

MinePlanner: A Benchmark for Long-Horizon Planning in Large Minecraft Worlds

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Abstract

We propose a new benchmark for planning tasks based on the Minecraft game. Our benchmark contains 45 tasks overall, but also provides support for creating both propositional and numeric instances of new Minecraft tasks automatically. We benchmark numeric and propositional planning systems on these tasks, with results demonstrating that state-of-the-art planners are currently incapable of dealing with many of the challenges advanced by our new benchmark, such as scaling to instances with thousands of objects. Based on these results, we identify areas of improvement for future planners. Our framework is made available at <https://github.com/IretonLiu/mine-pddl/>.

Introduction

A major challenge in AI is the construction of autonomous agents capable of solving extremely long-horizon tasks. While approaches such as reinforcement learning (RL) struggle with such tasks, especially with sparse feedback, task-level planners are well-suited to such problems. Additionally, these planners are typically domain-independent and so can be applied to a wide variety of problems, which is necessary if we desire generally intelligent agents.

However, these approaches require an abstract representation of a problem (typically using a structured language such as PDDL (McDermott et al. 1998)) as input. Furthermore, these representations are carefully crafted by a human designer to contain only the necessary information required to solve the task (Fishman et al. 2020). If we hope to scale these approaches to real-world tasks and develop truly autonomous agents, then planners must be capable of operating in domains that contain a large number of objects that may or may not be relevant to the task at hand.

While the issue of scaling to large domains is currently an area of active research (Illanes and McIlraith 2019), current planning domains continue to focus on simplified world models by simply increasing the number of objects present in standard benchmarks (Silver et al. 2021). This, however, fails to accurately reflect the difficulty a planner would face in a noisy real-world task. Additionally, recent work has demonstrated how PDDL representations can be directly learned from data (Asai and Fukunaga 2018; James, Rosman, and Konidaris 2020; Ahmetoglu et al. 2022). While



Figure 1: A classical planning problem in our benchmark, requiring the agent to collect the necessary blocks and build a log cabin (outlined in green). This task contains over 4000 objects that the agent must reason about, including many that make up the surrounding trees and ground that are irrelevant to the goal.

these representations are often sound (Konidaris, Kaelbling, and Lozano-Perez 2018), they typically contain many irrelevant symbols and action operators (James, Rosman, and Konidaris 2022); planners that are robust to this issue would further bridge the gap between learning and planning.

Concurrently, the game of Minecraft has recently emerged as a promising testbed for RL research (Johnson et al. 2016), with its open-ended nature serving as a valuable proxy for the real world. As a domain, Minecraft has several desirable characteristics for planning research: (a) it supports a wide variety of tasks in the form of structures that can be assembled, all of which require long-term planning (see Figure 1 for an example); (b) the game is naturally populated by objects in the form of blocks and items, removing the need for a human designer to inflate the number of objects in the domain artificially; and (c) there is an inherent hierarchy in building large Minecraft structures (Beukman et al. 2023), which may be of interest to hierarchical planners (Höller et al. 2020).

In this paper, we present MinePlanner, a long-horizon planning benchmark in large Minecraft worlds. Our framework is capable of automatically generating tasks and verifying solutions in Minecraft, and supports both propositional and numeric planners. We additionally provide a collection of 45 tasks which we used to benchmark representa-

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tive propositional and numeric planners. These results show that there is significant work still left to be done for planning in large domains with many objects.

Motivation

Owing to its open-world nature, Minecraft has proven to be a popular testbed for machine learning research (Johnson et al. 2016). One such platform is *MineRL* (Guss et al. 2019), which provides a set of Minecraft-related tasks for the agent to solve. More recently, Fan et al. (2022) incorporate background knowledge of the game in the form of on-line documentation, forums and videos of human gameplay to assist agents in learning to play the game. In both cases, the focus is typically RL, where an agent is required to act in a high-dimensional environment with partially observable pixel input.

These benchmarks require agents to grapple with multiple problems simultaneously—high-dimensional function approximation, continuous control, partial observability and long-term planning. While a generally capable agent will ultimately be required to solve all of these problems, it also makes progress along any of these dimensions difficult to measure. Our proposed benchmark abstracts away these low-level intricacies, allowing researchers to focus on what is perhaps the most interesting aspect of Minecraft—the ability to create impressive structures, such as entire cities (Salge et al. 2020), through long-term planning.

One immediate challenge presented by Minecraft is the number of objects in the world. While previous work has identified the need to apply planners to domains with hundreds of objects, these domains are either scaled-up versions of classic problems such as *Blocksworld* (Silver et al. 2021) or are created by combining multiple existing planning problems to introduce irrelevant objects (Fishman et al. 2020). While these testbeds may be useful for developing better planning algorithms, the domains are disjoint from those considered by the RL community, squandering the opportunity for collaboration between the fields. Furthermore, these approaches may not capture the true complexity of the real world, which often contains objects and actions that may or may not be relevant to a given task.

Finally, while our benchmark hopes to spur research in planning, it can be combined with tools such as PDDL Gym (Silver and Chitnis 2020) to act as a reinforcement learning environment. This would benefit RL researchers who wish to focus on the challenging long-term planning problem posed by Minecraft, while avoiding the complexity of continuous control in pixel space.

A Framework for Generating Minecraft Planning Tasks

We now present MinePlanner: a framework for generating Minecraft planning tasks that makes use of the APIs provided by MineDojo (Fan et al. 2022). At the highest level, we define a specification schema for tasks that are used to generate Minecraft worlds. We next extract objects and states (such as the agent’s inventory) from the world and automatically generate a PDDL representation that can be used

by planners. To provide support for multiple approaches, the framework can generate both numeric and propositional planning. The difference between the two is primarily how locations are represented, and we discuss this further in subsequent sections.

Our framework also supports the verification and visualisation of a plan—given the output of a planner, MinePlanner executes the proposed action in the game and verifies that the necessary predicates are achieved to solve the task. The frames collected during this process are saved and exported to video, which can then be used to promote research in a visually appealing manner. Finally, we provide a utility for extracting a list of objects, along with their coordinates, from saved Minecraft worlds¹ allowing users to easily specify new tasks without having to manually list the position of each object in the world.

Minecraft World Specification

We define a task as a set of blocks and items that are initially placed in the Minecraft world and the agent’s inventory. For simplicity, we restrict the items to only those that can be placed in the world (e.g. wood blocks, but not pickaxes). We specify the goal of the task as a set of blocks that are to be placed in the world at some location, a set of items the agent must have in its inventory, the agent’s location, or any combination of the three. An example of a task specification is shown in Listing 1, where an agent must place a log at location (0, 4, 2) and additionally have at least one log in its inventory to solve the task.

To produce a tractable representation of a Minecraft world, we make the following simplifications that vary slightly from the original game:

- Each task is created using a flat world with a single layer of grass blocks serving as the ground.
- There are no non-player characters, and items placed in the world do not despawn.²
- The agent does not require the necessary tools to break certain blocks. For example, the agent can break a tree block without an axe.
- Broken blocks are immediately added to the agent’s inventory without being dropped on the ground as items.
- The agent is constrained by allowing it to move only one unit (block) in any cardinal direction at a given time.

State Representations

The types of each object, such as `agent`, `grass-block` or `flower`, is specified directly by Minecraft itself. To represent the state of the world, we must keep track of the location of all items and objects, as well as the agent’s inventory. Using PDDL 2.1 (Fox and Long 2003), this is relatively straightforward: the domain is defined by a predicate governing whether an object is present in the world (or in the agent’s inventory), or whether it has been destroyed, and several numeric fluents that keep track of each object’s x ,

¹Using the PyBlock library (github.com/alex4200/PyBlock).

²Both of these would violate the frame assumption (Pasula, Zettlemoyer, and Kaelbling 2004).

Listing 1: Example task specification in YAML.

```

1 # the task name
2 name: "Example Problem"
3
4 # initialise all block positions
5 blocks:
6   - position:
7       x: '0'
8       y: '4'
9       z: '1'
10    type: obsidian
11 items:
12   - position:
13       x: '1'
14       y: '5'
15       z: '5'
16     quantity: 1
17     type: diamond
18 inventory:
19   - type: log
20     quantity: '64'
21   - type: obsidian
22     quantity: '64'
23 goal:
24   agent:
25     - position:
26         x: '6'
27         y: '4'
28         z: '-5'
29   blocks:
30     - position:
31         x: '0'
32         y: '4'
33         z: '-2'
34       type: log
35   inventory:
36     - type: log
37       quantity: '1'

```

y and z positions. Fluents are also used to track how many items are in the agent’s inventory, since the agent can collect multiple objects of the same type. There is one fluent for each type present in the world; for example, to track the number of grass blocks and flowers in the inventory, we would have the following: (agent-num-grass_block ?ag - agent) and (agent-num-flower ?ag - agent).

For planners that do not support numeric fluents, we represent positions and count using predicates only. This is achieved by defining “integer” objects (e.g., position36, count0) along with predicates that enforce relationships between these objects, such as sequentiality ((are-seq ?x1 - int ?x2 - int)) and whether an object is at a particular location (e.g., (at-x ?l - locatable ?x - position)). The inventory is represented by determining whether the count of a particular item matches some number.³ The predicates equivalent to their numeric counterparts above are (agent-has-n-grass_block ?ag -

³Minecraft enforces a maximum inventory count of 64 per object, which can be enumerated.

agent ?n - count) and (agent-has-n-flower ?ag - agent ?n - count).

Operator Representations

We model two types of operators in our Minecraft worlds: *movement* and *interaction* actions. Movement involves the agent navigating one unit in a cardinal direction, and includes the ability to jump in a particular direction. As in the game, an agent’s movement is restricted by objects around it (it cannot move through blocks), and the preconditions for movement operators reflect this.

Another challenge is that in Minecraft, there is no explicit action for picking up an item—an agent simply walks over an item to collect it. To avoid inconsistency between the PDDL representations and the game, we account for this by introducing two separate actions for every movement: a movement action that *cannot* be executed if the destination is occupied by an item and an action that combines a movement with a pickup. Additionally, the agent can only move to a destination above an existing block. The complete list of movement operators is as follows:

Listing 2: Example of a movement action using fluents

```

1 (:action move-north
2   :parameters (?ag - agent)
3   :precondition (and (agent-alive ?ag)
4     (exists (?b - block) (and
5       (block-present ?b) (= (x ?b) (x ?ag))
6       (= (y ?b) (+ (y ?ag) -1)) (= (z ?b)
7         (+ (z ?ag) -1)))) (and
8       (not (exists (?b - block) (and
9         (block-present ?b) (= (x ?b) (x ?ag))
10        (or (= (y ?b) (+ (y ?ag) 1)) (= (y ?b)
11          (y ?ag)))
12        (= (z ?b) (+ (z ?ag) -1))))))
13   (not (exists (?i - item) (and (
14     item-present ?i) (
15       = (x ?i) (x ?ag)) (= (y ?i) (y ?ag))
16       (= (z ?i)
17         (+ (z ?ag) -1))))))
15   :effect (and (decrease (z ?ag) 1))
16 )

```

- `move_[direction]`: Moves the agent by one block in the specified direction. The agent cannot move into a block that is occupied by an item.
- `move_and_pickup_[item]_[direction]`: Moves the agent by one block in the specified direction and collects an item at the resulting position.
- `jumpup_[direction]`: Moves the agent by one block in the specified direction and one block along the positive vertical axis. The agent cannot move into a position that is occupied by an item.
- `jumpdown_[direction]`: Moves the agent by one block in the specified direction and one block along the negative vertical axis. The agent cannot move into a position that is occupied by an item.
- `jumpup_and_pickup_[item]_[direction]`: Moves the agent by one block in the specified direction

and one block along the positive vertical axis and collects an item at the resulting position.

- `jumpdown-and-pickup-[item]-[direction]`: Moves the agent by one block in the specified direction and one block along the negative vertical axis and collects an item at the resulting position.

An example of moving north without collecting an object is given by Listing 8, while the corresponding propositional operator can be found in the appendix.

Listing 3: Example of an interaction action using predicates

```

1 (:action break-grass_block-north
2  :parameters (?ag - agent ?b -
   grass_block-block ?x - position ?y -
   position ?y_up - position ?z -
   position ?z_front -
3  position ?n_start - count ?n_end -
   count)
4  :precondition (and (agent-alive ?ag) (
   at-x ?ag ?x) (at-y ?ag ?y) (at-z ?
   ag ?z)
5  (at-x ?b ?x) (at-y ?b ?y) (at-z ?b ?
   z_front) (are-seq ?z_front ?z) (
   are-seq ?y ?y_up)
6  (block-present ?b) (not (exists (?i -
   item) (and (item-present ?i)
7  (at-x ?i ?x) (at-y ?i ?y_up) (at-z ?i
   ?z_front))))
8  (are-seq ?n_start ?n_end) (
   agent-has-n-grass_block ?ag ?
   n_start)
9  )
10 :effect (and (not (block-present ?b))
11  (not (at-x ?b ?x)) (not (at-y ?b ?y))
12  (not (at-z ?b ?z_front))
13  (not (agent-has-n-grass_block ?ag ?
   n_start))
14  (agent-has-n-grass_block ?ag ?n_end))
15 )

```

The agent is also capable of manipulating blocks, and we support two such interaction operators:

- `place-[item]-[direction]`: Places an item in the agent’s inventory one block in front of the agent in the specified direction. The agent cannot place an item in a position that is occupied by another block and there must be a block below the item.
- `break-[direction]`: Breaks the block one unit in front of the agent in the specified direction. The block is collected and added to the agent’s inventory.

An example of breaking a grass block is given by Listing 3, while the corresponding PDDL 2.1 operator is listed in the appendix.

Goal Representations

Since Minecraft objects of the same type are interchangeable, we use existential preconditions when specifying a goal related to the location of a block. This allows us to specify that, for example, *any* wood block should be placed

at a particular location, since all wood blocks are functionally identical. However, not all planners provide support for the `exist` keyword in the goal specification. To make our representation as accessible as possible, we introduce a “virtual” operator called `checkgoal` whose precondition is the actual condition for solving the task and whose effect sets a predicate `goal-achieved` to true. This is the only operator that can affect `goal-achieved`, which allows us to specify that the goal for all tasks is simply `goal-achieved`. For numeric planning, an example of a task whose goal is to place a `plank-block` at location (0, 4, 2) is given by Listing 4, while Listing 5 shows the corresponding propositional equivalent.

Listing 4: Example of goal attainment using fluents

```

1 (:action checkgoal
2  :parameters (?ag - agent)
3  :precondition (and (agent-alive ?ag)
4  (exists (?b - planks-block)
5  (and (block-present ?b)
6  (= (x ?b) 0) (= (y ?b) 4) (= (z ?b) 2)
7  ))
8  :effect (and (goal-achieved ?ag))
9  )

```

Listing 5: Example of goal attainment using predicates

```

1 (:action checkgoal
2  :parameters (?ag - agent)
3  :precondition (and (agent-alive ?ag)
4  (exists (?b - planks-block) (and
5  (block-present ?b) (at-x ?b position0
6  (at-y ?b position4) (at-z ?b
   position2)))
7  )
8  :effect (and (goal-achieved ?ag))
9  )

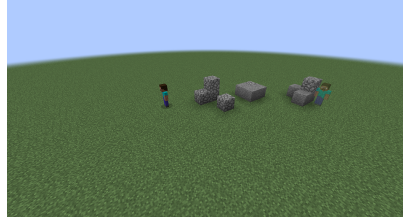
```

Benchmark Tasks in Minecraft

Using MinePlanner, we create an initial suite of tasks to serve as challenging problems for current planners. To create a finite representation of a (near infinite) Minecraft world, we consider only those blocks within some radius of the agent’s initial location, termed the *observation range*. We define 15 types of tasks, where each task comes in three difficulty settings. Broadly speaking, the easiest version of a task contains only those blocks necessary to solve the task and also has the smallest observation range. A medium difficulty task contains more blocks that typically exist in the world, but are not strictly relevant to the task at hand. Finally, the hardest version of each task takes place in a “realistic” Minecraft setting with a much larger observation range. The difference between difficulties is illustrated by Figure 2 and a list of all tasks is given by Table 1.



(a) Easy variant



(b) Medium variant



(c) Hard variant

Figure 2: Three variants for the task of navigating to a particular location. (a) The easy task contains no irrelevant blocks, and so the world is empty. (b) The medium contains a few additional blocks which serve as obstacles and make navigation more challenging. (c) The hard task requires navigating within a small village consisting of hundreds of objects that are irrelevant for this particular task.

Results

We benchmark Fast Downward (Helmert 2006), a propositional planner, and ENHSP-20 (Scala et al. 2020), a numerical planner, on the tasks provided with MinePlanner. All experiments were conducted using a cluster of AMD Ryzen 9 7900X3D CPUs, using 128 virtual cores and 250GB of RAM per trial. We record the time taken for planning, including the amount of time spent preprocessing the PDDL file by each planner. For Fast Downward, this refers to the time taken to translate PDDL to SAS, while for ENHSP, this measures grounding. We set a timeout limit of 2 hours for each planning task, since an autonomous agent must ultimately be capable of planning in large environments within a reasonable timeframe. Results are reported in Table , with the means over five runs reported.⁴

Discussion

The results indicate that both planners cannot solve most of the tasks. The translation step of Fast Downward was particularly problematic, with most of the tasks exhausting all memory before the file was translated to SAS. However, for those tasks where translation was successful, the subsequent search procedure was extremely fast (taking a few seconds at most). In contrast, ENHSP-20 is capable of grounding almost all of the problems, but fails to find a successful plan for most. For tasks that were successfully solved, planning is significantly slower than Fast Downward, illustrating the tradeoff between the two.

It is clear that there is still work to be done if we wish to solve large problems—no planner was able to solve any of the hard tasks. If we wish to apply planning in realistic domains, we need planners to operate within these object-dense environments in a reasonable amount of time. Algorithms that operate directly on the lifted representation (Corrêa et al. 2020) may be a promising future direction in this regard.

Another future direction is to leverage modern computing clusters to solve these challenging tasks, as has been done for previous “grand challenges” (Silver et al. 2016).

However, at present, there are several issues that prevent the full utilisation of our hardware. While planners like ENHSP-20 could potentially benefit from parallelisation, especially due to their long search times, they are also not able to ground larger problems despite being provided with 250GB of RAM. Similarly, the tasks Fast Downward failed to complete were due to the high memory requirements needed during the translation phase. Modern planners will require more than parallelisation to scale effectively to object-dense environments.

Conclusion

We presented MinePlanner—a framework for generating Minecraft tasks in PDDL that can serve as challenging domains for classical planners. We also proposed a set of 45 initial tasks, varying in difficulty, and benchmarked two domain-independent planners on these domains. The results indicated that there is still a significant technical gap to overcome to solve these large problems. We hope that our benchmark will serve as a catalyst for developing new approaches to planning in complex domains, and form a bridge between the learning and planning communities.

⁴For readability, we include only the means here, but report the full table along with standard deviations in the appendix.

Task	Variant	Observation Range	Initial Objects	Initial Predicates	Goal Predicates	Description
move	Easy	(13, 9, 13)	0	870/986	1	Navigate to a specific location.
	Medium	(21, 15, 21)	12	2079/2489	1	
	Hard	(71, 31, 71)	1071	45043/56067	1	
pickup diamond	Easy	(13, 9, 13)	2	875/991	1	Navigate and pickup a single diamond in the world.
	Medium	(21, 15, 21)	8	2065/2469	1	
	Hard	(71, 31, 71)	1072	45033/56077	1	
gather wood	Easy	(13, 9, 13)	1	875/992	1	Navigate and pickup a single log in the world.
	Medium	(21, 15, 21)	6	2053/2455	1	
	Hard	(71, 31, 71)	1071	45018/30157	1	
place wood	Easy	(13, 9, 13)	1	875/991	2	Navigate to a specific location and place a log from inventory.
	Medium	(21, 15, 21)	13	2090/2499	2	
	Hard	(71, 31, 71)	1071	45017/56061	2	
pickup and place	Easy	(13, 9, 13)	1	875/992	1	First locate a plank in the world, then place it at a specific location.
	Medium	(21, 15, 21)	16	2097/2511	1	
	Hard	(71, 31, 71)	1071	45018/56077	1	
gather multi wood	Easy	(13, 9, 13)	3	883/1002	1	Navigate and pickup a three logs in the world.
	Medium	(21, 15, 21)	18	2106/2521	1	
	Hard	(71, 31, 71)	1071	45019/56077	1	
climb	Easy	(13, 9, 13)	18	933/1063	1	Place a block at an elevated y location by climbing a staircase.
	Medium	(21, 15, 21)	7	2065/2468	1	
	Hard	(71, 31, 71)	18	20958/26024	1	
cut tree	Easy	(21, 13, 21)	60	2285/2733	1	Cut down a tree by removing its wood.
	Medium	(41, 31, 41)	75	7476/9208	1	
	Hard	(65, 31, 65)	946	38115/47462	9	
build bridge	Easy	(13, 9, 13)	80	881/997	2	Build a wooden bridge over water.
	Medium	(21, 15, 21)	255	2091/2503	4	
	Hard	(71, 31, 71)	409	20917/25974	6	
build cross	Easy	(13, 9, 13)	5	896/1017	5	Collect blocks to build a cross shape.
	Medium	(21, 15, 21)	10	2072/2479	5	
	Hard	(71, 31, 71)	1071	45003/30152	5	
build wall	Easy	(13, 9, 13)	9	914/1040	9	Collect blocks to build a wall.
	Medium	(21, 15, 21)	16	2099/2512	9	
	Hard	(71, 31, 71)	1071	45013/56077	9	
build well	Easy	(13, 9, 13)	26	983/1126	26	Collect blocks to build a well.
	Medium	(21, 15, 21)	36	2182/2614	26	
	Hard	(71, 31, 71)	1071	45039/56078	26	
build shape	Easy	(13, 9, 13)	1	880/996	5	Build a variety of shapes with items from inventory.
	Medium	(21, 15, 21)	12	2094/2503	9	
	Hard	(71, 31, 71)	1071	24308/56078	27	
collect and build shape	Easy	(13, 9, 13)	5	896/1017	5	Collect blocks to build a variety of shapes.
	Medium	(21, 15, 21)	11	2082/2490	11	
	Hard	(71, 31, 71)	1071	45023/30167	27	
build cabin	Easy	(21, 11, 21)	1	2079/2476	186	Build a log cabin.
	Medium	(41, 11, 41)	216	8058/9929	186	
	Hard	(65, 11, 65)	4066	30269/37664	186	

Table 1: A list of tasks provided by MinePlanner and their relevant statistics. Initial Objects does not include the ground (i.e. only objects explicitly specified in the YAML configuration is included). Initial Predicates is the number of predicates specified in the initial state of the problem file and is formatted as proposition/numerical. Goal Predicates is the number of goal conditions specified in the YAML configuration.

Task	Variant	FastDownward			ENHSP		
		Transl. (s)	Search (ms)	Total (s)	Ground (s)	Search (ms)	Total (s)
move	Easy	41.80	6.80	41.91	11.64	20.20	20.40
	Medium	237.69	14.60	237.68	73.43	168 000	317.20
	Hard	—	—	—	—	—	—
pickup diamond	Easy	341.21	497.36	341.96	11.83	45.40	20.52
	Medium	—	—	—	72.18	49 676	196.24
	Hard	—	—	—	—	—	—
gather wood	Easy	343.76	481.64	344.43	12.26	1125	25.26
	Medium	—	—	—	71.82	12 065	157.05
	Hard	—	—	—	—	—	—
place wood	Easy	786.31	7528	792.21	12.81	> 7.2e6	> 7.2e6
	Medium	—	—	—	58.49	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
pickup and place	Easy	341.21	993.7	343.94	11.53	1.63e6	1655
	Medium	—	—	—	73.79	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
gather multi wood	Easy	—	—	—	11.76	241 840	256.86
	Medium	—	—	—	75.91	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
climb	Easy	—	—	—	15.52	> 7.2e6	> 7.2e6
	Medium	—	—	—	57.51	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
cut tree	Easy	—	—	—	72.90	> 7.2e6	> 7.2e6
	Medium	—	—	—	—	—	—
	Hard	—	—	—	—	—	—
build bridge	Easy	—	—	—	16.26	> 7.2e6	> 7.2e6
	Medium	—	—	—	84.29	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
build cross	Easy	—	—	—	15.04	> 7.2e6	> 7.2e6
	Medium	—	—	—	81.24	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
build wall	Easy	—	—	—	13.20	> 7.2e6	> 7.2e6
	Medium	—	—	—	79.54	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
build well	Easy	—	—	—	13.04	> 7.2e6	> 7.2e6
	Medium	—	—	—	81.24	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
build shape	Easy	—	—	—	10.44	> 7.2e6	> 7.2e6
	Medium	—	—	—	61.32	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
collect and build shape	Easy	—	—	—	12.39	> 7.2e6	> 7.2e6
	Medium	—	—	—	68.17	> 7.2e6	> 7.2e6
	Hard	—	—	—	—	—	—
build cabin	Easy	—	—	—	—	—	—
	Medium	—	—	—	—	—	—
	Hard	—	—	—	—	—	—

Table 2: The running times for Fast Downward and ENHSP-20 when run on the MinePlanner task suite. No result could be obtained for results marked as — because the planner failed to translate (in the case of Fast Downward) or ground (for ENHSP-20). Entries marked > 7.2e6 indicate that the planner timed out.

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Appendix

A. Examples of Operators

The following are examples of operators for moving north for two styles of planners. The precondition is this operator describes how there must be no block at the location the agent wishes to move to (since this would obstruct the agent) and that no item exists either, since the effect would then include picking up the item. The effect in this case is simply a change in the agent's z position.

Listing 6: Example of a movement action using fluents

```
1 (:action move-north
2   :parameters (?ag - agent)
3   :precondition (and (agent-alive ?ag)
4     (exists (?b - block) (and (block-present ?b) (= (x ?b) (x ?ag))
5       (= (y ?b) (+ (y ?ag) -1)) (= (z ?b) (+ (z ?ag) -1)))) (and
6       (not (exists (?b - block) (and (block-present ?b) (= (x ?b) (x ?ag))
7         (or (= (y ?b) (+ (y ?ag) 1)) (= (y ?b) (y ?ag)) (= (z ?b) (+ (z ?ag) -1))))))
8       (not (exists (?i - item) (and (item-present ?i) (= (x ?i) (x ?ag)) (= (y ?i) (y ?ag)) (=
9         (z ?i) (+ (z ?ag) -1)))))))
9   :effect (and (decrease (z ?ag) 1))
10 )
```

Listing 7: Example of a movement action using predicates

```
1 (:action move-north
2   :parameters (?ag - agent ?x - position ?y_up - position ?y_down - position ?y_2_down -
3     position ?z_start - position ?z_end - position)
4   :precondition (and (agent-alive ?ag) (at-x ?ag ?x) (at-y ?ag ?y_down)
5     (at-z ?ag ?z_start) (are-seq ?z_end ?z_start) (are-seq ?y_down ?y_up) (are-seq ?
6       y_2_down ?y_down) (exists (?b - block) (and (block-present ?b) (at-x ?b ?x) (at-y
7         ?b ?y_2_down) (at-z ?b ?z_end)))) (not (exists (?b - block) (and (block-present ?b)
8         (at-x ?b ?x) (or (at-y ?b ?y_up) (at-y ?b ?y_down)) (at-z ?b ?z_end)))) (not (
9         exists (?i - item) (and (item-present ?i) (at-x ?i ?x) (at-y ?i ?y_down) (at-z ?i
10         ?z_end)))))
11   :effect (and (not (at-z ?ag ?z_start)) (at-z ?ag ?z_end))
12 )
```

The listings below illustrate an example of the agent interacting with a block. Here, the agent breaks a grass block in the north direction. The precondition checks that there is a grass block north of the agent (and no other items that could be picked up mistakenly), and the effect is that the block is no longer in the world, and the count for the agent’s inventory of grass blocks increases by 1.

Listing 8: Example of an interaction action using fluents

```

1 (:action break-grass_block-north
2   :parameters (?ag - agent ?b - grass_block-block)
3   :precondition (and
4     (= (x ?b) (x ?ag)) (= (y ?b) (y ?ag)) (= (z ?b) (+ (z ?ag) -1)) (block-present ?b) (
5       not (exists (?i - item) (and (item-present ?i) (= (x ?b) (x ?ag)) (= (y ?i) (+ (y
6         ?ag) 1)) (= (z ?b) (+ (z ?ag) -1))))))
7   :effect (and (not (block-present ?b)) (increase (agent-num-grass_block ?ag) 1))
8 )
9 )

```

Listing 9: Example of an interaction action using predicates

```

1 (:action break-grass_block-north
2   :parameters (?ag - agent ?b - grass_block-block ?x - position ?y - position ?y_up -
3     position ?z - position ?z_front - position ?n_start - count ?n_end - count)
4   :precondition (and
5     (agent-alive ?ag) (at-x ?ag ?x) (at-y ?ag ?y) (at-z ?ag ?z) (at-x ?b ?x) (at-y ?b ?y)
6     (at-z ?b ?z_front) (are-seq ?z_front ?z) (are-seq ?y ?y_up) (block-present ?b) (not (
7       exists (?i - item) (and (item-present ?i) (at-x ?i ?x) (at-y ?i ?y_up) (at-z ?i ?
8         z_front))))
9     (are-seq ?n_start ?n_end) (agent-has-n-grass_block ?ag ?n_start)
10    )
11   :effect (and (not (block-present ?b)) (not (at-x ?b ?x)) (not (at-y ?b ?y)) (not (at-z ?b
12     ?z_front)) (not (agent-has-n-grass_block ?ag ?n_start)) (agent-has-n-grass_block ?ag
13     ?n_end)
14   )
15 )

```

B. Results

We benchmark Fast Downward, a propositional planner, and ENHSP-20, a numerical planner, on the tasks provided with MinePlanner. All experiments were conducted using a cluster of AMD Ryzen 9 7900X3D CPUs, using 128 virtual cores and 250GB of RAM per trial. We record the time taken for planning, including the amount of time spent preprocessing the PDDL file by each planner. For Fast Downward, this refers to the time taken to translate PDDL to SAS, while for ENHSP, this measures grounding. We set a timeout limit of 2 hours for each planing task, since an autonomous agent must ultimately be capable of planning in large environments within a reasonable timeframe. Results are reported in Table 1, with the means and standard deviations over 5 runs reported.

Task	Variant	FastDownward			ENHSP		
		Transl. (s)	Search (ms)	Total (s)	Ground (s)	Search (ms)	Total (s)
move	Easy	41.80 ± 0.15	6.80 ± 0.55	41.91 ± 0.17	11.64 ± 0.13	20.20 ± 0.40	20.40 ± 0.30
	Medium Hard	237.69 ± 0.86	14.60 ± 5.88	237.68 ± 0.71	73.43 ± 0.94	168e3 ± 6.9e3	317.20 ± 5.92
pickup diamond	Easy	341.21 ± 2.12	497.36 ± 3.67	341.96 ± 2.08	11.83 ± 0.14	45.40 ± 1.36	20.52 ± 0.14
	Medium Hard	—	—	—	72.18 ± 0.34	49 676 ± 919	196.24 ± 1.72
gather wood	Easy	343.76 ± 0.66	481.64 ± 1.45	344.43 ± 0.66	12.26 ± 0.75	1125 ± 37.26	25.26 ± 0.91
	Medium Hard	—	—	—	71.82 ± 0.67	12 065 ± 144	157.05 ± 3.17
place wood	Easy	786.31 ± 2.03	7528 ± 28.1	792.21 ± 1.98	12.81 ± 0.03	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	58.49 ± 0.23	> 7.2e6	> 7.2e6
pickup and place	Easy	341.21 ± 2.12	993.7 ± 3.33	343.94 ± 1.52	11.53 ± 0.11	1.63e6 ± 0.006e6	1655 ± 60.4
	Medium Hard	—	—	—	73.79 ± 0.85	> 7.2e6	> 7.2e6
gather multi wood	Easy	—	—	—	11.76 ± 0.075	241 840 ± 7150	256.86 ± 7.78
	Medium Hard	—	—	—	75.91 ± 0.72	> 7.2e6	> 7.2e6
climb	Easy	—	—	—	15.52 ± 0.07	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	57.51 ± 0.14	> 7.2e6	> 7.2e6
cut tree	Easy	—	—	—	72.90 ± 1.21	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	—	—	—
build bridge	Easy	—	—	—	16.26 ± 0.08	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	84.29 ± 3.01	> 7.2e6	> 7.2e6
build cross	Easy	—	—	—	15.04 ± 0.82	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	81.24 ± 2.13	> 7.2e6	> 7.2e6
build wall	Easy	—	—	—	13.20 ± 0.10	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	79.54 ± 1.54	> 7.2e6	> 7.2e6
build well	Easy	—	—	—	13.04 ± 0.08	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	81.24 ± 2.13	> 7.2e6	> 7.2e6
build shape	Easy	—	—	—	10.44 ± 0.83	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	61.32 ± 0.25	> 7.2e6	> 7.2e6
collect and build shape	Easy	—	—	—	12.39 ± 0.06	> 7.2e6	> 7.2e6
	Medium Hard	—	—	—	68.17 ± 1.98	> 7.2e6	> 7.2e6
build cabin	Easy	—	—	—	—	—	—
	Medium Hard	—	—	—	—	—	—

Table 3: The running times for Fast Downward and ENHSP-20 when run on the MinePlanner task suite. For results marked as —, no result could be obtained because the planner failed to translate (in the case of Fast Downward) or ground (for ENHSP-20). Entries marked > 7.2e6 indicate that the planner timed out.