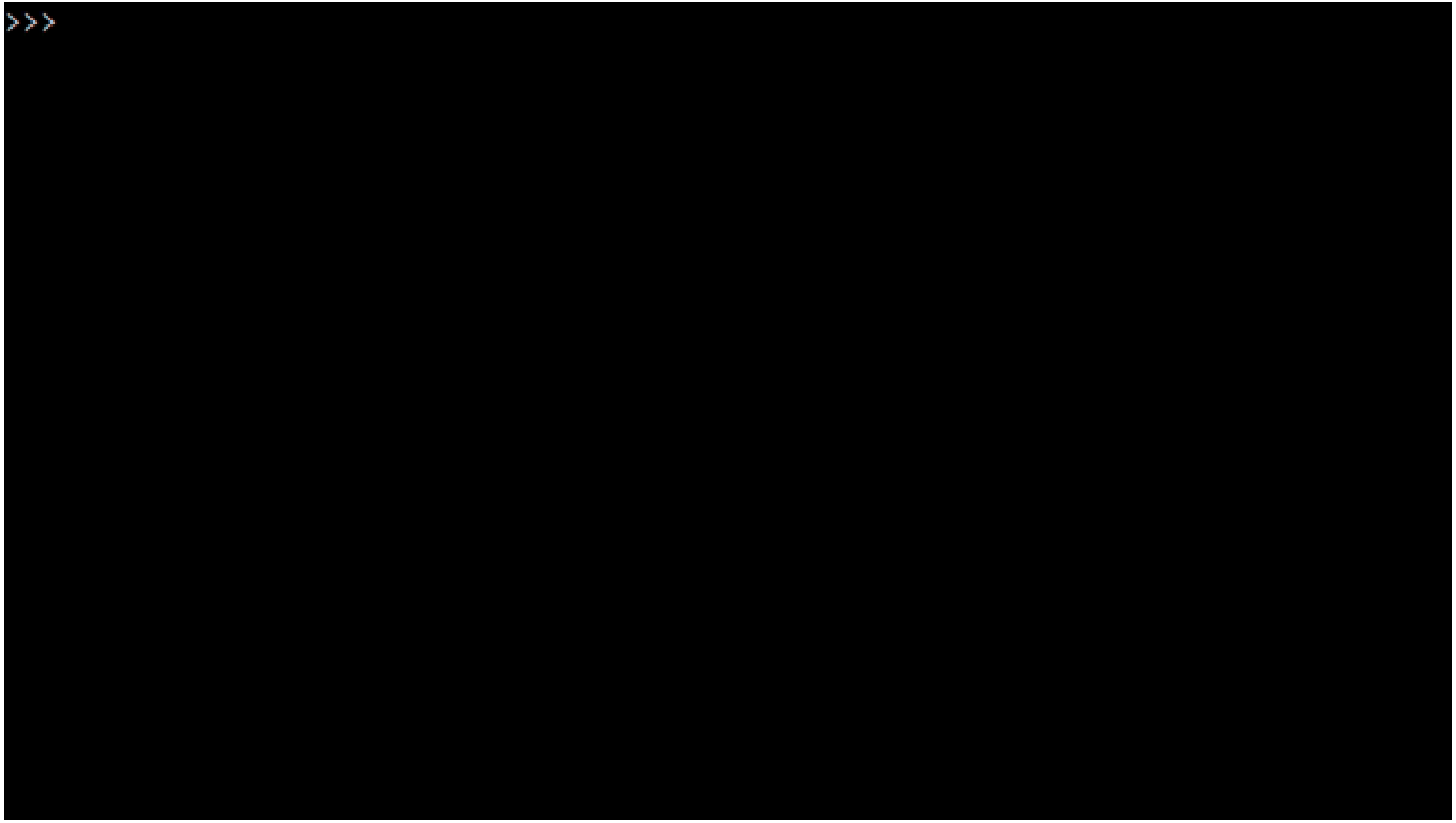
• From PDDL files
• From a problem ID
• Raw data, i.e. from a CSV file
	• Generate trace data
	• Dynamically change the initial state and/or goal
	• Examples:
	  ◦ Vanilla Sampling
	  ◦ Goal-Oriented Sampling
		• Convert traces into observation tokens
		• Examples:
		  ◦ Partial obs.
		  ◦ Noisiness
		  ◦ Parallel actions
		  ◦ Disordered actions
			• Extract actions from observations
			• Convert to PDDL
			• Examples:
			  ◦ Observer
			  ◦ SLAF
			  ◦ ARMS
			  ◦ AMDN
			  ◦ LOCM
			  ◦ …

Initial Choice of MACQ Techniques

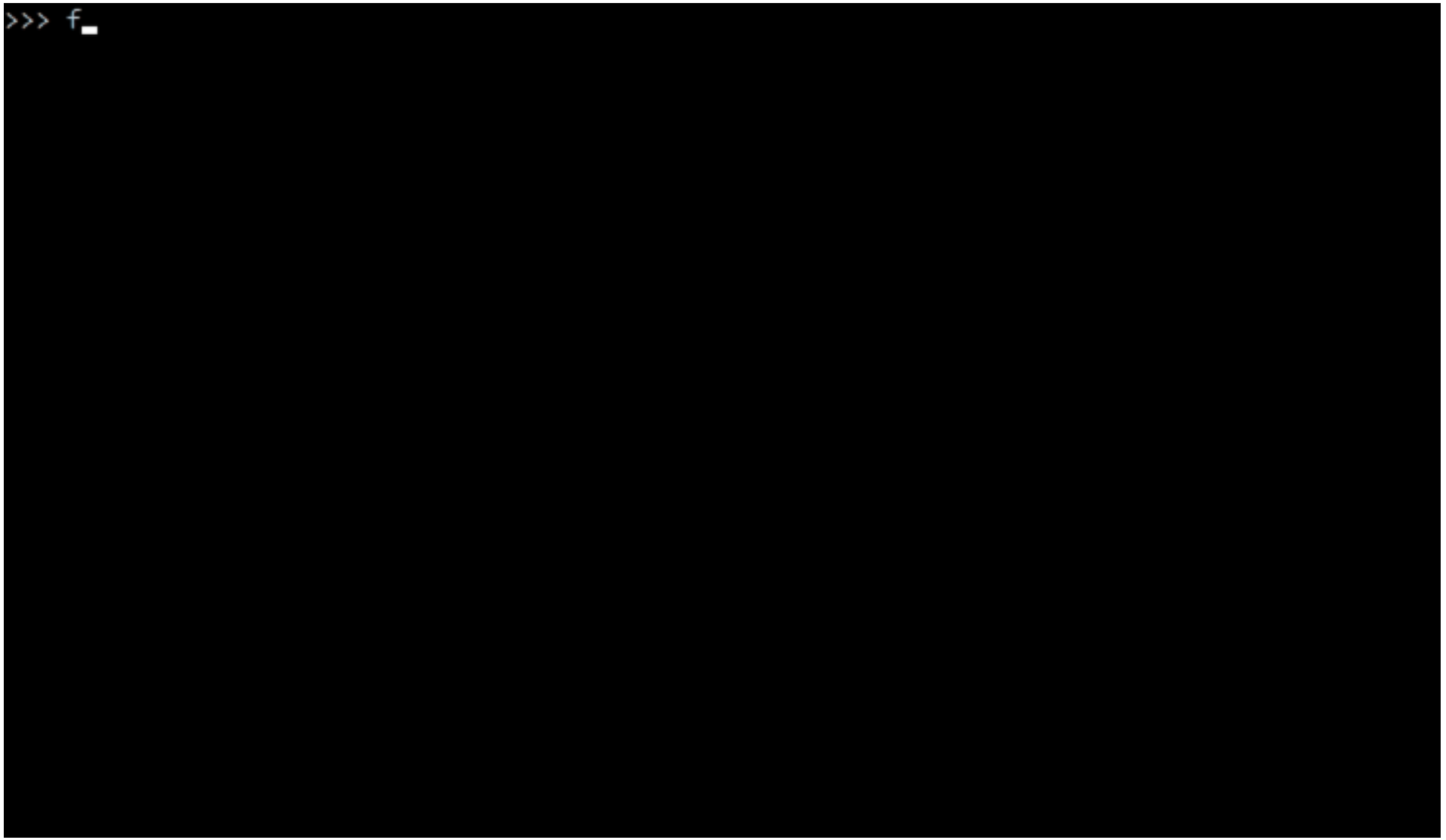
- Covers a large set of trace features, i.e.
  - Unmodified data
  - Partially observable data
  - Noisy data
  - Disordered and parallel actions
- Makes the library simple and easy to use upon release
- Open source, extensible API encourages the addition of more techniques



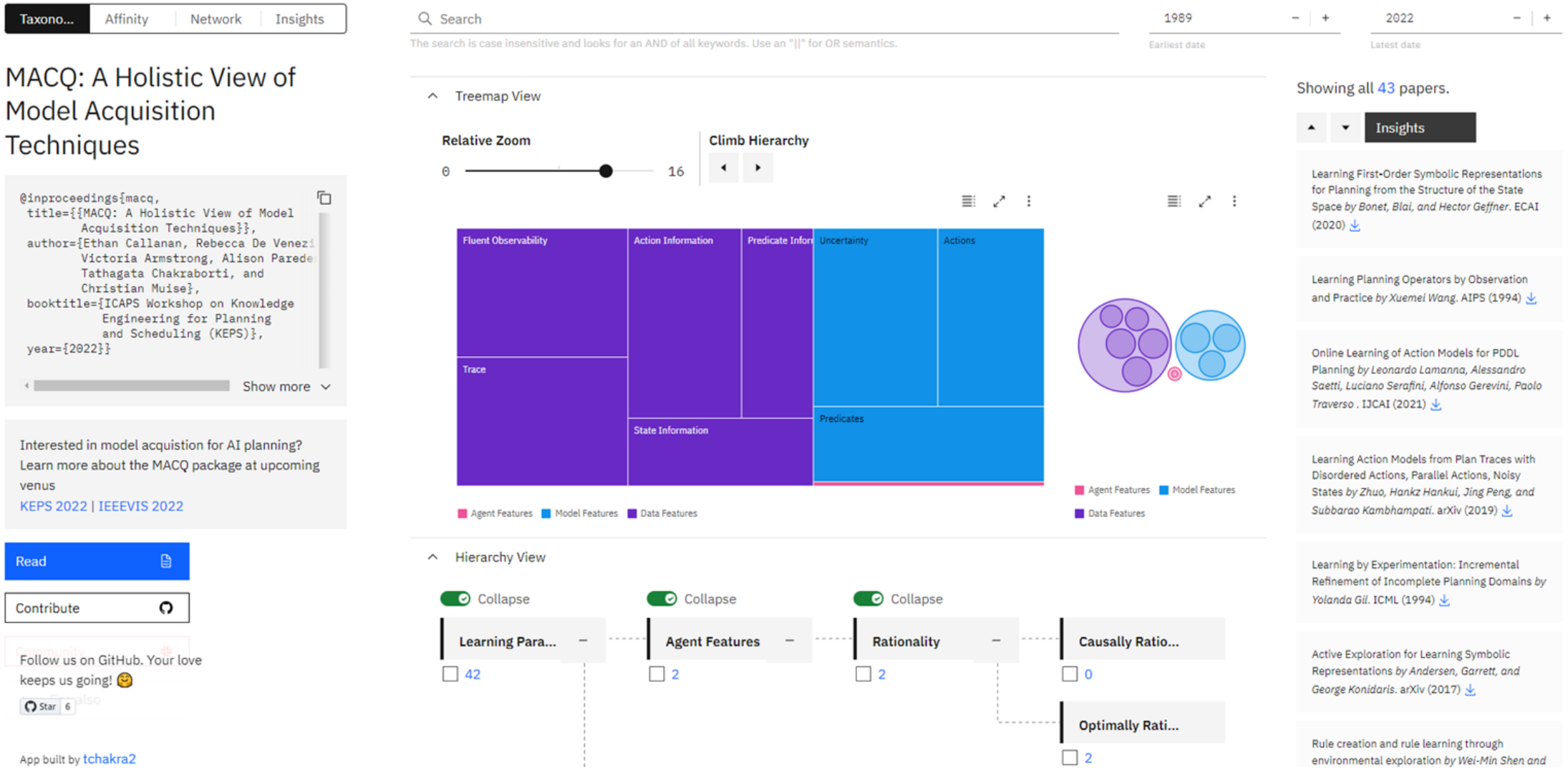
Trace Generation



Tokenization + Model Acquisition

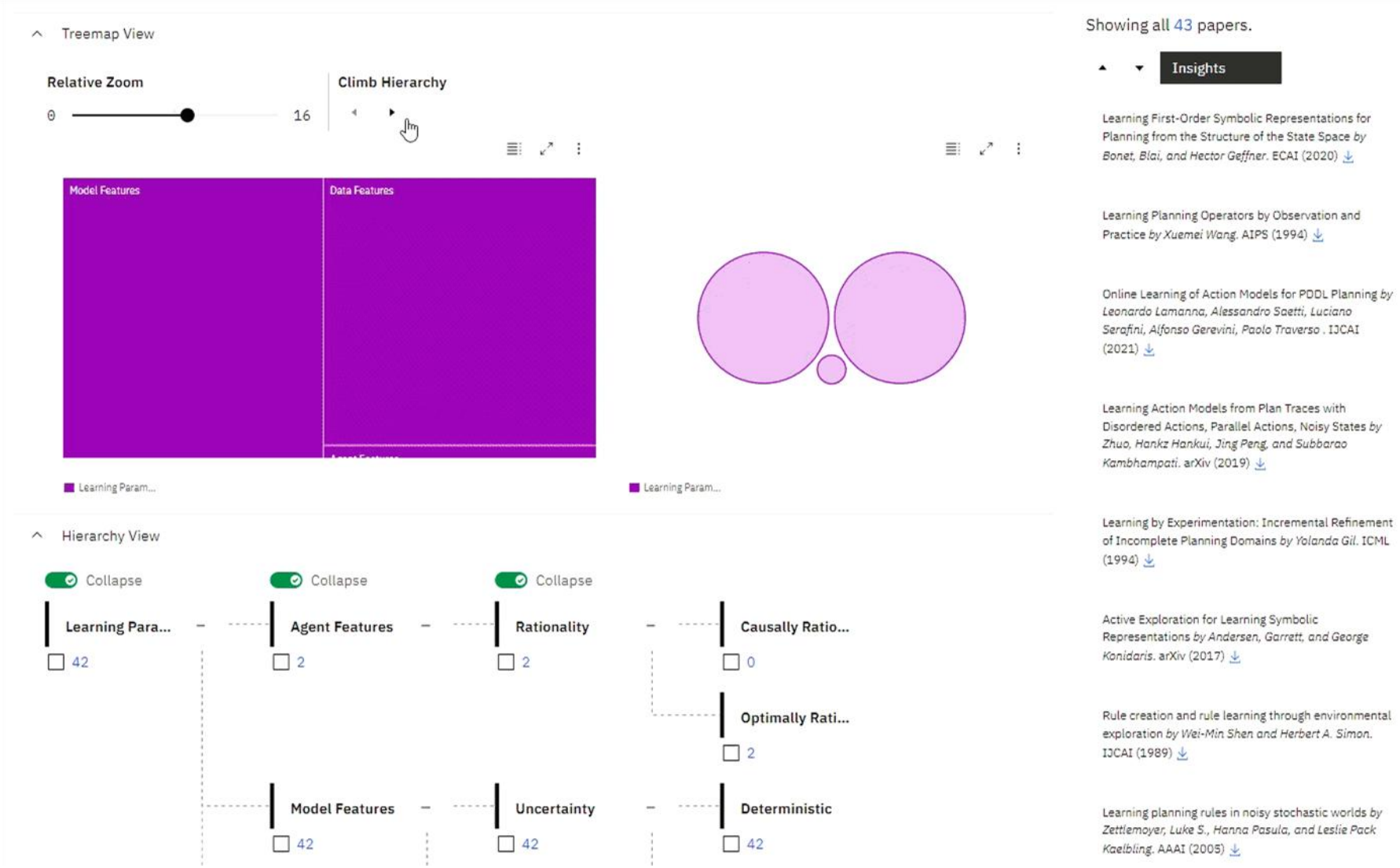


MACQ Visualizer: A Holistic View of Model Acquisition Techniques



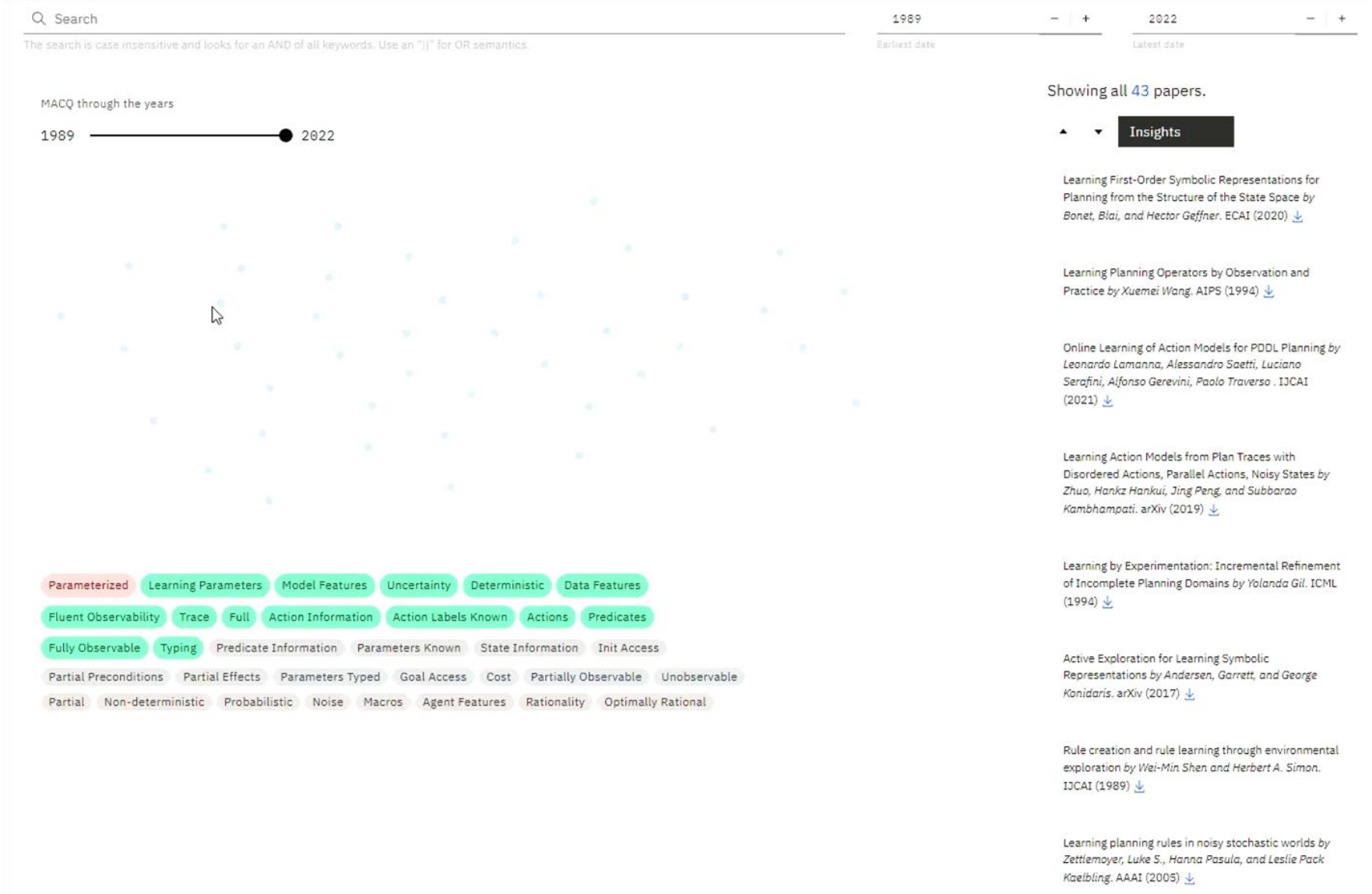
macq.planning.domains

MACQ Visualizer: Taxonomy



macq.planning.domains

MACQ Visualizer: Affinity

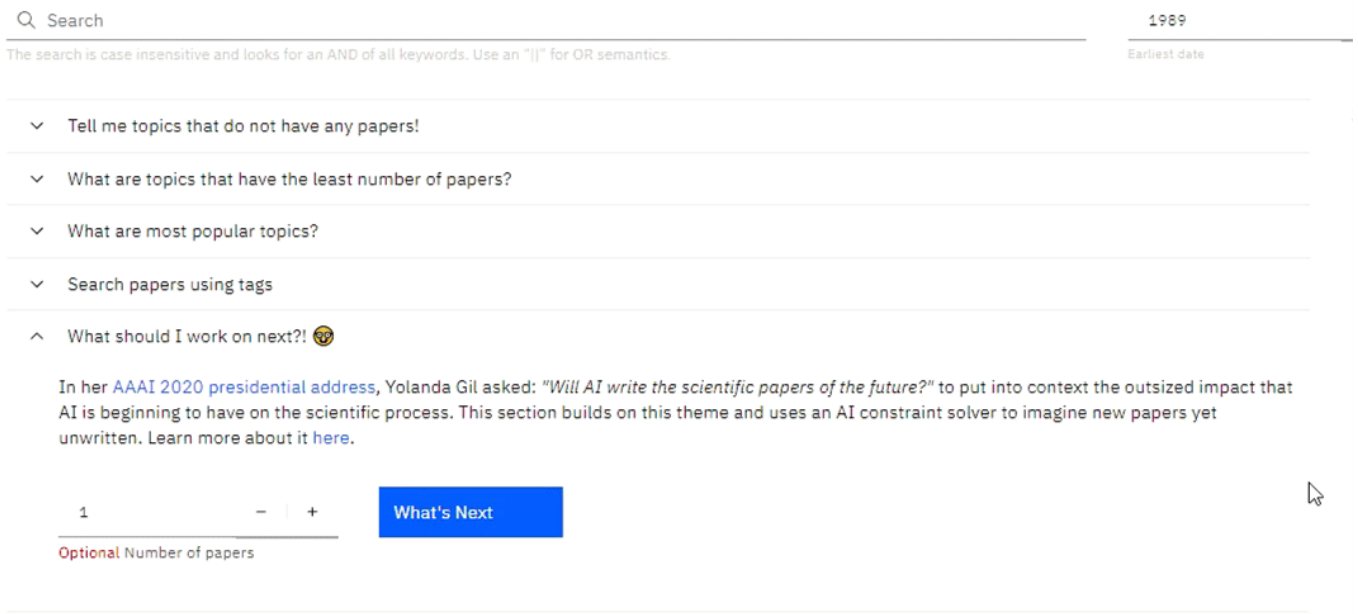


macq.planning.domains

MACQ Visualizer: Network

macq.planning.domains

MACQ Visualizer: Insights

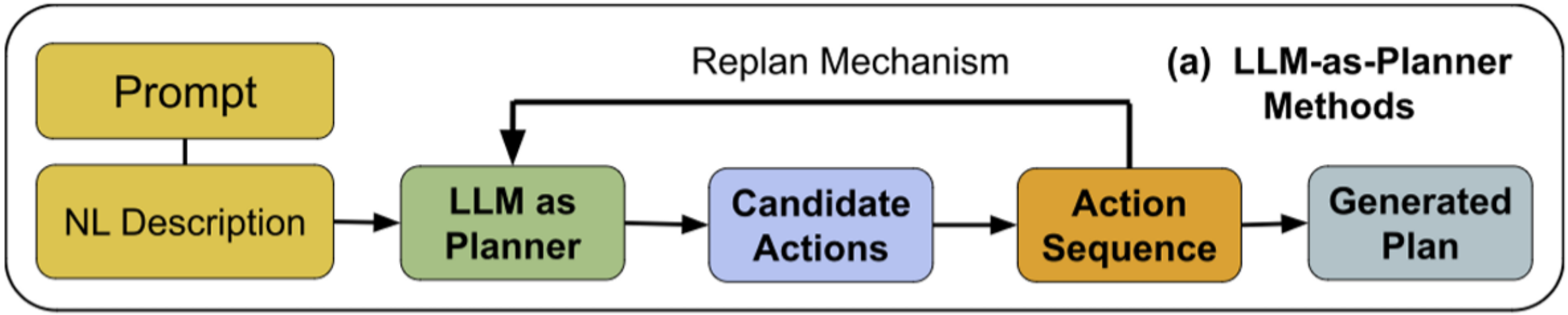


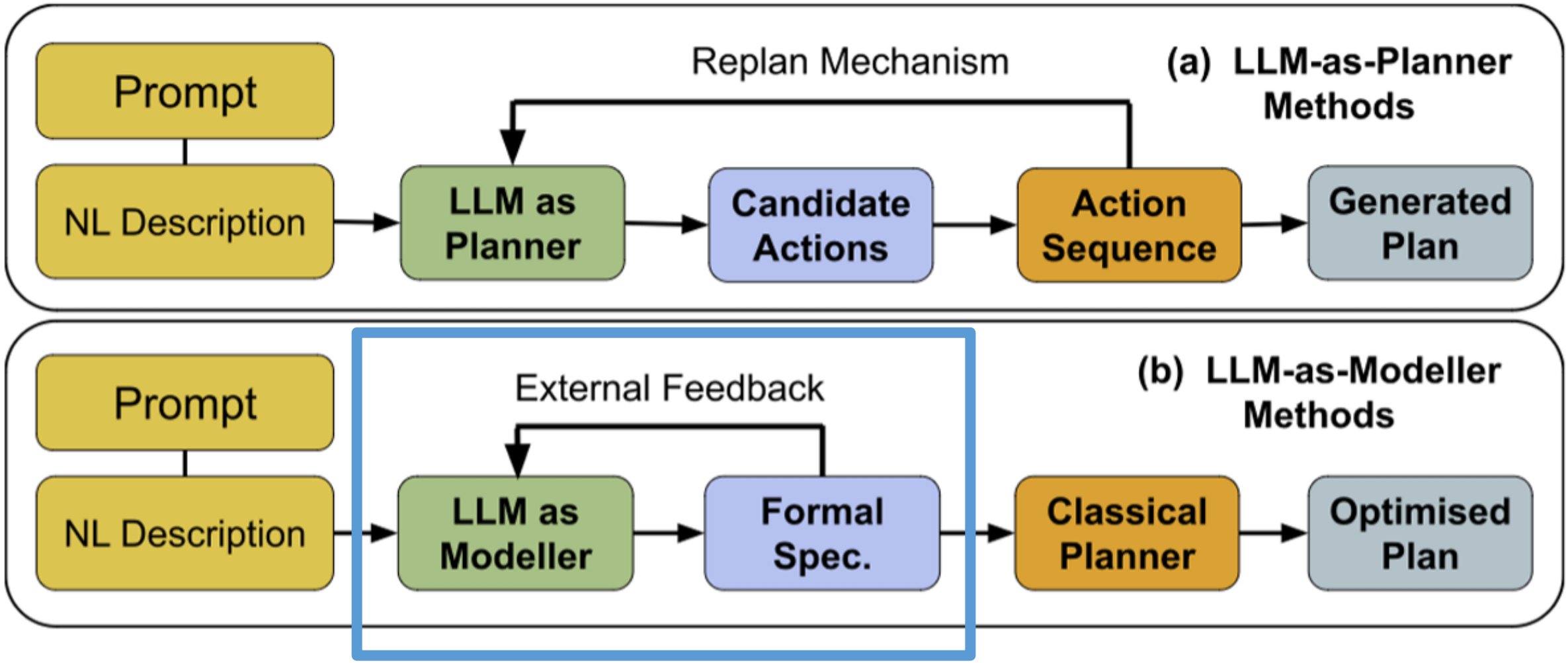
macq.planning.domains

Summary

- MACQ is an open-source Python library that offers:
  - Trace generation
  - Trace visualization
  - Trace tokenization
  - Model acquisition
- The MACQ Visualizer is a website that offers:
  - A holistic view of model acquisition techniques
  - AI-Generated suggestions for future papers
- Contributions are welcome!

L2P:
Language-to-Plan


Prompt
NL Description
Replan Mechanism
(a) LLM-as-Planner Methods
LLM as Planner
Candidate Actions
Action Sequence
Generated Plan


Prompt
NL Description
Replan Mechanism
LLM as Planner
Candidate Actions
Action Sequence
Generated Plan
(a) LLM-as-Planner Methods
Prompt
NL Description
External Feedback
LLM as Modeller
Formal Spec.
Classical Planner
Optimised Plan
(b) LLM-as-Modeller Methods

PROBLEM

LLMs can be a bit … unpredictable

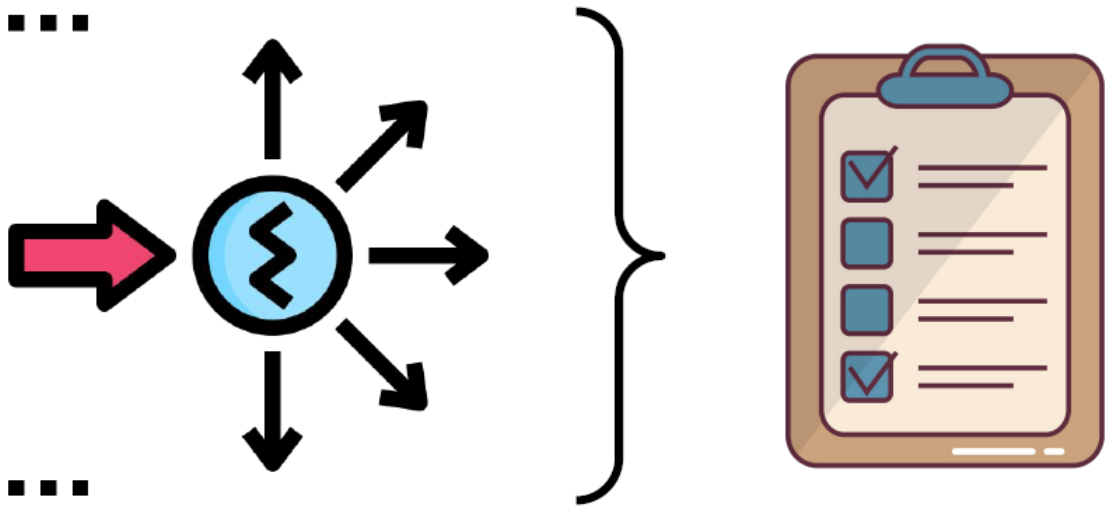
There is a fragmented landscape of NL-PDDL methods with each work possessing **different levels of assumptions:**

1. **Granularity** of natural language descriptions? — Explicit vs. Minimal Descriptions
2. What kind of **assumptions** are given? — Given info (levels of grounding)
3. What kind of **prompting styles** are used? — In-context, CoT, other styles…
4. What **generative techniques** are used? — Direct vs. Incremental Generation

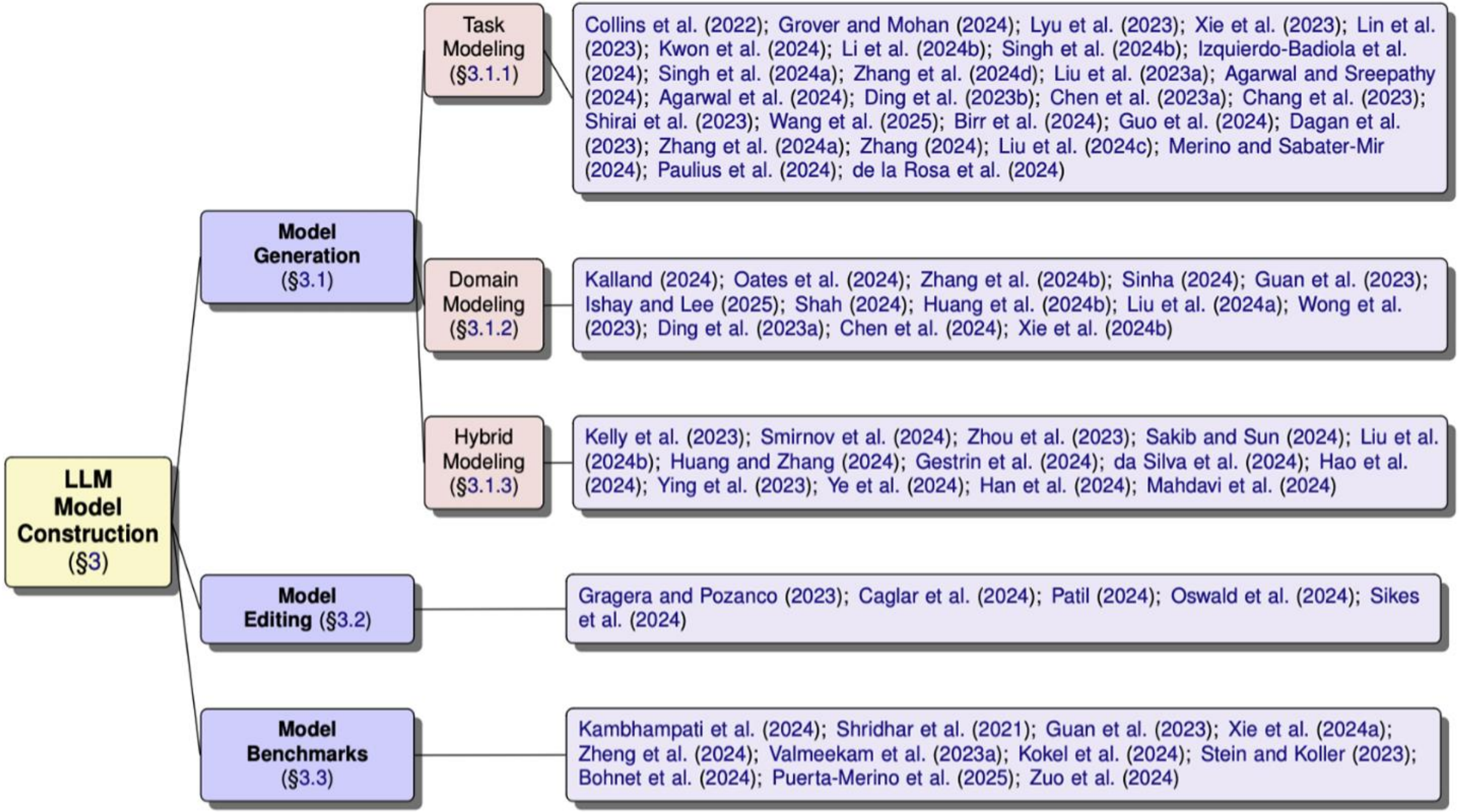
MOTIVATION

Narrow down these techniques to provide actual insights to the limitations and advantages each of these works possess.

Huge list of existing pipelines / techniques / assumptions



The next steps towards applying LLMs in **real-world applications** is to establish a **standard, fair-comparison** of these frameworks – **What works? What doesn't work?**


LLM Model Construction (§3)
Model Generation (§3.1)
Task Modeling (§3.1.1)
Collins et al. (2022); Grover and Mohan (2024); Lyu et al. (2023); Xie et al. (2023); Lin et al. (2023); Kwon et al. (2024); Li et al. (2024b); Singh et al. (2024b); Izquierdo-Badiola et al. (2024); Singh et al. (2024a); Zhang et al. (2024d); Liu et al. (2023a); Agarwal and Sreepathy (2024); Agarwal et al. (2024); Ding et al. (2023b); Chen et al. (2023a); Chang et al. (2023); Shirai et al. (2023); Wang et al. (2025); Birr et al. (2024); Guo et al. (2024); Dagan et al. (2023); Zhang et al. (2024a); Zhang (2024); Liu et al. (2024c); Merino and Sabater-Mir (2024); Paulius et al. (2024); de la Rosa et al. (2024)
Domain Modeling (§3.1.2)
Kalland (2024); Oates et al. (2024); Zhang et al. (2024b); Sinha (2024); Guan et al. (2023); Ishay and Lee (2025); Shah (2024); Huang et al. (2024b); Liu et al. (2024a); Wong et al. (2023); Ding et al. (2023a); Chen et al. (2024); Xie et al. (2024b)
Hybrid Modeling (§3.1.3)
Kelly et al. (2023); Smirnov et al. (2024); Zhou et al. (2023); Sakib and Sun (2024); Liu et al. (2024b); Huang and Zhang (2024); Gestrin et al. (2024); da Silva et al. (2024); Hao et al. (2024); Ying et al. (2023); Ye et al. (2024); Han et al. (2024); Mahdavi et al. (2024)
Model Editing (§3.2)
Gragera and Pozanco (2023); Caglar et al. (2024); Patil (2024); Oswald et al. (2024); Sikes et al. (2024)
Model Benchmarks (§3.3)
Kambhampati et al. (2024); Shridhar et al. (2021); Guan et al. (2023); Xie et al. (2024a); Zheng et al. (2024); Valmeekam et al. (2023a); Kokel et al. (2024); Stein and Koller (2023); Bohnet et al. (2024); Puerta-Merino et al. (2025); Zuo et al. (2024)

Language-to-Plan (L2P)

With the proliferations of emerging NL-PDDL extraction techniques, we introduce **Language-to-Plan (L2P)**, an open-source Python library that **unifies NL-PDDL frameworks into to a single umbrella** which can then be tested on rigorous benchmarks.

L2P possesses capabilities of constructing core PDDL components that enables researchers to create their own NL-PDDL pipelines

Comprehensive Tool Suite: easily plug in various LLMs for streamlined extraction experiments with our extensive collection of PDDL extraction and refining tools.

Modular Design: facilitates flexible PDDL generation, allowing users to explore prompting and create customized pipelines.

Autonomous Capability: building block support for fully autonomous pipeline, reducing manual efforts of producing LLM-AP pipelines from scratch.

Language-to-Plan (L2P) – Examples

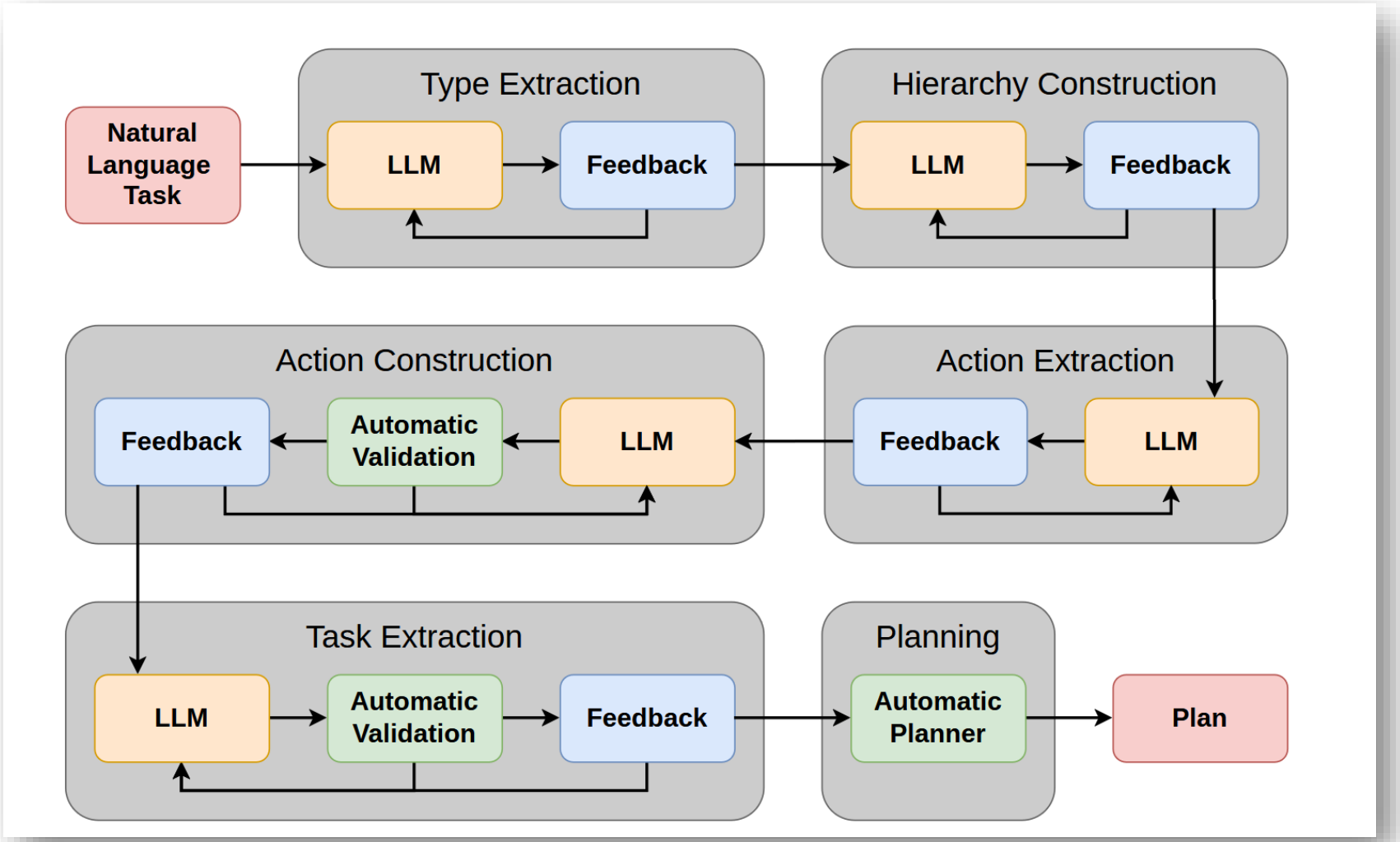
L2P can **recreate and encompass previous frameworks** for converting NL-PDDL, serving as a comprehensive foundation that integrates past approaches.

Some examples:

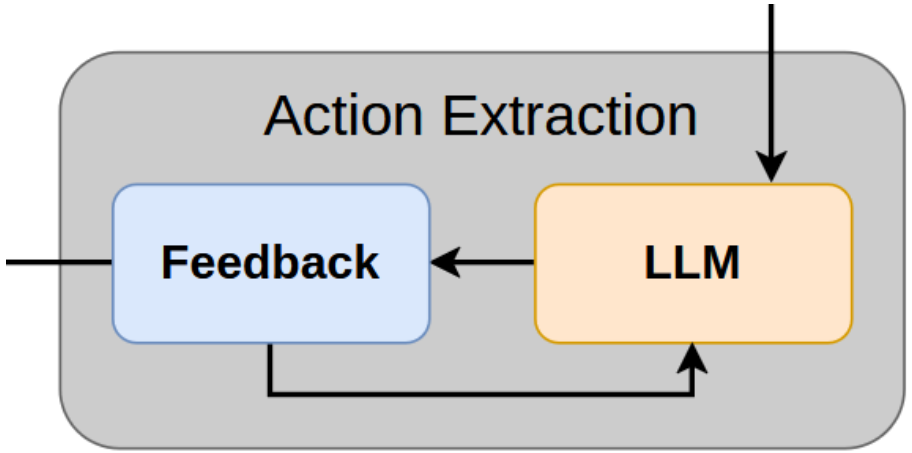
- ❑ LLM+P
- ❑ LLM-DM (example to the right)
- ❑ NL2Plan
- ❑ P+S
- ❑ PROC2PDDL

Shortened example of “Action-by-action” algorithm from (Guan et al. 2023)

```
import os
from l2p import *

def run_aba_alg(model: LLM, action_model,
    domain_desc, hierarchy, prompt, max_iter: int=2
    ) -> tuple[list[Predicate], list[Action]]:
actions = list(action_model.keys())
pred_list = []

for _ in range(max_iter):
  action_list = []
  # iterate each action spec. + new predicates
  for _, action in enumerate(actions):
    if len(pred_list) == 0:
      prompt = prompt.replace('{predicates}',
      '\nNo predicate has been defined yet')
    else: res = ""
      for i, p in enumerate(pred_list):
        res += f'\n{i + 1}. {p["raw"]}'
        prompt = prompt.replace('{predicates}', res)
    # extract pddl action and predicates (L2P)
    pddl_action, new_preds, response = (
      builder.extract_pddl_action(
        model=model,
        domain_desc=domain_desc,
        prompt_template=prompt,
        action_name=action,
        action_desc=action_model[action]['desc'],
        action_list=action_list,
        predicates=pred_list,
        types=hierarchy["hierarchy"]
      )
    )
    new_preds = parse_new_predicates(response)
    pred_list.extend(new_preds)
    action_list.append(pddl_action)
  pred_list = prune_predicates(pred_list,action_list)
return pred_list, action_list
```

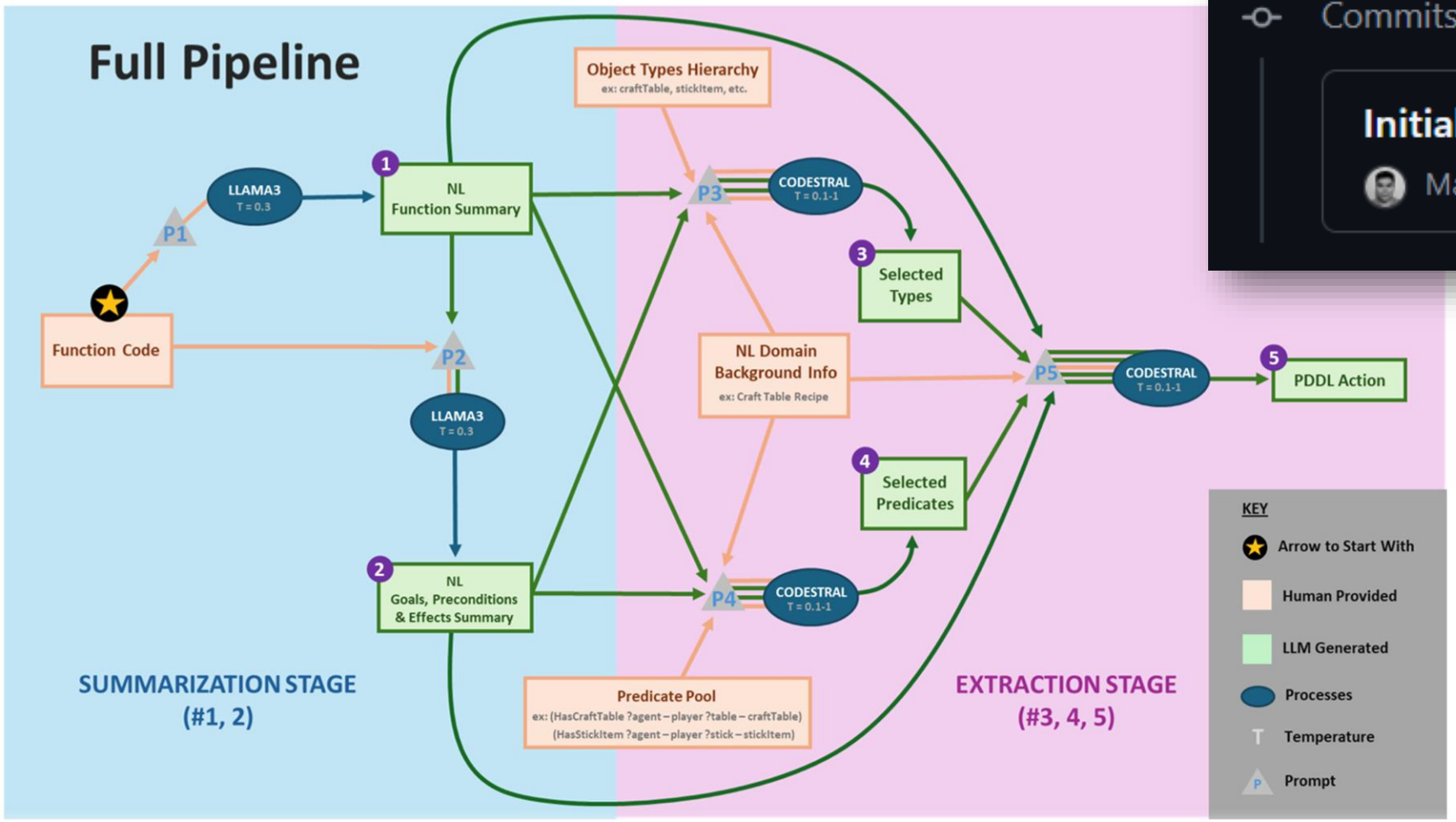


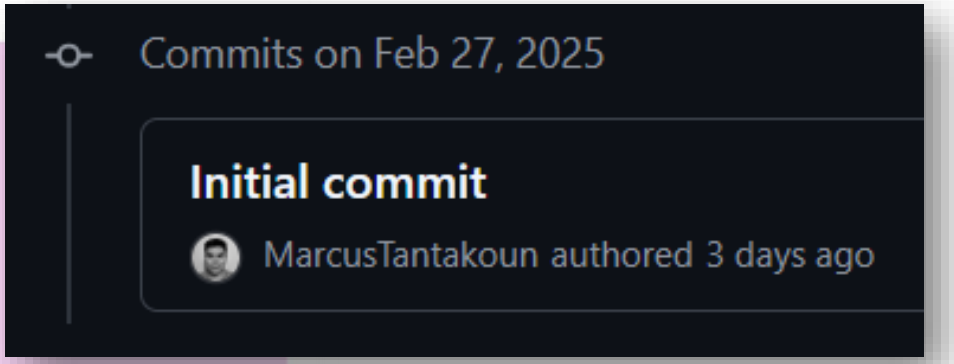
"**NL2Plan: Robust LLM-Driven Planning from Minimal Text Descriptions**" *Gestrin et al.* (2024)




```
6: Should any action examples be modified?
    All examples involve the relevant objects and clearly specify what happens. Thereby: No.

As such: No feedback.

----------------------------------------

Here is the original output:

## Domain
{domain_desc}

## Available types
{types}

## Actions you gave
{nl_actions}

## Original LLM response
{llm_response}
```

```python
def action_extraction(
    model, domain_desc, action_extraction_prompt, type_hierarchy
) -> dict[str, str]:
    # STEP THREE: action extraction
    nl_actions, response = domain_builder.extract_nl_actions(
        model=model,
        domain_desc=domain_desc,
        prompt_template=action_extraction_prompt.generate_prompt(),
        types=type_hierarchy,
    )

    feedback_template = open_file(
        "paper_reconstructions/nl2plan/prompts/action_extraction/feedback.txt"
    )
    nl_actions, _ = feedback_builder.nl_action_feedback(
        model=model,
        domain_desc=domain_desc,
        llm_response=response,
        feedback_template=feedback_template,
        feedback_type="llm",
        nl_actions=nl_actions,
        type_hierarchy=type_hierarchy,
    )

    print("Natural Language Actions")
    for i in nl_actions:
        print(i)
    return nl_actions
```





github.com/MarcusTantakoun/JS-PDDL

"**Creating PDDL Models from Javascript using LLMs: Preliminary Results**" (Sikes et al. 2025)

Try it out!

pip install l2p

https://github.com/AI-Planning/l2p