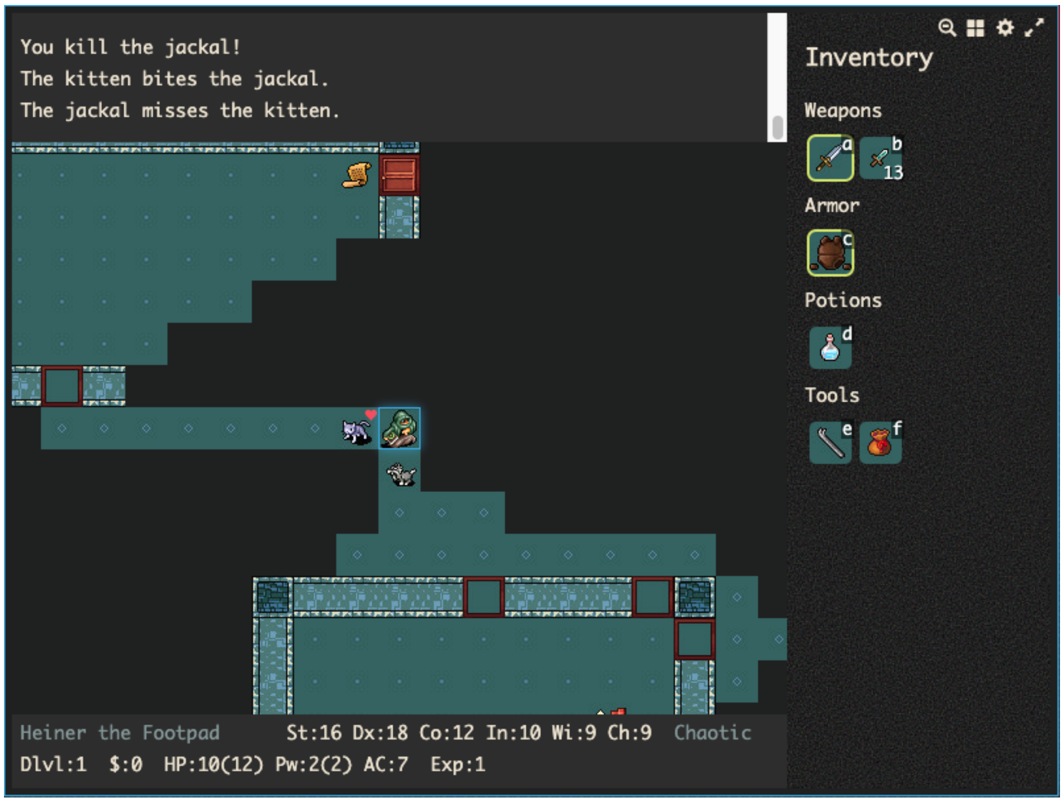
A Further Details on NetHack

Character options The player may choose (or pick randomly) the character from thirteen roles (archaeologist, barbarian, cave(wo)man, healer, knight, priest(ess), ranger, rogue, samurai, tourist, valkyrie, and wizard), five races (human, elf, dwarf, gnome, and orc), three moral alignments (neutral, lawful, chaotic), and two genders (male or female). Each choice determines some of the character's features, as well as how the character interacts with other entities (e.g., some species of monsters may not be hostile depending on the character race; priests of a particular deity may only help religiously aligned characters).

The hero's interaction with several game entities involves pre-defined stochastic dynamics (usually defined by virtual dice tosses), and the game is designed to heavily punish careless exploration policies.[5] This makes NetHack an ideal environment for evaluating exploration methods such as curiosity-driven learning [56, 12] or safe reinforcement learning [28].

Learning and planning in NetHack involves dealing with partial observability. The game, by default, employs *Fog of War* to hide information based on a simple 2D light model (see for example the difference between white ▪ and gray ▪ room tiles in Figure 1 or Figure 11), requiring the player not only to discover the topology of the level (including searching for hidden doors and passages), but to also condition their policy on a world that might change, e.g., due to monsters spawning and interacting outside of the visible range.

On top of the standard ASCII interface, NetHack supports many official and unofficial graphical user interfaces. Figure 6 shows a screenshot of Lu Wang's BrowserHack[6] as an example.


```
You kill the jackal!
The kitten bites the jackal.
The jackal misses the kitten.
```

```
Heiner the Footpad        St:16 Dx:18 Co:12 In:10 Wi:9 Ch:9  Chaotic
Dlvl:1  $:0  HP:10(12) Pw:2(2) AC:7  Exp:1
```

Figure 6: Screenshot of BrowserHack showing NetHack with a graphical user interface.

[5]Occasionally dying because of simple, avoidable mistakes is so common in the game that the online community has defined an acronym for it: *Yet Another Stupid Death* (YASD).

[6]Playable online at https://coolwanglu.github.io/BrowserHack/

Conducts While winning NetHack by retrieving and ascending with the Amulet of Yendor is already immensely challenging, experienced NetHack players like to challenge themselves even more by imposing additional restrictions on their play. The game tracks some of these challenges with the `#conduct` command [59]. These official challenges include eating only vegan or vegetarian food, or not eating at all, or playing the game in "pacifist" mode without killing a single monster. While very experienced players often try to adhere to several challenges at once, even moderately experienced players often limit their use of certain polymorph spells (e.g., "polypiling"—changing the form of several objects at once in the hope of getting better ones) or they try to beat the game while *minimizing* the in-game score. We believe this established set of conducts will supply the RL community with a steady stream of extended challenges once the standard `NetHack Learning Environment` is solved by future methods.

B Observation Space

The Gym environment is implemented by wrapping a more low-level `NetHack` Python object into a Python class responsible for the featurization, reward schedule and end-of-episode dynamics. While the low-level `NetHack` object gives access to a large number of NetHack game internals, the Gym wrapper exposes by default only a part of this data as numerical observation arrays, namely the observation tensors *glyphs*, *chars*, *colors*, *specials*, *blstats*, *message*, *inv_glyphs*, *inv_strs*, *inv_letters*, and *inv_oclasses*.

Glyphs, Chars, Colors, Specials: NetHack supports non-ASCII graphical user interfaces, dubbed window-ports (see Figure 6 for an example). To support displaying different monsters, objects and floor types in the NetHack dungeon map as different tiles, NetHack internally defines *glyphs* as ids in the range $0, \dots,$ `MAX_GLYPH`, where `MAX_GLYPH` $= 5991$ in our build[7]. The *glyph* observation is an integer array of shape $(21, 79)$ of these game glyph ids.[8] In NetHack's standard terminal-based user interface, these glyphs are mapped into ASCII characters of different colors which we return as the *chars*, *colors*, and *specials* observations, both all which are of shape $(21, 79)$; *chars* are ASCII bytes in the range $0, \dots, 127$ wheras *colors* are in range $0, \dots, 15$. For additional highlighting (e.g., flipping background and foreground colors for the hero's pet), NetHack also computes xor'ed values which we return as the *specials* tensor.

Blstats: "Bottom line statistics", a integer vector of length 25, containing the (x, y) coordinate of the hero and the following 23 character stats that typically appear in the bottom line of the ASCII interface: `strength_percentage`, `strength`, `dexterity`, `constitution`, `intelligence`, `wisdom`, `charisma`, `score`, `hitpoints`, `max_hitpoints`, `depth`, `gold`, `energy`, `max_energy`, `armor_class`, `monster_level`, `experience_level`, `experience_points`, `time`, `hunger_state`, `carrying_capacity`, `dungeon_number`, and `level_number`.

Message: A padded byte vector of length 256 representing the current message shown to the player, normally displayed in the top area of the GUI. We support different padding strategies and alphabet sizes, but by default we choose an alphabet size of 96, where the last character is used for padding.

Inventory: In NetHack's default ASCII user interface, the hero's inventory can be opened and closed during the game. Other user interfaces display a permanent inventory at all times. `NLE` follows that strategy. The inventory observations consist of the following four arrays: *inv_glyphs*: an integer vector of length 55 of glyph ids, padded with `MAX_GLYPH`; *inv_strs*: A padded byte array of shape $(55, 80)$ describing the inventory items; *inv_letters*: A padded byte vector of length 55 with the corresponding ASCII character symbol; *inv_oclasses*: An integer vector of shape 55 with ids describing the type of inventory objects, padded with `MAXOCLASSES` $= 18$.

[7]The exact number of monsters in NetHack depends on compile-time options as well as the target operating system. For instance, the mail daemon & is only available on Unix-like operating systems, where it delivers email in the form of a NetHack scroll if the system is configured to host a Unix mailbox.

[8]NetHack's set of glyph ids is not necessarily well suited for machine learning. For example, more than half of all glyph ids are of type "swallow", most of which are guaranteed not to show up in any actual game of NetHack. We provide additional tooling to determine the type of a given glyph id to process this observation further.

The low-level `NetHack` Python object has some additional methods to query and modify NetHack's game state, e.g. the current RNG seeds. We refer to the source code to describe these.[9]

C Action Space

The game of NetHack uses ASCII inputs, i.e., individual keyboard presses including modifiers like Ctrl and Meta. `NLE` pre-defines 98 actions, 16 of which are compass directions and 82 of which are command actions. Table 1 gives a list of command actions, including their ASCII value and the corresponding key binding in NetHack, while Table 3 lists the 16 compass directions. For a detailed description of these actions, as well as other NetHack commands, we refer the reader to the NetHack guide book [59]. Not all actions are sensible for standard RL training on `NLE`. E.g., the VERSION or QUIT actions are unlikely to be useful for direct input from the agent. `NLE` defines a list of `USEFUL_ACTIONS` that includes a subset of 76 actions; however, what is useful depends on the circumstances. In addition, even though an action like SAVE is unlikely to be useful in most game situations it corresponds to the letter `S`, which may be assigned to an inventory item or some other in-game menu entry such that it does become a useful action in that context.

By default, `NLE` will auto-apply the MORE action in situations where the game waits for input to display more messages.

Table 1: Command actions.[10]

Name	Value	Key	Description
EXTCMD	35	`#`	perform an extended command
EXTLIST	191	`M-?`	list all extended commands
ADJUST	225	`M-a`	adjust inventory letters
ANNOTATE	193	`M-A`	name current level
APPLY	97	`a`	apply (use) a tool (pick-axe, key, lamp...)
ATTRIBUTES	24	`C-x`	show your attributes
AUTOPICKUP	64	`@`	toggle the pickup option on/off
CALL	67	`C`	call (name) something
CAST	90	`Z`	zap (cast) a spell
CHAT	227	`M-c`	talk to someone
CLOSE	99	`c`	close a door
CONDUCT	195	`M-C`	list voluntary challenges you have maintained
DIP	228	`M-d`	dip an object into something
DOWN	62	`>`	go down (e.g., a staircase)
DROP	100	`d`	drop an item
DROPTYPE	68	`D`	drop specific item types
EAT	101	`e`	eat something
ESC	27	`C-[`	escape from the current query/action
ENGRAVE	69	`E`	engrave writing on the floor
ENHANCE	229	`M-e`	advance or check weapon and spell skills
FIRE	102	`f`	fire ammunition from quiver
FIGHT	70	`F`	Prefix: force fight even if you don't see a monster
FORCE	230	`M-f`	force a lock
GLANCE	59	`;`	show what type of thing a map symbol corresponds to
HELP	63	`?`	give a help message
HISTORY	86	`V`	show long version and game history
INVENTORY	105	`i`	show your inventory
INVENTTYPE	73	`I`	inventory specific item types
INVOKE	233	`M-i`	invoke an object's special powers
JUMP	234	`M-j`	jump to another location
KICK	4	`C-d`	kick something
KNOWN	92	`\`	show what object types have been discovered
KNOWNCLASS	96	`‘`	show discovered types for one class of objects
LOOK	58	`:`	look at what is here
LOOT	236	`M-l`	loot a box on the floor

[9] See, e.g., the `nethack.py` as well as `pynethack.cc` files in the `NLE` repository.

[10] The descriptions are mostly taken from the `cmd.c` file in the NetHack source code.

MONSTER	237	`M-m`	use monster's special ability
MORE	13	`C-m`	read the next message
MOVE	109	`m`	Prefix: move without picking up objects/fighting
MOVEFAR	77	`M`	Prefix: run without picking up objects/fighting
OFFER	239	`M-o`	offer a sacrifice to the gods
OPEN	111	`o`	open a door
OPTIONS	79	`O`	show option settings, possibly change them
OVERVIEW	15	`C-o`	show a summary of the explored dungeon
PAY	112	`p`	pay your shopping bill
PICKUP	44	`,`	pick up things at the current location
PRAY	240	`M-p`	pray to the gods for help
PREVMSG	16	`C-p`	view recent game messages
PUTON	80	`P`	put on an accessory (ring, amulet, etc)
QUAFF	113	`q`	quaff (drink) something
QUIT	241	`M-q`	exit without saving current game
QUIVER	81	`Q`	select ammunition for quiver
READ	114	`r`	read a scroll or spellbook
REDRAW	18	`C-r`	redraw screen
REMOVE	82	`R`	remove an accessory (ring, amulet, etc)
RIDE	210	`M-R`	mount or dismount a saddled steed
RUB	242	`M-r`	rub a lamp or a stone
RUSH	103	`g`	Prefix: rush until something interesting is seen
SAVE	83	`S`	save the game and exit
SEARCH	115	`s`	search for traps and secret doors
SEEALL	42	`*`	show all equipment in use
SEETRAP	94	`^`	show the type of adjacent trap
SIT	243	`M-s`	sit down
SWAP	120	`x`	swap wielded and secondary weapons
TAKEOFF	84	`T`	take off one piece of armor
TAKEOFFALL	65	`A`	remove all armor
TELEPORT	20	`C-t`	teleport around the level
THROW	116	`t`	throw something
TIP	212	`M-T`	empty a container
TRAVEL	95	`_`	travel to a specific location on the map
TURN	244	`M-t`	turn undead away
TWOWEAPON	88	`X`	toggle two-weapon combat
UNTRAP	245	`M-u`	untrap something
UP	60	`<`	go up (e.g., a staircase)
VERSION	246	`M-v`	list compile time options
VERSIONSHORT	118	`v`	show version
WAIT / SELF	46	`.`	rest one move while doing nothing / apply to self
WEAR	87	`W`	wear a piece of armor
WHATDOES	38	`&`	tell what a command does
WHATIS	47	`/`	show what type of thing a symbol corresponds to
WIELD	119	`w`	wield (put in use) a weapon
WIPE	247	`M-w`	wipe off your face
ZAP	112	`z`	zap a wand

D Environment Speed Comparison

Table 4 shows a comparison between popular Gym environments and `NLE`. All environments were controlled with a uniformly random policy using reset on terminal states. The tests were conducted on a MacBook Pro equipped with an Intel Core i7 2.9 GHz, 16GB of RAM, MacOS Mojave, Python 3.7, Conda 4.7.12, and latest available packages as of May 2020. *ObstacleTowerEnv* was instantiated with `(retro=False, real_time=False)`. Note that this data does not necessarily reflect performance of these environments with better—or worse—policies, as each environment has computational dynamics that depend on its state. However, we expect the difference in terms of magnitude to remain mostly unchanged across these environments.

Table 3: Compass direction actions.

	one-step		move far	
Direction	Value	Key	Value	Key
North	107	`k`	75	`K`
East	108	`l`	76	`L`
South	106	`j`	74	`J`
West	104	`h`	72	`H`
North East	117	`u`	85	`U`
South East	110	`n`	78	`N`
South West	98	`b`	66	`B`
North West	121	`y`	89	`Y`

Table 4: Comparison between `NLE` and popular environments when using their respective Python Gym interface. SPS stands for "environment steps per second". All environments but `ObstacleTowerEnv` were run via `gym` with standard settings (and headless when possible), for 60 seconds.

Environment	SPS	steps	episodes
`NLE` (score)	14.4K	868.75K	477
CartPole-v1	76.88K	4612.65K	207390
ALE (MontezumaRevengeNoFrameskip-v4)	0.90K	53.91K	611
Retro (Airstriker-Genesis)	1.31K	78.56K	52
ProcGen (procgen-coinrun-v0)	13.13K	787.98K	1283
ObstacleTowerEnv	0.06K	3.61K	6
MineRLNavigateDense-v0	0.06K	3.39K	0

E Task Details

For all tasks described below, we add a penalty of -0.001 to the reward function if the agent's action did not advance the in-game timer, which, for example, happens when the agent tries to move against a wall or navigates menus. For all tasks, except the *Gold* task, we disable NetHack's *autopick* option [59]. Furthermore, we disable so-called *bones files* that would otherwise lead to agents occasionally discovering the remains and ghosts of previous agents, considerably increasing the variance across episodes.

Staircase The agent has to find the staircase down `>` to the next dungeon level. This task is already challenging, as there is often no direct path to the staircase. Instead, the agent has to learn to reliably open doors `+`, kick-in locked doors, search for hidden doors and passages `#`, avoid traps `^`, or move

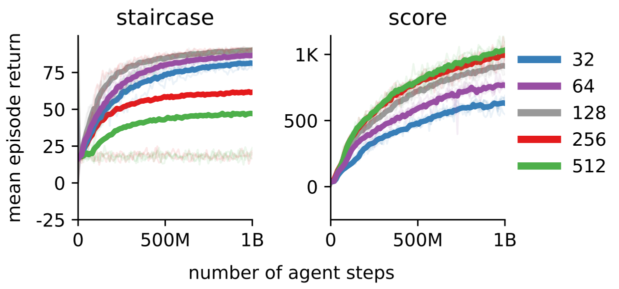


Figure 7: Mean episode return of the last 100 episodes for models with different hidden sizes averaged over five runs.

boulders 0 that obstruct a passage. The agent receives a reward of 100 once it reaches the staircase down and the the episode terminates after 1000 agent steps.

Pet Many successful strategies for NetHack rely on taking good care of the hero's pet (e.g., the little dog d or kitten f that the hero starts with). Pets are controlled by the game, but their behavior is influenced by the agent's actions. In this task, the agent only receives a positive reward of 100 when it reaches the staircase while the pet is next to the agent.

Eat To survive in NetHack, players have to make sure their character does not starve to death. There are many edible objects in the game, for example food rations %, tins, and monster corpses. In this task, the agent receives the increase of nutrition as determined by the in-game "Hunger" status as reward [see 50, "Nutrition" entry for details]. A steady source of nutrition are monster corpses, but for that the agent has to learn to locate and to kill monsters while avoiding to consume rotten corpses, poisonous monster corpses such as Kobolds k or acidic monster corpses such as Acid Blobs b.

Gold Throughout the game, the player can collect gold $ to, for example, trade for useful items with shopkeepers. The agent receives the amount of gold it collects as reward. This incentivizes the agent to explore dungeon maps fully and to descend dungeon levels to discover new sources of gold. There are many advanced strategies for obtaining large amounts of gold such as finding, identifying and selling gems; stealing from or killing shopkeepers; or hunting for vaults or leprechaun halls. To make this task easier for the agent, we enable NetHack's *autopickup* option for gold.

Scout An important part of the game is exploring dungeon levels. Here, we reward the agent $(+1)$ for uncovering previously unknown tiles in the dungeon, for example by entering a new room or following a newly discovered passage. Like the previous task, this incentivizes the agent to explore dungeon levels and to descend.

Score In this task, the agent receives the increase of the in-game score between two time steps as reward. The in-game score is governed by a complex calculation, but in early stages of the game it is dominated by killing monsters and the number of dungeon levels that the agent descends [see 50, "Score" entry for details].

Oracle While levels are procedurally generated, there are a number of landmarks that appear in every game of NetHack. One such landmark is the Oracle @, which is randomly placed between levels five and nine of the dungeon. Reliably finding the Oracle is difficult, as it requires the agent to go down multiple staircases and often to exhaustively explore each level. In this task, the agent receives a reward of 1000 if it manages to reach the Oracle.

F Baseline CNN Details

As embedding dimension of the glyphs we use 32 and for the hidden dimension for the observation $\mathbf{o}_t$ and the output of the LSTM $\mathbf{h}_t$, we use 128. For encoding the full map of glyphs as well as the 9×9 crop, we use a 5-layer ConvNet architecture with filter size 3×3, padding 1 and stride 1. The input channel of the first layer of the ConvNet is the embedding size of the glyphs (32). Subsequent layers have an input and output channel dimension of 16. We employ a gradient norm clipping of 40 and clip rewards using $r_c = \tanh(r/100)$. We use RMSProp with a learning rate of 0.0002 without momentum and with $\varepsilon_{\text{RMSProp}} = 0.000001$. Our entropy cost is set to 0.0001.

G Random Network Distillation Details

For RND hyperparameters we mostly follow the recommendations by the authors [13]:

- we initialize the weights according to the original paper, using an orthogonal distribution with a gain of $\sqrt{2}$
- we use a two-headed value function rather than merely summing the intrinsic and extrinsic reward
- we use a discounting factor of 0.999 for the extrinsic reward and 0.99 for the intrinsic reward

- we use non-episodic intrinsic reward and episodic extrinsic reward
- we use reward normalization for the intrinsic reward, dividing it by a running estimate of its standard deviation

We modify a few of the parameters for use in our setting:

- we use exactly the same feature extraction architecture as the baseline model instead of the pixel-based convolutional feature extractor
- we do not use observation normalization, again due to the symbolic nature of our observation space
- before normalizing, we divide the intrinsic reward by ten so that it has less weight than the extrinsic reward
- we clip intrinsic rewards in the same way that we clip extrinsic rewards, i.e., using $r_c = \tanh(r/100)$, so that the intrinsic and extrinsic rewards are on a similar scale

We downscale the forward modeling loss by a factor of 0.01 to slow down the rate at which the model becomes familiar with a given state, since the intrinsic reward often collapsed quickly despite the reward normalization. We determined these settings during a set of small-scale experiments.

We also tried using subsets of the full feature set (only the embedding of the full display of glyphs, or only the embedding of the crop of glyphs around the agent) as well as the exact architecture used by the original authors, but with the pixel input replaced by a random 8-dimensional embedding of the symbolic observation space. However, we did not observe this improved results.

We tried using intrinsic reward only as the authors did in the original RND paper, but we found that agents trained in this way made no significant progress through the dungeon, even on a single fixed seed. This indicates that this form of intrinsic reward is not sufficient to make progress on NetHack. As noted in Section 3, the intrinsic reward did help in some tasks for some characters when combined with the extrinsic reward. Crucially, RND exploration is not sufficient for agents to learn to find the Oracle, which leaves this as a difficult challenge for future exploration techniques.

H Dashboard

We release a web dashboard built with NodeJS (see Figure 10) to visualize experiment runs and statistics for `NLE`, including replaying episodes that were recorded as `tty` files.

I NetHack Bots

Since the early stages of the development of NetHack, players have tried to build bots to play and solve the game. Notable examples are *TAEB*, *BotHack*, and *Saiph* [65, 50]. These bot frameworks largely rely on search heuristics and common planning methods, without generally making use of any statistical learning methods. An exception is *SWAGGINZZZ* [2] which uses lookups, exhaustive simulation and manipulation of the random number generator.

Successful bots have made use of exploits that are no longer present in recent versions of NetHack. For example, *BotHack* employs the "pudding farming" strategy [see 50, "Pudding farming" entry] to level up and to create items for the character by spawning and killing a large number of black puddings `P`. This enabled the bot to become quite strong, which rendered late-game fights considerably easier. This strategy was disabled by the NetHack DevTeam with a patch that is incorporated into versions of NetHack above 3.6.0. Likewise, the random number generator manipulations employed in *SWAGGINZZZ* are no longer possible.

We believe that it is very unlikely that in the future we will see a hand-crafted bot solving NetHack in the way we defined it in Section 2.4. In fact, the creator of *SWAGGINZZZ* remarked that "[e]ven with RNG manipulation, writing a bot that 99% ascends NetHack is **extremely** complicated. So much stuff can go wrong, and there is no shortage of corner cases" [2].

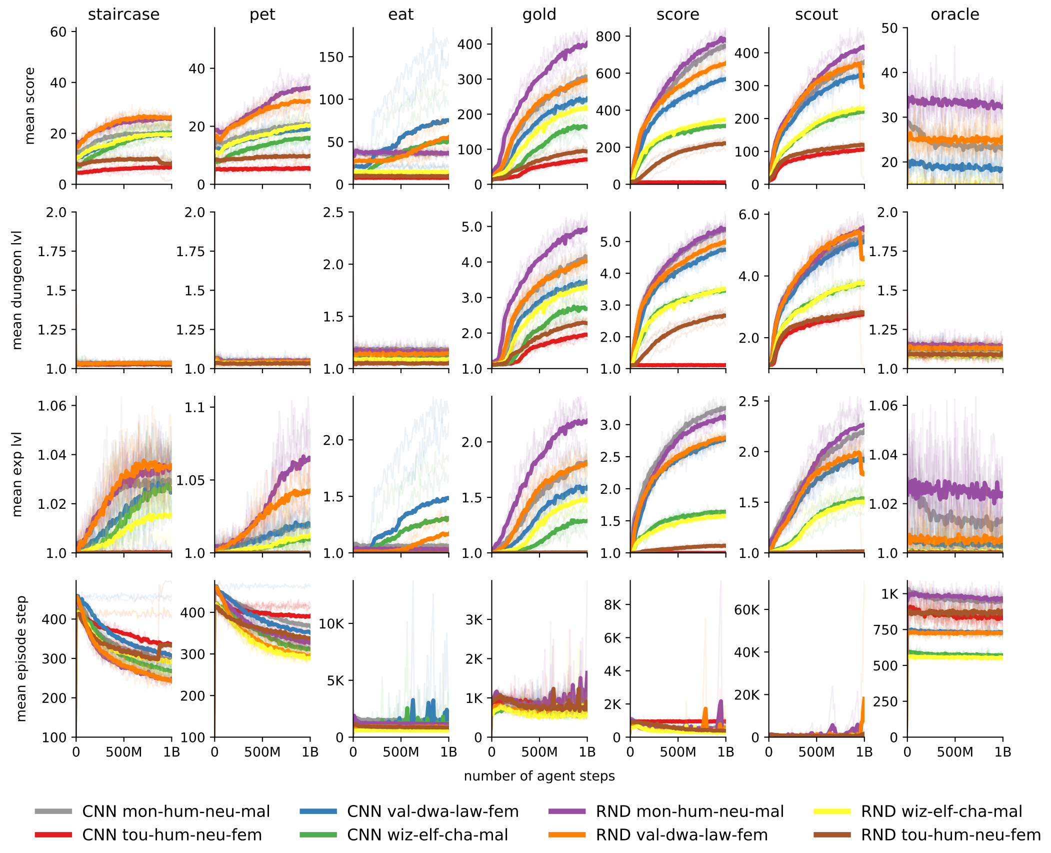


Figure 8: Mean score, dungeon level reached, experience level achieved, and steps performed in the environment in the last 100 episodes averaged over five runs.

J Viewing Agent Videos

We have uploaded some agent recordings to `https://asciinema.org/~nle`. These can be either watched on the Asciinema portal, or on a terminal by running `asciinema play -s 0.2` *url* (`asciinema` itself is available as a pip package at `https://pypi.org/project/asciinema`). The `-s` flag regulates the speed of the recordings, which can also be modified on the web interface by pressing > (faster) or < (slower).

Table 5: Metrics averaged over last 1000 episodes for each task.

Task	Model	Character	Score	Time	Exp Lvl	Dungeon Lvl	Win
staircase	CNN	mon-hum-neu-mal	20	252	1.0	1.0	77.26
		tou-hum-neu-fem	6	288	1.0	1.0	50.42
		val-dwa-law-fem	19	329	1.0	1.0	74.62
		wiz-elf-cha-mal	20	253	1.0	1.0	80.42
	RND	mon-hum-neu-mal	26	199	1.0	1.0	90.84
		tou-hum-neu-fem	8	203	1.0	1.0	56.94
		val-dwa-law-fem	25	242	1.0	1.0	90.96
		wiz-elf-cha-mal	20	317	1.0	1.0	67.46
pet	CNN	mon-hum-neu-mal	20	297	1.0	1.1	62.02
		tou-hum-neu-fem	6	407	1.0	1.0	25.66
		val-dwa-law-fem	18	379	1.0	1.0	63.30
		wiz-elf-cha-mal	16	273	1.0	1.0	66.80
	RND	mon-hum-neu-mal	33	319	1.1	1.0	74.38
		tou-hum-neu-fem	10	336	1.0	1.0	49.38
		val-dwa-law-fem	28	311	1.0	1.0	81.56
		wiz-elf-cha-mal	20	278	1.0	1.0	70.48
eat	CNN	mon-hum-neu-mal	36	1254	1.1	1.2	–
		tou-hum-neu-fem	7	423	1.0	1.0	–
		val-dwa-law-fem	75	1713	1.5	1.1	–
		wiz-elf-cha-mal	50	1181	1.3	1.1	–
	RND	mon-hum-neu-mal	36	1102	1.0	1.2	–
		tou-hum-neu-fem	9	404	1.0	1.0	–
		val-dwa-law-fem	55	1421	1.2	1.1	–
		wiz-elf-cha-mal	14	808	1.0	1.1	–
gold	CNN	mon-hum-neu-mal	307	947	1.8	4.2	–
		tou-hum-neu-fem	71	788	1.0	2.0	–
		val-dwa-law-fem	245	1032	1.6	3.5	–
		wiz-elf-cha-mal	162	780	1.3	2.7	–
	RND	mon-hum-neu-mal	403	1006	2.2	5.0	–
		tou-hum-neu-fem	92	816	1.0	2.2	–
		val-dwa-law-fem	298	998	1.8	4.0	–
		wiz-elf-cha-mal	217	789	1.5	3.3	–
score	CNN	mon-hum-neu-mal	748	932	3.2	5.4	–
		tou-hum-neu-fem	11	795	1.0	1.1	–
		val-dwa-law-fem	573	908	2.8	4.8	–
		wiz-elf-cha-mal	314	615	1.6	3.5	–
	RND	mon-hum-neu-mal	780	863	3.1	5.4	–
		tou-hum-neu-fem	219	490	1.1	2.6	–
		val-dwa-law-fem	647	857	2.8	5.0	–
		wiz-elf-cha-mal	352	585	1.6	3.5	–
scout	CNN	mon-hum-neu-mal	372	838	2.2	5.3	–
		tou-hum-neu-fem	105	580	1.0	2.7	–
		val-dwa-law-fem	331	852	1.9	5.1	–
		wiz-elf-cha-mal	222	735	1.5	3.8	–
	RND	mon-hum-neu-mal	416	924	2.3	5.5	–
		tou-hum-neu-fem	119	599	1.0	2.8	–
		val-dwa-law-fem	304	1021	1.8	4.6	–
		wiz-elf-cha-mal	231	719	1.5	3.8	–
oracle	CNN	mon-hum-neu-mal	24	876	1.0	1.1	0.00
		tou-hum-neu-fem	9	674	1.0	1.1	0.00
		val-dwa-law-fem	18	1323	1.0	1.1	0.02
		wiz-elf-cha-mal	10	742	1.0	1.1	0.00
	RND	mon-hum-neu-mal	32	967	1.0	1.1	0.00
		tou-hum-neu-fem	13	811	1.0	1.1	0.00
		val-dwa-law-fem	26	1353	1.0	1.1	0.00
		wiz-elf-cha-mal	14	791	1.0	1.1	0.00

Table 6: Top five of the last 1000 episodes in the score task.

Model	Character	Killer Name	Score	Exp Lvl	Dungeon Lvl
CNN	mon-hum-neu-mal	warg	4408	7	9
		forest centaur	4260	7	11
		hill orc	2880	6	8
		gnome lord	2848	6	9
		crocodile	2806	6	8
	tou-hum-neu-fem	jackal	200	1	3
		hobgoblin	200	1	5
		hobbit	200	1	3
		giant rat	190	1	4
		large kobold	174	1	4
	val-dwa-law-fem	gnome lord	2176	5	12
		ape	1948	6	7
		gremlin	1924	5	11
		gnome king	1916	5	11
		vampire	1864	4	10
	wiz-elf-cha-mal	dingo	1104	3	9
		giant ant	1008	3	8
		gnome mummy	988	3	8
		coyote	988	3	9
		kicking a wall	972	3	8
RND	mon-hum-neu-mal	rothe	3664	5	7
		rotted dwarf corpse	3206	5	7
		leocrotta	2771	5	11
		winter wolf cub	2724	6	9
		starvation	2718	6	6
	tou-hum-neu-fem	grid bug	1432	1	7
		sewer rat	1253	1	4
		bolt of cold	1248	1	3
		goblin	1125	1	4
		goblin	1078	1	4
	val-dwa-law-fem	bugbear	2186	6	9
		starvation	2150	5	10
		ogre	2095	5	9
		rothe	2084	6	8
		Uruk-hai called Haiaigrisai of Aruka	2036	5	6
	wiz-elf-cha-mal	cave spider	1662	2	7
		iguana	1332	2	5
		starvation	1329	1	5
		starvation	1311	1	5
		gnome lord	1298	5	9

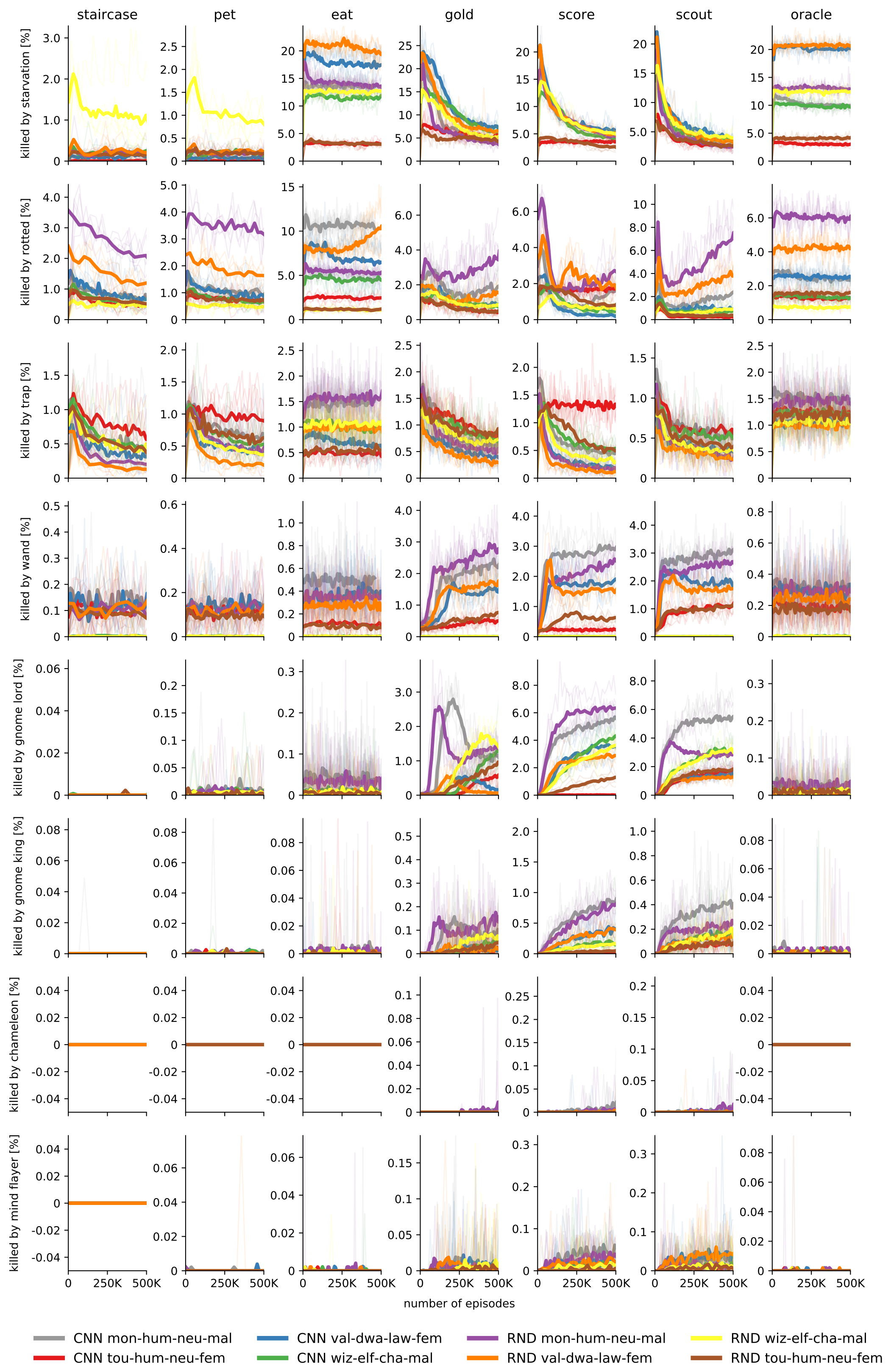
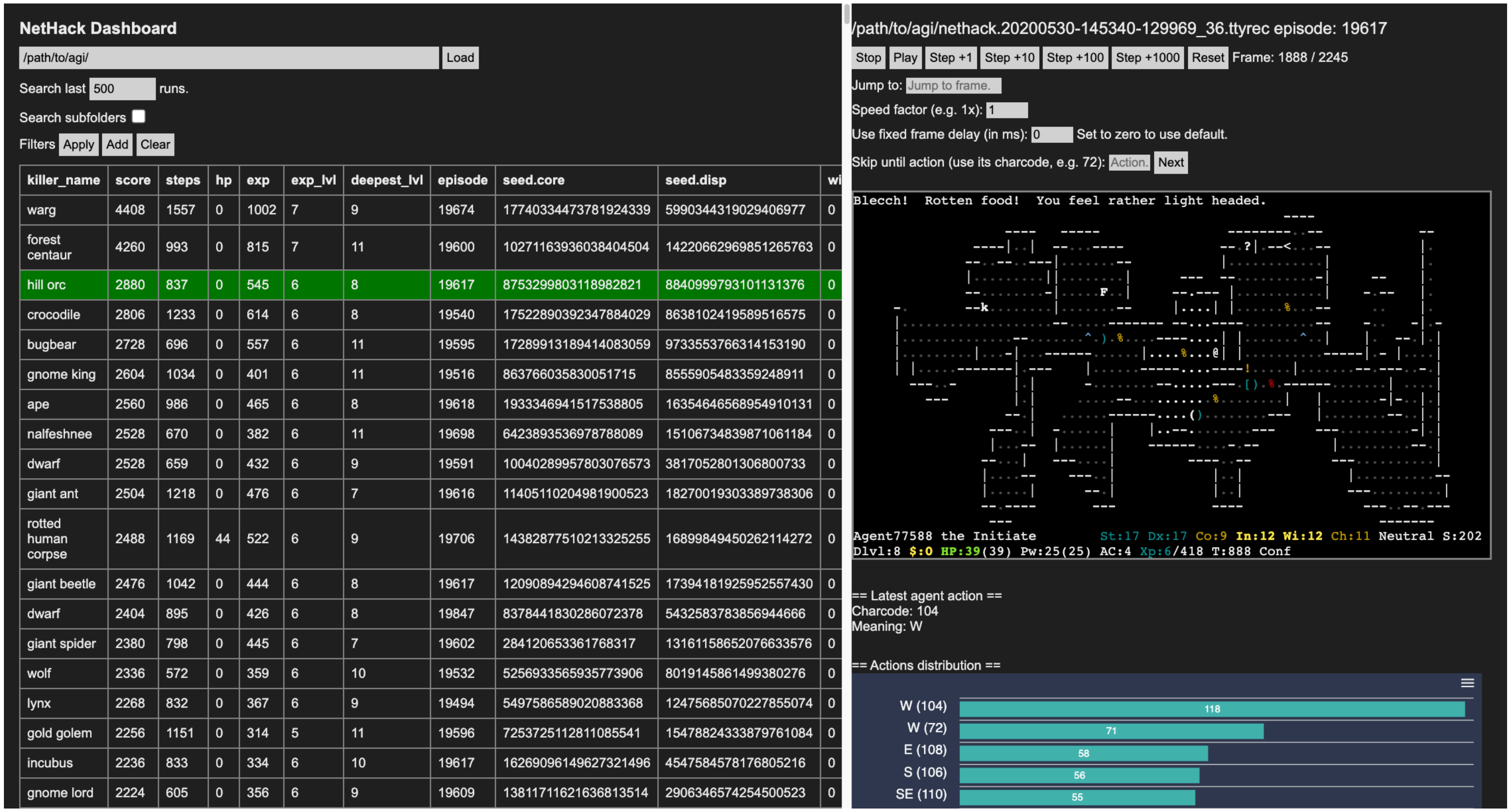


Figure 9: Analysis of different causes of death during training, averaged over the last 1000 episodes and over five runs.



NetHack Dashboard

/path/to/agi/ Load

Search last 500 runs.

Search subfolders

Filters Apply Add Clear

killer_name	score	steps	hp	exp	exp_lvl	deepest_lvl	episode	seed.core	seed.disp	wi
warg	4408	1557	0	1002	7	9	19674	17740334473781924339	5990344319029406977	0
forest centaur	4260	993	0	815	7	11	19600	10271163936038404504	14220662969851265763	0
hill orc	2880	837	0	545	6	8	19617	8753299803118982821	8840999793101131376	0
crocodile	2806	1233	0	614	6	8	19540	17522890392347884029	8638102419589516575	0
bugbear	2728	696	0	557	6	11	19595	17289913189414083059	9733553766314153190	0
gnome king	2604	1034	0	401	6	11	19516	863766035830051715	8555905483359248911	0
ape	2560	986	0	465	6	8	19618	1933346941517538805	16354646568954910131	0
nalfeshnee	2528	670	0	382	6	11	19698	6423893536978788089	15106734839871061184	0
dwarf	2528	659	0	432	6	9	19591	10040289957803076573	3817052801306800733	0
giant ant	2504	1218	0	476	6	7	19616	11405110204981900523	18270019303389738306	0
rotted human corpse	2488	1169	44	522	6	9	19706	14382877510213325255	16899849450262114272	0
giant beetle	2476	1042	0	444	6	8	19617	12090894294608741525	17394181925952557430	0
dwarf	2404	895	0	426	6	8	19847	8378441830286072378	5432583783856944666	0
giant spider	2380	798	0	445	6	7	19602	284120653361768317	13161158652076633576	0
wolf	2336	572	0	359	6	10	19532	5256933565935773906	8019145861499380276	0
lynx	2268	832	0	367	6	9	19494	5497586589020883368	12475685070227855074	0
gold golem	2256	1151	0	314	5	11	19596	7253725112811085541	15478824333879761084	0
incubus	2236	833	0	334	6	10	19617	16269096149627321496	4547584578176805216	0
gnome lord	2224	605	0	356	6	9	19609	13811711621636813514	2906346574254500523	0

/path/to/agi/nethack.20200530-145340-129969_36.ttyrec episode: 19617

Stop Play Step +1 Step +10 Step +100 Step +1000 Reset Frame: 1888 / 2245

Jump to: Jump to frame.

Speed factor (e.g. 1x): 1

Use fixed frame delay (in ms): 0 Set to zero to use default.

Skip until action (use its charcode, e.g. 72): Action. Next

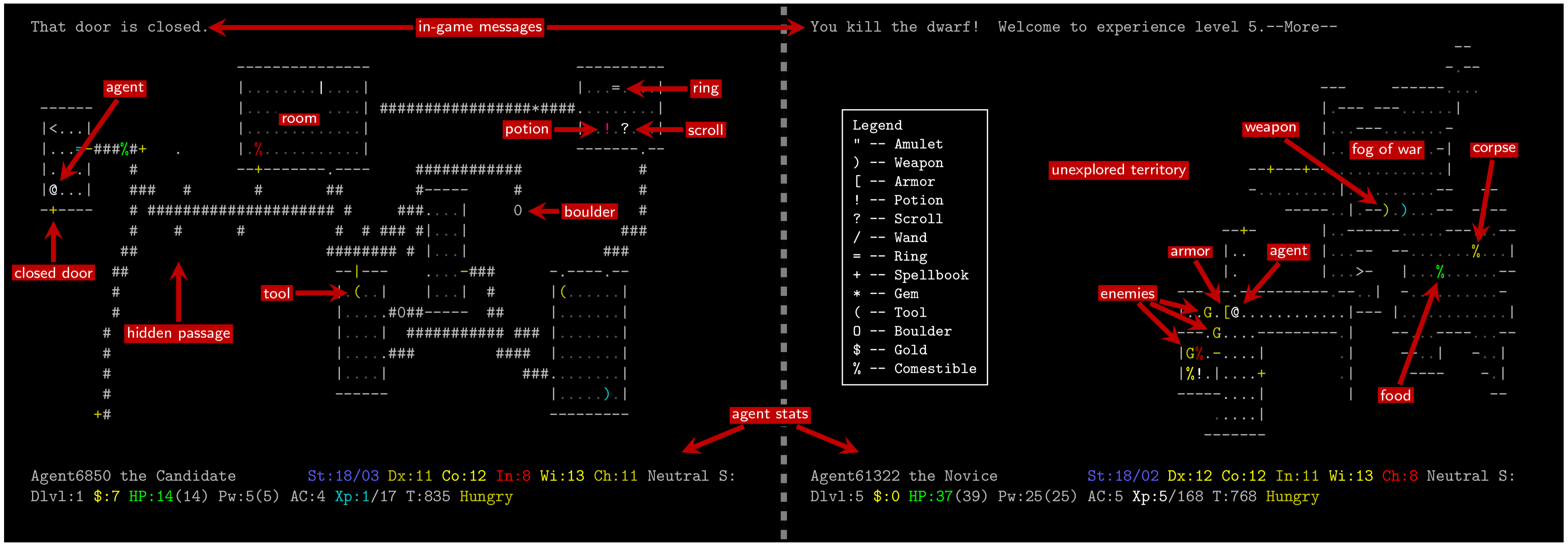
```
Blecch!  Rotten food!  You feel rather light headed.

Agent77588 the Initiate          St:17 Dx:17 Co:9 In:12 Wi:12 Ch:11 Neutral S:202
Dlvl:8 $:0 HP:39(39) Pw:25(25) AC:4 Xp:6/418 T:888 Conf
```

== Latest agent action ==
Charcode: 104
Meaning: W

== Actions distribution ==

W (104)	118
W (72)	71
E (108)	58
S (106)	56
SE (110)	55

Figure 10: Screenshot of the web dashboard included in the `NetHack Learning Environment`.



```
That door is closed.
```

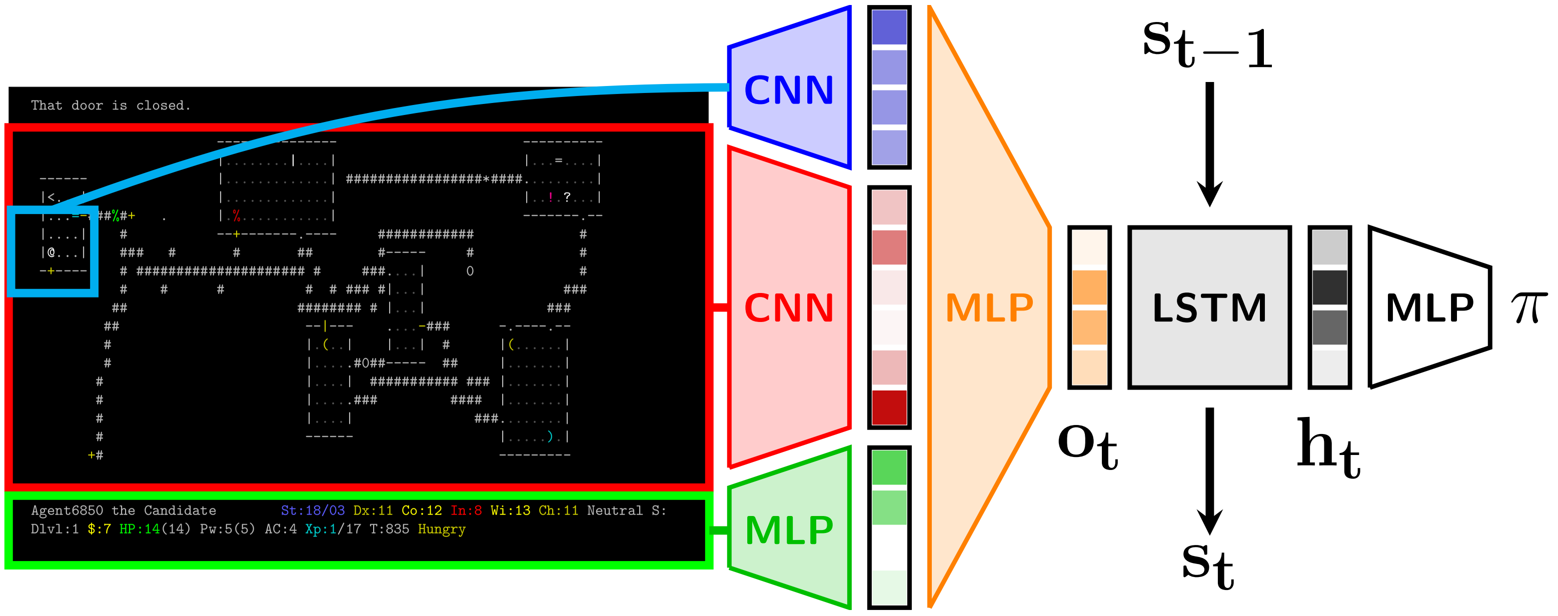
```
Agent6850 the Candidate         St:18/03 Dx:11 Co:12 In:8 Wi:13 Ch:11 Neutral S:
Dlvl:1 $:7 HP:14(14) Pw:5(5) AC:4 Xp:1/17 T:835 Hungry
```

```
You kill the dwarf!  Welcome to experience level 5.--More--
```

```
Legend
" -- Amulet
) -- Weapon
[ -- Armor
! -- Potion
? -- Scroll
/ -- Wand
= -- Ring
+ -- Spellbook
* -- Gem
( -- Tool
0 -- Boulder
$ -- Gold
% -- Comestible
```

```
Agent61322 the Novice           St:18/02 Dx:12 Co:12 In:11 Wi:13 Ch:8 Neutral S:
Dlvl:5 $:0 HP:37(39) Pw:25(25) AC:5 Xp:5/168 T:768 Hungry
```

Figure 11: Annotated example of an agent at two different stages in NetHack (Left: a procedurally generated first level of the Dungeons of Doom, right: Gnomish Mines).



```
That door is closed.
```

```
Agent6850 the Candidate        St:18/03 Dx:11 Co:12 In:8 Wi:13 Ch:11 Neutral S:
Dlvl:1 $:7 HP:14(14) Pw:5(5) AC:4 Xp:1/17 T:835 Hungry
```

Figure 12: Overview of the core architecture of the baseline models released with `NLE`.