BEDD: The MineRL BASALT Evaluation and Demonstrations Dataset for Training and Benchmarking Agents that Solve Fuzzy Tasks

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Abstract

The MineRL BASALT competition has catalyzed advances in learning from human feedback through four hard-to-specify tasks in Minecraft, such as create and photograph a waterfall. Building on two successful years of competitions, we introduce the BASALT Evaluation and Demonstrations Dataset (BEDD), a resource for algorithm development and performance assessment. BEDD contains 26 million image-action pairs from nearly 14,000 videos of human players completing the BASALT tasks. It also includes over 3,000 dense pairwise human evaluations of both human and algorithmic agents, complete with natural language justifications for the preference assessments. Collectively, these components are designed to support the development and evaluation of multi-modal AI systems in the context of Minecraft. The code and data are available at: https://github.com/minerllabs/basalt-benchmark.

1. Introduction

In recent years, multi-modal foundation models (MFMs) have advanced the field of machine learning by integrating diverse data modalities such as text, images, and actions (Baker et al., 2022; Alayrac et al., 2022; Ramesh et al., 2021). The integration of different modalities enables MFMs to better interpret complex input, making them highly effective for applications involving embodied agents. However, because agents are often still evaluated on tasks with well-defined objectives, there exists a gap for training and evaluating agents on real-world tasks with ill-defined, or fuzzy, goals.

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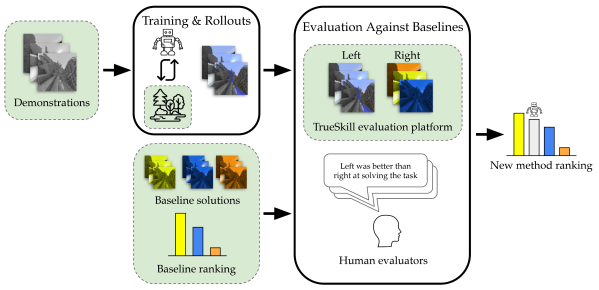


Figure 1: Overview of the BASALT benchmark, with the components of the included datasets highlighted in green. Agents are evaluated through video recordings of task completions. Our contributions include datasets for both training agents to perform fuzzy tasks and for evaluating agents with human evaluators. We also contribute code for further benchmarking and data analysis.

Learning from human feedback (LfHF) (Arumugam et al., 2019; Christiano et al., 2017; Shah et al., 2021; Jeon et al., 2020) is a technique that can help these multi-modal models accomplish these fuzzy tasks. This feedback can take on various modalities — such as corrections and comparisons — to guide the agent toward more performant and aligned behavior. By incorporating human feedback, models can be trained to prioritize human intent, which is essential for tasks that are subjective or difficult to specify with traditional reward signals.

Despite the potential of LfHF, most algorithms and models are evaluated in standard reinforcement learning benchmarks (Bellemare et al., 2013; Cobbe et al., 2019; Duan et al., 2016; Tassa et al., 2018) with well-defined goals and rewards. These tasks do not emphasize the critical role of human feedback in task identification. The MineRL BASALT challenge (Shah et al., 2021) addressed this gap by requiring human feedback for task identification due to the inherently fuzzy nature of its tasks. However, despite two years of BASALT competitions, no agents have yet matched human performance (Milani et al., 2023), emphasizing the need to establish the BASALT tasks as a consistent, standardized benchmark.

Figure 2: Two example images of the visual input received by the agent. The agent must interpret these pixel observations and use regular keyboard and mouse actions to perform the complex BASALT tasks and subtasks, such as navigating through the game world, interacting with objects, and crafting items.

To support this benchmark we introduce the BASALT Evaluation and Demonstrations Dataset (BEDD), an open and accessible dataset for learning to solve fuzzy tasks from human feedback. Shown in Figure 1, this dataset consists of three main ingredients: (1) the `Demonstrations Dataset`, (2) the `Evaluation Dataset`, and (3) supporting code for utilizing and analyzing the data. The `Demonstrations Dataset` comprises over 26 million image-action pairs from 14,000 videos of action-labeled Minecraft gameplay of human players completing BASALT tasks. To illustrate, Figure 2 provides two example images.

To enable rigorous evaluation using human judgments, we present the `Evaluation Dataset`, derived from the most recent BASALT competition (Kanervisto et al., 2022). The `Evaluation Dataset` features over 3,000 dense pairwise human evaluations of agent performance on BASALT tasks. Each evaluation includes pairwise comparisons of agent capabilities and additional assessments such as human-likeness. Taken together, these comparisons result in 27,905 comparison points across 15 different AI agents and 2 human players. This dataset functions as a leaderboard, allowing researchers to benchmark new algorithms and models against a diverse set of agents without the need for repeated costly human evaluations.

To streamline the use of the datasets, we provide a codebase that facilitates training new models using the demonstration dataset and evaluating them against the provided leaderboard. Alongside these resources, we offer detailed documentation and tools for analyzing the data and algorithms, all with the goal of guiding algorithm development and evaluation. Our overarching goal is to expedite the development and assessment of algorithms and models that can learn from diverse modalities of human feedback. By providing these resources, we aim to drive progress toward the creation of multi-modal agents that align more closely with human intent.

Related Work Minecraft is as a valuable platform for machine learning research (Hafner et al., 2023; Lifshitz et al., 2023; Smit & Smuts, 2023) due to its complex, dynamic environment and customizable game engine. As a result, numerous competitions and benchmarks (Grbic et al., 2021; Hafner, 2021; Johnson et al., 2016; Salge et al., 2018) have been developed to improve AI capabilities. These often include tasks with concrete or programmatic reward functions, such as learning to collect diamonds in a sample-efficient way (Guss et al., 2019), multi-agent learning of cooperative and competitive tasks (Perez-Liebana et al., 2019), and more (Fan et al., 2022). A more detailed comparison to Minedojo is in Appendix F.1. In contrast, the BASALT challenge emphasizes tasks that are challenging to specify through a reward function alone. Other research has focused on natural language as a specific modality for communicating intent (Gray et al., 2019; Kiseleva et al., 2021; 2022; Narayan-Chen et al., 2019); instead, the BASALT challenge aims to promote the development of algorithms that learn from various *modalities* of human feedback, including but not limited to natural language.

2. BASALT Dataset

We now introduce BEDD, our extensive dataset of human demonstrations and algorithm evaluations. This dataset consists of the following components. First, it includes the `Demonstrations Dataset`, a set of 13,928 videos (state-action pairs) demonstrating largely successful task completion attempts of the reward-free tasks, Second, it includes the `Evaluation Dataset`, a set of 3,049 dense pairwise comparisons of algorithmic and human agents attempting to complete the BASALT tasks. Finally, it includes code for utilizing and analyzing these datasets for developing LfHF algorithms. For a full datasheet (Gebru et al., 2021a), please see Appendix B. In this section, we provide relevant details about each of the three components in turn.

Task	Videos	Episodes	Hours	Size	Ep. len, s	Success %
`FindCave`	5,466	5,466	91	165GB	60	93%
`MakeWaterfall`	4,230	4,176	97	175GB	84	98%
`CreateVillageAnimalPen`	2,833	2,708	89	165GB	119	95%
`BuildVillageHouse`	1,399	778	85	146GB	391	92%
Total	13,928	13,128	361	651GB	99	95%

Table 1: High-level demonstration data statistics decomposed by task. Episode length is the average episode length in seconds. A demonstration is counted as success if the player manually ended the episode instead of dying or timing-out. Importantly, the data consists of a 95% success rate overall, with no task incuring less than a 92% success rate.

2.1. `Demonstrations Dataset`: Completing Reward-Free Tasks in Minecraft

The `Demonstrations Dataset` consists of 361 hours of human demonstrations of the reward-free BASALT tasks. This large-scale dataset, totaling 651 GB, provides trajectories featuring 26 million high-resolution (640x360 RGB) image observations and precise keyboard and mouse actions for each frame. Table 1 decomposes the high-level data statistics by task, and more details about this dataset are in Appendix C. To generate each trajectory, the player's character is placed in the world described by the task. They are provided with natural language description of the task.

The inclusion of natural language instructions contributes to the multi-modality of the dataset because it enables the development of agents that can understand and follow human instructions. This multi-modal data — visual, action-based, and linguistic — facilitates the creation of AI agents that can learn from human feedback to generate more aligned behavior.

2.2. `Evaluation Dataset`: Evaluating BASALT Agents

The `Evaluation Dataset` is the result of 273 hours of dedicated human labeling effort by 65 unique MTurk workers. We presented the recordings of two agents completing the same task to human evaluators, and asked them to choose which one more successfully completed the task. Table 2 decomposes the dataset by task. Each evaluation in the dataset consists of the following: (i) the names of the two agents used in the comparison, (ii) the corresponding videos shown to the human judge, (iii) an answer to the question of which player is better overall (Left, Right, Draw), (iv) a natural-language justification of this choice, (v) answers to at least one specific question about concrete achievements by the players (Left, Right, or Both), and answers to 4-7 comparative questions, such as which agent was more human-like (Left, Right, Draw, N/A). The dataset comprises 27,905 comparisons across various factors.

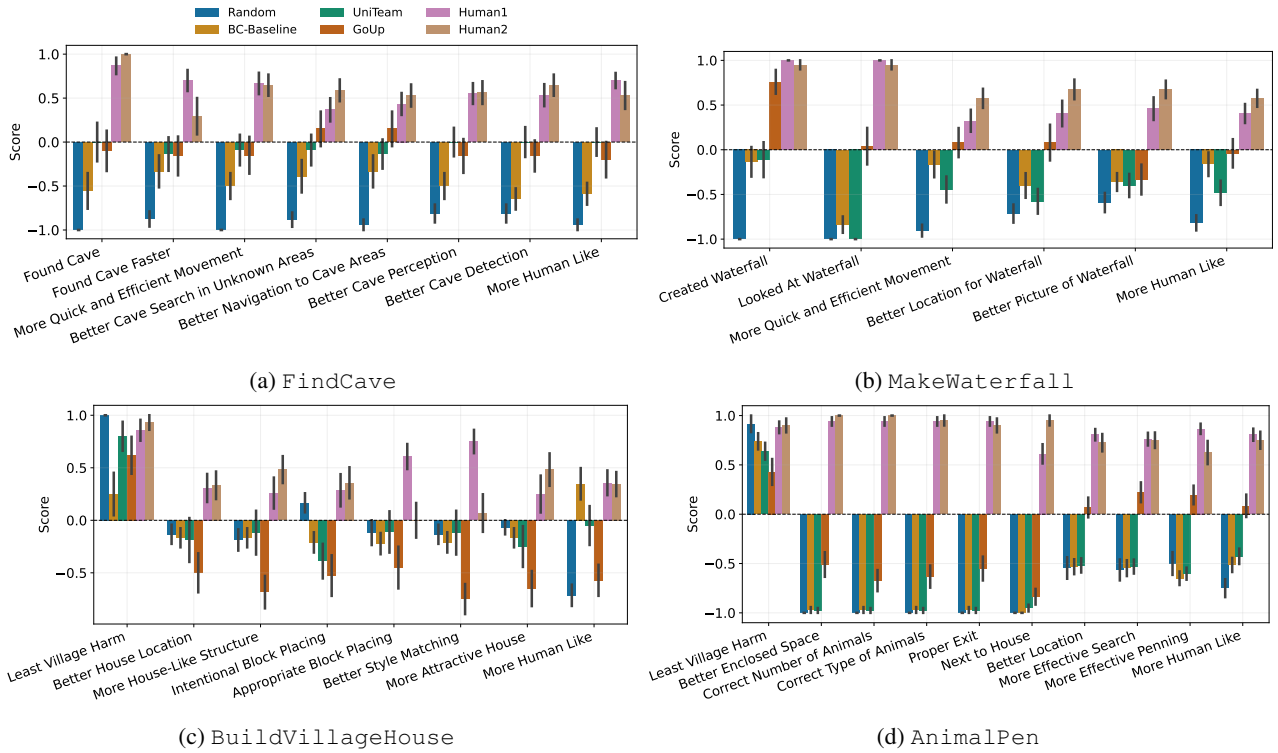
Task	Comparis.	Hours
`FindCave`	722	60
`MakeWaterfall`	682	56
`CreateVillageAnimalPen`	914	81
`BuildVillageHouse`	731	76
Total	3,049	273

Table 2: High-level evaluation data statistics decomposed by task. We report the total number of agent-agent comparisons and the human labor hours dedicated to conducting the evaluations.

Analysis We now investigate the comparisons between agents, summarizing each question into a single factor for clarity. For example, we use "More Human Like" to capture the question, "Which player seemed more human-like (rather than a bot or computer player)?". The summarized results are shown in Figure 3. Importantly, no AI system outperforms humans on any factors, indicating substantial room for improvement. When analyzing future algorithms, we suggest preserving this decomposition for validating the sensibility of responses and achieving a fine-grained, nuanced understanding of agent strengths and weaknesses. An interesting discovery from our decomposed evaluation criteria is illustrated in Figure 3b. Although Team GoUp's agent can create waterfalls at a level comparable to humans, it falls short in other areas, such as selecting a good location and taking high-quality photographs. Evaluating success merely based on the binary condition of creating a waterfall overlooks these critical aspects of the agent's performance.

2.3. Codebase: Benchmarking Algorithms on BASALT

To assist with the development of LfHF algorithms and automated evaluations, we share a codebase containing an example of training a LfHF algorithm with the shared data in the `Demonstrations Dataset`and the tools for performing evaluations presented in this work. The code is a Python-installable library, which allows the functionality to be imported into other codebases for use in research.



(a) `FindCave` (b) `MakeWaterfall`

(c) `BuildVillageHouse` (d) `AnimalPen`

Figure 3: Comparison of baseline solutions, top BASALT 2022 competition solutions, and humans on decomposed evaluations. Bars represent average score, and error bars represent standard error. Higher is better: it means that agent exhibited more of that factor according to human judges. The human players generally outperform all AI agents on all factors, indicating that the BASALT challenge is still open.

Inspired by the success of an imitation-learning approach[1] in the BASALT 2022 competition, we provide an example of training a behavior cloning model as the base algorithm with the rich embeddings from the Video PreTraining (VPT) (Baker et al., 2022) model as input. VPT is a large and powerful Minecraft foundation model that is difficult to fine-tune on new tasks due to its size. The final output is a set of videos to use in evaluations against the shared recordings of other agents in the `Evaluation Dataset`.

Because setting up human evaluations is time-consuming, we share our platform for conducting human evaluations. The platform is served as a webpage backed by a simple Python-based webserver. The platform includes a flexible API to add or remove agents from the set of comparisons. After a simple setup, researchers can point human evaluators to a specific URL to provide answers. We provide examples of the form that the human evaluators will see in Appendix D. We also share code to create figures of the TrueSkill ratings (and all analyses), given the answers contained in the resulting database. This whole process serves as an end-to-end example of creating a new method with `Demonstrations Dataset`, then evaluating it with data from `Evaluation Dataset`.

[1] https://github.com/shuishida/minerl_2022

3. Conclusion

We proposed BEDD, a large and accessible dataset to facilitate algorithm development for the BASALT benchmark on learning from human feedback. BEDD consists of three key parts: the `Demonstrations Dataset`, the `Evaluation Dataset`, and the codebase. To our knowledge, this dataset is the largest of its type: one that supports both training and evaluating LfHF agents on tasks with hard-to-specify reward functions.

We believe that BEDD is well-positioned to enable and unlock a wide range of research opportunities into LfHF and multi-modality. For example, researchers can explore multi-modal alignment strategies for AI agents with human intent. Rather than asking for pairwise preferences over trajectories, agents could additionally summarize their behavior in natural language for multi-modal feedback and alignment. Furthermore, the natural language task descriptions can be paired with the trajectories in the `Demonstrations Dataset` to better align text-image task completion representations. Overall, we hope that this dataset can be used to promote the training of generally capable, multi-modal AI agents that are better aligned with human intent using various modalities of human feedback.

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References

Alayrac, J.-B., Donahue, J., Luc, P., Miech, A., Barr, I., Hasson, Y., Lenc, K., Mensch, A., Millican, K., Reynolds, M., et al. Flamingo: a visual language model for few-shot learning. *Advances in neural information processing systems*, 35:23716–23736, 2022.

Arumugam, D., Lee, J. K., Saskin, S., and Littman, M. L. Deep reinforcement learning from policy-dependent human feedback. *arXiv preprint arXiv:1902.04257*, 2019.

Baker, B., Akkaya, I., Zhokov, P., Huizinga, J., Tang, J., Ecoffet, A., Houghton, B., Sampedro, R., and Clune, J. Video pretraining (vpt): Learning to act by watching unlabeled online videos. *Advances in Neural Information Processing Systems*, 35:24639–24654, 2022.

Bellemare, M. G., Naddaf, Y., Veness, J., and Bowling, M. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279, 2013.

Christiano, P. F., Leike, J., Brown, T., Martic, M., Legg, S., and Amodei, D. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30, 2017.

Cobbe, K., Hesse, C., Hilton, J., and Schulman, J. Leveraging procedural generation to benchmark reinforcement learning, 2019.

Devlin, S., Georgescu, R., Momennejad, I., Rzepecki, J., Zuniga, E., Costello, G., Leroy, G., Shaw, A., and Hofmann, K. Navigation turing test (ntt): Learning to evaluate human-like navigation. In *International Conference on Machine Learning*, pp. 2644–2653. PMLR, 2021.

Duan, Y., Chen, X., Houthooft, R., Schulman, J., and Abbeel, P. Benchmarking deep reinforcement learning for continuous control. In *International conference on machine learning*, pp. 1329–1338. PMLR, 2016.

Elo, A. E. *The rating of chessplayers, past and present*. Arco Pub., 1978.

Fan, L., Wang, G., Jiang, Y., Mandlekar, A., Yang, Y., Zhu, H., Tang, A., Huang, D. A., Zhu, Y., and Anandkumar, A. Minedojo: Building open-ended embodied agents with internet-scale knowledge. *arXiv preprint arXiv:2206.08853*, 2022.

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé III, H., and Crawford, K. Datasheets for datasets. *Communications of the ACM*, 64(12):86–92, 2021a. ISSN 1557-7317. doi: 10.1145/3458723. URL http://dx.doi.org/10.1145/3458723.

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé III, H., and Crawford, K. Datasheets for datasets. *Communications of the ACM*, 64(12):86–92, 2021b. ISSN 1557-7317. doi: 10.1145/3458723. URL http://dx.doi.org/10.1145/3458723.

Gray, J., Srinet, K., Jernite, Y., Yu, H., Chen, Z., Guo, D., Goyal, S., Zitnick, C. L., and Szlam, A. Craftassist: A framework for dialogue-enabled interactive agents. *arXiv preprint arXiv:1907.08584*, 2019.

Grbic, D., Palm, R. B., Najarro, E., Glanois, C., and Risi, S. Evocraft: A new challenge for open-endedness. In *Applications of Evolutionary Computation: 24th International Conference*, 2021.

Guss, W. H., Codel, C., Hofmann, K., Houghton, B., Kuno, N., Milani, S., Mohanty, S., Liebana, D. P., Salakhutdinov, R., Topin, N., et al. Neurips 2019 competition: the minerl competition on sample efficient reinforcement learning using human priors. *The 33rd Conference on Neural Information Processing Systems (NeurIPS) Competition Track*, 2019.

Hafner, D. Benchmarking the spectrum of agent capabilities. *arXiv preprint arXiv:2109.06780*, 2021.

Hafner, D., Pasukonis, J., Ba, J., and Lillicrap, T. Mastering diverse domains through world models. *arXiv preprint arXiv:2301.04104*, 2023.

Herbrich, R., Minka, T., and Graepel, T. Trueskill™: a bayesian skill rating system. *Advances in neural information processing systems*, 19, 2006.

Jeon, H. J., Milli, S., and Dragan, A. Reward-rational (implicit) choice: A unifying formalism for reward learning. *Advances in Neural Information Processing Systems*, 33: 4415–4426, 2020.

Johnson, M., Hofmann, K., Hutton, T., and Bignell, D. The malmo platform for artificial intelligence experimentation. In *Proceedings of the International Joint Conference on Artificial Intelligence*, pp. 4246–4247, 2016.

Kanervisto, A., Scheller, C., and Hautamäki, V. Action space shaping in deep reinforcement learning. In *2020 IEEE Conference on Games (CoG)*, pp. 479–486. IEEE, 2020.

Kanervisto, A., Milani, S., Ramanauskas, K., Galbraith, B. V., Wang, S. H., Houghton, B., Mohanty, S., and Shah, R. The MineRL BASALT competition on learning from human feedback. In *The 36th Conference on Neural Information Processing Systems (NeurIPS) Competition Track*, 2022.

Kiseleva, J., Li, Z., Aliannejadi, M., Mohanty, S., ter Hoeve, M., Burtsev, M., Skrynnik, A., Zholus, A., Panov, A., Srinet, K., et al. Neurips 2021 competition iglu: Interactive grounded language understanding in a collaborative environment. *arXiv preprint arXiv:2110.06536*, 2021.

Kiseleva, J., Skrynnik, A., Zholus, A., Mohanty, S., Arabzadeh, N., Côté, M.-A., Aliannejadi, M., Teruel, M., Li, Z., Burtsev, M., ter Hoeve, M., Volovikova, Z., Panov, A., Sun, Y., Srinet, K., Szlam, A., and Awadallah, A. Iglu 2022: Interactive grounded language understanding in a collaborative environment at neurips 2022. *arXiv preprint arXiv:2205.13771*, 2022.

Lifshitz, S., Paster, K., Chan, H., Ba, J., and McIlraith, S. Steve-1: A generative model for text-to-behavior in minecraft. *arXiv preprint arXiv:2306.00937*, 2023.

Malato, F., Leopold, F., Raut, A., Hautamäki, V., and Melnik, A. Behavioral cloning via search in video pretraining latent space. *arXiv preprint arXiv:2212.13326*, 2022.

Milani, S., Kanervisto, A., Ramanauskas, K., Schulhoff, S., Houghton, B., Mohanty, S., Galbraith, B., Chen, K., Song, Y., Zhou, T., et al. Towards solving fuzzy tasks with human feedback: A retrospective of the minerl basalt 2022 competition. *arXiv preprint arXiv:2303.13512*, 2023.

Narayan-Chen, A., Jayannavar, P., and Hockenmaier, J. Collaborative dialogue in Minecraft. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 5405–5415, July 2019. doi: 10.18653/v1/P19-1537. URL https://aclanthology.org/P19-1537.

Patterson, A., Neumann, S., White, M., and White, A. Empirical design in reinforcement learning. *arXiv preprint arXiv:2304.01315*, 2023.

Perez-Liebana, D., Hofmann, K., Mohanty, S. P., Kuno, N., Kramer, A., Devlin, S., Gaina, R. D., and Ionita, D. The multi-agent reinforcement learning in Malmö (MARLÖ) competition. *arXiv preprint arXiv:1901.08129*, 2019.

Ramesh, A., Pavlov, M., Goh, G., Gray, S., Voss, C., Radford, A., Chen, M., and Sutskever, I. Zero-shot text-to-image generation. In *International conference on machine learning*, pp. 8821–8831. Pmlr, 2021.

Salge, C., Green, M. C., Canaan, R., and Togelius, J. Generative design in minecraft (gdmc) settlement generation competition. In *Proceedings of the 13th International Conference on the Foundations of Digital Games*, pp. 1–10, 2018.

Shah, R., Wild, C., Wang, S. H., Alex, N., Houghton, B., Guss, W., Mohanty, S., Kanervisto, A., Milani, S., Topin, N., et al. The minerl basalt competition on learning from human feedback. In *The 35th Conference on Neural Information Processing Systems (NeurIPS) Competition Track*, 2021.

Smit, R. and Smuts, H. Game-based learning-teaching artificial intelligence to play minecraft: a systematic. *Proceedings of Society*, 93:188–202, 2023.

Tassa, Y., Doron, Y., Muldal, A., Erez, T., Li, Y., de Las Casas, D., Budden, D., Abdolmaleki, A., Merel, J., Lefrancq, A., et al. Deepmind control suite. *arXiv preprint arXiv:1801.00690*, 2018.

Task	Evaluation Environment Seeds
`MineRLBasaltFindCave-v0`	14169, 65101, 78472, 76379, 39802, 95099, 63686, 49077, 77533, 31703, 73365
`MineRLBasaltMakeWaterfall-v0`	95674, 39036, 70373, 84685, 91255, 56595, 53737, 12095, 86455, 19570, 40250
`MineRLBasaltCreateVillageAnimalPen-v0`	21212, 85236, 14975, 57764, 56029, 65215, 83805, 35884, 27406, 5681265, 20848
`MineRLBasaltBuildVillageHouse-v0`	52216, 29342, 67640, 73169, 86898, 70333, 12658, 99066, 92974, 32150, 78702

Table 3: Evaluation environment seeds for each task.

A. BASALT Benchmark

A.1. Evaluation Protocol

To fairly compare algorithms on a benchmark, the parameters of that benchmark must be concretely defined. Previously, many techniques claimed to solve MineRL `ObtainDiamond`. Often, these successes involved giving the agent access to the full game state instead of pixel observations, building in human priors through extensive action shaping, or simplifying the underlying environment dynamics. Changes like these should be clearly stated and applied equally to compared methods. To avoid such discrepancies in the future, we specify some methodological best practices when using the BASALT benchmark: i) only pixel observations provided by the four environments should be used, ii) the environments should not be modified in any way, iii) action shaping (Kanervisto et al., 2020) is permitted, as long as it applied to all methods, iv) algorithms should be evaluated with TrueSkill (Herbrich et al., 2006) using the specific hold-out test seeds provided in Appendix A, and v) the final evaluations must be conducted with human evaluators. For further guidance on how to fairly compare algorithms, we refer the reader to recent work (Patterson et al., 2023).

We summarize the evaluation protocol for BASALT here:

- Only pixel observations provided by the four environments should be used. You may read other observations from the environment for developing purposes, but the agent (or the system acting) should *only* see the image pixel observations.
- The environments should not be modified in any way.
- Action shaping is okay, as long as it is done in line with other methods.
- Algorithms should be evaluated with TrueSkill using the specific hold-out environment test seeds provided below.
- The final evaluations must be conducted with human evaluators.
- The final evaluation must be conducted using the random seeds detailed in Table 3.

A.2. TrueSkill Procedure

Please see the previous specification (Milani et al., 2023) and the evaluation server code.

A.3. Discussion of Evaluation Metrics

We choose TrueSkill as the metric for assessing the performance of agents on the BASALT task. In this section, we provide a detailed comparison of TrueSkill with other alternatives. For a summary of these comparisons, see Table 4.

TrueSkill vs. Elo The Elo rating system (Elo, 1978) is a popular zero-sum system that was initially created for chess. The gain in rating points of a player, or algorithm, after a win is equivalent to the loss in points for their competitor. The

	TrueSkill	Elo	Individual Analysis
Easily compare algorithms	✓	✓	✗
Handle multi-algorithm comparisons	✓	✗	✗
Provide uncertainty estimates	✓	✗	✗

Table 4: Comparison of different potential evaluation systems for the BASALT benchmark.

outcome of the game and the difference in ratings between algorithms influence the specific number of points transferred. Elo was designed for two-player games, whereas TrueSkill can handle multi-player games. In the case of BASALT, this means that human evaluations can be performed over more than two algorithms, which may be more cost-effective for researchers to deploy. Furthermore, Elo does not incorporate uncertainty estimates for an algorithm's performance, whereas TrueSkill does. This uncertainty estimate not only makes results easier to interpret but also enables more adaptive ratings: performance estimates more quickly adjust for new algorithms because of high uncertainty and less quickly adjust for more established algorithms because of lower uncertainty.

TrueSkill vs. Independent Algorithm Performance Assessment Due to the difficulty of the BASALT tasks, independently assessing the performance of an algorithm is challenging. For example, in the absence of any comparisons, how would one assess the performance of an algorithm that only partially completes a task? How could we ensure that the score is calibrated for the assessment of other algorithms? These standalone assessments do not offer ways to directly compare multiple algorithms or adjust the rating of an algorithm based on its performance over time, as TrueSkill and Elo do.

A.4. Task Descriptions

Here, we provide more detailed descriptions of the four reward-free BASALT tasks.

BuildVillageHouse The agent spawns in a village, which is a naturally-occurring structure in Minecraft that contains houses and other buildings, villagers, and other structures. The style of the buildings depends on the biome in which the village is generated. The agent must build a new house for itself in the same style as the other village houses; however, it must not damage the village. To assist agents with achieving this task, we provide the agent with the materials required to build a house in a variety of village types.

CreateVillageAnimalPen The agent spawns in a village. It is tasked with building an animal pen next to one of the houses in the village. It must then corral a pair of farm animals (chickens, cows, sheep, or pigs) into the pen. In Minecraft, players perform this task to breed the animals to create a steady source of food. We provide the agent with materials to use to build the pen. Because different animals are lured with different types of food, we also equip the agent with the food to lure any of the animals.

MakeWaterfall The agent must create a waterfall and subsequently take a picture of it. The agent spawns in an extreme hills biome to enable easier task completion. Because taking a photograph is not a supported task in Minecraft, we implement it by having the agent throw a snowball. We interpret the moment that the agent throws it as its photograph. The challenge with this task is it involves both the evaluation of task completion and human aesthetic preferences. We provide the agent with the tools needed for efficiently moving around the often-treacherous biome, a snowball for taking a picture, and two buckets of water to construct the waterfall.

FindCave The objective of this task is for the agent to discover a naturally-generated cave. The agent spawns in a plains biome and must explore the surrounding area to find a cave.

B. Datasheet for BEDD

We present a datasheet (Gebru et al., 2021b) for BEDD, which includes details on our 651GB human demonstrations dataset (Demonstrations Dataset) and our TrueSkill evaluations dataset (Evaluation Dataset).

B.1. Motivation

For what purpose was the dataset created?

Originally, both datasets were created for the BASALT 2022 competition (Milani et al., 2023). The Demonstrations Dataset was provided as a training dataset for competitors, while the Evaluation Dataset was generated at the end of the competition when evaluating submissions. Below, we describe further purposes for the datasets.

Demonstrations Dataset We believe that this set of successful demonstrations could be useful for training machine learning algorithms to perform complex tasks in Minecraft. All task completions can be thought of as having a positive label denoting successful completion. The dataset could serve as a basis for generating pretrained embeddings, similar to the VPT method. These embeddings could be further finetuned with additionally collected demonstrations, corrections, or other feedback modalities to further refine the behavior. This dataset could also be leveraged for a wealth of insights. Since these tasks are complex and require sequential dependencies, one could analyze and extract the crucial subtasks required to complete the full task. This analysis would support the development of various hierarchical methods. This task decomposition would support further subtask-specific analysis. Understanding the required time to complete each subtask would help identify which tasks take longer or are completed more quickly. This information could provide meaningful insights into task difficulty.

Evaluation Dataset We envision this dataset to be used for both analysis and development. The detailed task-specific questions may be useful for understanding which factors most strongly influence overall assessments of behavior. We envision this dataset to be used to develop reward models that better align with human preferences. This aim aligns with the BASALT benchmark of both understanding and utilizing human preferences to solve fuzzy tasks. Training reward models on pairwise comparisons over algorithms may reveal the latent structure of human preferences over the task space. A more nuanced understanding would emerge as more of the task-specific questions and long-form justification of responses are processed and understood. This training regime would promote the development of more intuitive and human-aligned algorithms.[2] Furthermore, we envision that this dataset could provide a wealth of insights into more general human preferences, which could prove invaluable when transferred or used to warm-start reward models in different domains. By identifying these underlying general preferences, we could inform the design of more universally acceptable and effective AI systems (bearing in mind individual, cultural, and other important differences). As an example, people may favor algorithms that show a more structured, stepwise approach to problem-solving tasks. One interpretation of this preference is orderly progression, which could help design algorithms that behave in ways that are more interpretable.

Who created the dataset?

The dataset was created by Anssi Kanervisto (Microsoft Research), Stephanie Milani (Carnegie Mellon University), Karolis Ramanauskas (University of Bath), Byron V. Galbraith (Seva Inc.), Steven H. Wang (ETH Zürich), Sander Schulhoff (University of Maryland), Brandon Houghton (OpenAI), Sharada Mohanty (AIcrowd), and Rohin Shah. The dataset was not created on the behalf of any entity.

Who funded the creation of the dataset?

The FTX Future Fund Regranting Program, Encultured.ai, and Microsoft funded the creation of the Evaluation Dataset, prizes, and compute. OpenAI sponsored the creation of the Demonstrations Dataset.

B.2. Composition

What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?

[2]We again stress that the goal is not necessarily to *completely replace* the human element involved in the evaluation of these algorithms. Instead, automated evaluations serve as a way to sidestep the issues with existing evaluation methods, which involve laborious manual assessments or rely on predefined metrics that may fail to capture all aspects of an algorithm's performance. With a dataset of human-based comparisons, we can train machine learning models to predict the superior algorithm for a given task, thereby reducing the need for extensive manual evaluations.

The `Demonstrations Dataset` contains videos of agent trajectories and associated actions taken. The `Evaluation Dataset` contains videos of trajectories and human evaluations on multiple factors such as "Found Cave" or "Least Village Harm".

Please refer to Section 2 for more information. Table 1 contains a breakdown of information on the `Demonstrations Dataset` and Table 2 contains a breakdown of information on the `Evaluation Dataset`. Further information is in Appendices C.2 and D.

Is there a label or target associated with each instance?

The `Evaluation Dataset` contains labeled data. Agents are evaluated across a range of quantitative and qualitative criteria. Some of these, such as "Found Cave" (Appendix E) can be considered to be labels. Additionally, the `Demonstrations Dataset` contains videos of trajectories paired with 'labels' of the action(s) being executed at each frame. Our codebase contains files that describe how each trajectory ends (e.g., by ESC key or death.).

Is any information missing from individual instances?

Not to our knowledge.

Are there recommended data splits (e.g., training, development/validation, testing)?

No.

Are there any errors, sources of noise, or redundancies in the dataset? There are instances of contractors doing a task incorrectly in the `Demonstrations Dataset`. For example, in some instances, contractors found a cave and did not stop the episode or made a waterfall and stared at it instead of ending the episode. Please see Appendix C.2 for more possible issues. We did not manually check the entire dataset, so it may contain additional anomalous activities.

Do/did we do any data cleaning on the dataset?

We did not. All data is presented exactly as collected. We provide information on which demonstrations may contain human errors in the repository. This information may be then used to conduct data cleaning by the end user of the dataset.

B.3. Collection Process

How was the data associated with each instance acquired?

The `Demonstrations Dataset` was collected using a modded, closed source Minecraft version that recorded users' game frames and actions. Contractors watched agent gameplay side by side in order to evaluate them and create the `Evaluation Dataset`.

Who was involved in the data collection process and how were they compensated?

For the `Demonstrations Dataset`, 20 contractors were hired and paid 20 USD an hour. Additionally, some members of the BASALT team collected data for this dataset. For the `Evaluation Dataset`, 65 high quality crowdsource workers from Amazon Mechanical Turk were paid to collect the data at approximately 15 USD an hour.

Over what timeframe was the data collected?

The `Demonstrations Dataset` was collected between April 2022 and July 2022. The `Evaluation Dataset` was collected between November 2022 and January 2023.

B.4. Uses

Has the dataset been used for any tasks already?

Both datasets were used for the BASALT 2022 competition. Please see more details in the competition retrospective (Milani et al., 2023) and this competitor white paper (Malato et al., 2022).

Is there a repository that links to any or all papers or systems that use the dataset?

This page contains a list of papers and project that use MineRL. Only some projects from 2022 onward use `BEDD` data. Competitor papers from the 2022 competition (Malato et al., 2022) only used the `Demonstrations Dataset`.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses?

We do not believe so because the data for both datasets was collected from paid contractors and high-quality paid crowdsourcers.

B.5. Distribution

Will the dataset be distributed to third parties?

Yes, it is free and available online.

How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?

The `Evaluation Dataset` exists on Zenodo (DOI:10.5281/zenodo.8021960) as a zip file. The `Demonstrations Dataset` exists on an OpenAI server as JSONL and MP4 files and does not have a DOI. All data is under the MIT license.

Have any third parties imposed IP-based or other restrictions on the data associated with the instances?

No.

Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?

No.

B.6. Maintenance

Who will be supporting/hosting/maintaining the dataset?

The authors on this paper will provide needed maintenance to the datasets (`Demonstrations Dataset`, `Evaluation Dataset`). We do not expect much maintenance to be needed as we will not be adding data to the dataset. However, we will accept PRs from users who have improvements to make to the supporting codebase.

How can the owner/curator/manager of the dataset be contacted (e.g., email address)?

Please email us at stephemilani@gmail.com

Is there an erratum?

There is not, but 1) we mention potential issues with the data in this datasheet, and 2) we provide a list of data within the dataset that we believe to be invalid due to issues such as not properly completing the given task (Appendix C.2.2).

Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?

Yes, but we expect minimal updates to be required, as we do not intend to add more data to the dataset.

C. Demonstrations Dataset Details

C.1. Human Data Collection Details

Contractors were originally hired through Upwork by responding to the following job posting:

> We are looking for people who want to get paid to play Minecraft. We will want you to describe some things about your experience, so our ideal candidate would possess Native English fluency and have a microphone. You'll need to install java, download a modified version of Minecraft (that collects and uploads your play data and voice), and play Minecraft survival mode! Paid per hour of gameplay. Prior experience in Minecraft is not necessary. We do not collect any data that is unrelated to Minecraft from your computer.

Prior to recording this dataset, all contractors had been working on other datasets in Minecraft[3], and were proficient in taking English language instructions via UpWork and using the provided recording scripts for generating demonstration data. The contractors were initially hired in the context of collecting narrated Minecraft play. However, narrations were not requested for the BASALT dataset, and any incidentally collected narrations will not be released. In total, 20 contractors were recruited and paid 20 USD per hour. We allocated a total of 10k USD for this. To supplement this dataset, three members of BASALT contributed data. Below are the exact transcripts we used to instruct the contractors for the four tasks.

C.1.1. FindCave

> Task 1 - Recorder version find-cave Look around for a cave. When you are inside one, quit the game by opening main menu and pressing "Save and Quit To Title". You are not allowed to dig down from the surface to find a cave.
>
> Timelimit: 3 minutes.
>
> Example recordings: https://www.youtube.com/watch?v=TclP_ozH-eg

C.1.2. MakeWaterfall

> After spawning in a mountainous area with a water bucket and various tools, build a beautiful waterfall and then reposition yourself to "take a scenic picture" of the same waterfall, and then quit the game by opening the menu and selecting "Save and Quit to Title"
>
> Timelimit: 5 minutes.
>
> Example recordings: https://youtu.be/NONcbS85NLA

C.1.3. CreateVillageAnimalPen

> After spawning in a village, build an animal pen next to one of the houses in a village. Use your fence posts to build one animal pen that contains at least two of the same animal. (You are only allowed to pen chickens, cows, pigs, sheep or rabbits.) There should be at least one gate that allows players to enter and exit easily. The animal pen should not contain more than one type of animal. (You may kill any extra types of animals that accidentally got into the pen.) Don't harm the village. After you are done, quit the game by opening the menu and pressing "Save and Quit to Title".
>
> You may need to terraform the area around a house to build a pen. When we say not to harm the village, examples include taking animals from existing pens, damaging existing houses or farms, and attacking villagers. Animal pens must have a single type of animal: pigs, cows, sheep, chicken or rabbits.
>
> The food items can be used to lure in the animals: if you hold seeds in your hand, this attracts nearby chickens to you, for example.
>
> Timelimit: 5 minutes.

[3]Previous Minecraft experience was not a hard requirement in the job posting. However, in practice, those without experience did not continue their work.

> Example recordings: https://youtu.be/SLO7sep7BO8

C.1.4. BUILDVILLAGEHOUSE

> Taking advantage of the items in your inventory, build a new house in the style of the village (random biome), in an appropriate location (e.g. next to the path through the village), without harming the village in the process. Then give a brief tour of the house (i.e. spin around slowly such that all of the walls and the roof are visible).
>
> You start with a stone pickaxe and a stone axe, and various building blocks. It's okay to break items that you misplaced (e.g. use the stone pickaxe to break cobblestone blocks). You are allowed to craft new blocks.
>
> Please spend less than ten minutes constructing your house.
>
> You don't need to copy another house in the village exactly (in fact, we're more interested in having slight deviations, while keeping the same "style"). You may need to terraform the area to make space for a new house. When we say not to harm the village, examples include taking animals from existing pens, damaging existing houses or farms, and attacking villagers.
>
> After you are done, quit the game by opening the menu and pressing "Save and Quit to Title".
>
> Timelimit: 12 minutes.
>
> Example recordings: https://youtu.be/WeVqQN96V_g

C.2. Dataset Details

Like most other datasets, this one contains some issues. Instead of waiting for users to discover them, we preemptively investigate the dataset ourselves. We document the issues below. This is done in the interest of transparency and to ensure the dataset is maximally useful.

C.2.1. EPISODE BOUNDARIES

The recording software employed for our dataset splits video and action label files into 5-minute segments. This has no bearing on the `FindCave` task, as its time limit is 3 minutes. However, the time limits for `MakeWaterfall` and `CreateVillageAnimalPen` tasks are 5 minutes, and occasionally episodes exceed this limit by up to 3 seconds, triggering the video splitter. For the `BuildVillageHouse` task, the time limit is 12 minutes, causing some episodes to be divided into three parts.

Certain training or analysis methods necessitate knowledge of episode boundaries, requiring a reliable method for identifying which videos belong to the same episode. While file labels being unique to an episode would simplify this process, this is not the case. We investigated various systematic approaches to detect where an episode ends and a new one begins, but none proved 100% reliable. Some challenges we faced include: different episodes sharing the same file ID; video splitter not generating filenames with timestamps exactly 5 minutes apart; ESC keys not consistently triggering episode ends, because ESC is also used to close inventory; some episodes concluding in exactly 5 minutes; and a few episodes missing their first 5 minutes, rendering the loading screen in the initial video frame an unreliable boundary indicator. Our most reliable and straightforward solution was to consider two files as part of the same episode if the first file is exactly 5 minutes long, no ESC key is pressed with the GUI closed, and the filename ID is identical. This approach resulted in an error rate of less than 1%, based on manual inspection of the first frames of all videos in the final split.

Leveraging this heuristic, we produced a file for each task containing a list of episodes, with each episode having an associated file list. We also included the step count per episode and two tags specifying (1) whether the episode ended with an ESC key press, (2) whether it was incomplete due to a saving error. Episode ending with an ESC key press indicates a successfully completed task. If an episode does not conclude with an ESC key press, the step count can be utilized to determine the type of episode end — a step count at or slightly above the time limit implies a timeout, while a lower step count indicates player death. The four files are located in the same repository mentioned above. This is the recommended way of using the dataset if episode boundaries are important for the training algorithm.

C.2.2. IDIOSYNCRATIC EPISODES

We also noticed some episodes, which pass our filters for being valid and complete episodes but have some unique characteristics. This might be useful to know for data cleaning purposes. We provide some examples below, including the associated file names.

- `gloppy-persimmon-ferret-3e42e8e14be0-20220716-190015` - `FindCave` episode finishes in under 2 seconds with an ESC press, likely a misclick.
- `squeaky-ultramarine-chihuahua-bbf328311fb8-20220726-132144` - `FindCave` episode where the player spawns, then falls into a ravine and dies in less than 5 seconds.
- `gloppy-persimmon-ferret-1d8dcc4e2446-20220716-144806` - successful `FindCave` episode, where the player finds a cave and hits ESC in under 3 seconds.
- `pokey-cyan-spitz-62e7b7415aaf-20220714-093544` - `FindCave` episode where the video lasts longer than the 3 minute time limit, but the action labels only cover 20 seconds.
- `whiny-ecru-cougar-f153ac423f61-20220712-192050` - `FindCave` episode, where the player seems to just play Minecraft, making stone tools and such, instead of finding a cave.
- `shabby-pink-molly-*` - a total of 67 `FindCave` episodes, where the player finds a cave, but does not press ESC to finish the episode. Instead the player proceeds to explore the cave, then exits it and goes looking for other caves.
- `thirsty-lavender-koala-479e09882ca6-20220717-203846` - `MakeWaterfall` episode, one of several, where the player finishes the waterfall, and stares at it for 3 minutes to timeout instead of pressing ESC.

These were the outliers we found by sorting the data based on various metrics and checking the extremes. They are rare, on the order of tens of episodes total in a dataset with over 13,000 episodes. It would add up to a total of less than 1%. Although we believe that these rare outliers would not influence training outcomes, we recommend that users of this dataset either remove this data from the training set or more carefully check these episodes before including them.

C.2.3. VIDEO ENCODING DIFFERENCES

We also noticed that the codecs used to encode the videos were not always the same, likely due to subtle differences in the systems contractors used to play the game to generate the data. Codecs are how the data in the videos gets compressed and decompressed. Roughly 88% use `H.264 (Constrained Baseline Profile)`, while most of the remaining ones use `H.264 (High Profile)`. Also, the bitrate of the videos varies. Most bitrates are roughly 4 Mbps, but there are a few outliers on both ends of the distribution. While these differences are imperceptible to the human eye, the training algorithms might pick up on them. Having different encodings has both benefits and issues for training algorithms. The benefits are robustness, adaptability and real-world applicability. The issues include biased training data and increased computational complexity.

D. Evaluation Dataset Details

This section contains details about the Evaluation Dataset. In this section, we hope to provide enough detail such that our evaluation pipeline can be easily reproduced.

D.1. Human Evaluation Details

We estimated that one answer would take 15 minutes. We paid 3.75 USD per HIT for a total of 15 USD per hour. In actuality, workers took 5.12 minutes on average to complete each evaluation, meaning the pay was closer to 43.95 USD per hour. We also provided bonuses to MTurk workers that helped us debug issues with the form during the evaluation. In total, we spent 14,849.16 USD on collecting this data.

MTurk Task Description The human judges viewed the following task description on MTurk.

> In this questionnaire, you will watch videos of different players completing tasks in Minecraft, and your task is to judge which of the players is more successful at completing the task. This will take roughly 15 minutes of your time.

D.1.1. Qualification Criteria

We set the following criteria for selecting human judges. To preview the task, the judges must have had a 99% or greater HIT accept rate and a minimum of $10,000$ completed HITs on MTurk. If the judges had these qualifications, they then took an 8-question Minecraft validity test to confirm that they had at least basic knowledge of Minecraft. We define passing this test as reaching 65% or greater. This means that, for all checkboxes, the user correctly checked or unchecked at least 65% of the boxes.

The Minecraft Qualification Test For the purpose of completeness, we include this test. In this section, we detail the questions that we asked the human judges. To enable this questionnaire to be deployed, we have included deployable and more user-friendly versions of the quiz in our Github repository. Specifically, we provide a text file and an XML file. The former enables the questions to be more readily copied and pasted into new formats, while the latter slots easily into the MTurk UI. Before answering the quiz questions, the human judges viewed the following prompt:

> This is a Qualification Test to demonstrate your familiarity with Minecraft. This Qualification will enable you to accept HITs released by the BASALT team in relation to the NeurIPS 2022 BASALT Competition.

After reading this prompt, the human judges proceeded to the Minecraft Qualification Test. Figure 4 shows the questions and candidate responses in the quiz that the human judges answered to assess their knowledge of Minecraft. These questions were generated by a member of our team who has extensive experience playing Minecraft.

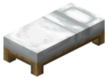
D.1.2. Protocol

Each time a human judge accepted one of our HIT, they were directed to the AICrowd site that collects their answer. Upon opening the webpage, the task was chosen at random from the four available ones. To choose the two videos to show the judge, we aimed to maximally reduce uncertainty by using the TrueSkill ranking of agents. We ensure that the compared videos are always in the same Minecraft seed (i.e., the same starting location and surroundings).

MTurk Task Instructions Below is the full text of the MTurk task instructions given to participants.

> Welcome to the MineRL BASALT 2022 evaluation questionnaire! This will take roughly 15 minutes of your time. Requirements: Knowledge of Minecraft (at least of 5 hours of gameplay time with Minecraft).
>
> In this questionnaire, you will watch videos of different players completing tasks in Minecraft, and your task is to judge which of the players is more successful at completing the task.
>
> Videos are shown in pairs, and your task is to select which one of the two is better at solving the task. The page shows the task description. You are also given a set of more specific questions which may help you decide which of the two

Q1: (select all that apply) A bed in Minecraft...



[ ] can be used to speed up the passage of the night **(correct)**
[ ] can be used to change the respawn location **(correct)**
[ ] Is built using an item dropped by an in-game animal **(correct)**
[ ] Can be built at a furnace, but not at a crafting table.

Q2: (select all that apply) The following events can drop experience orbs:

[ ] Killing monsters **(correct)**
[ ] Mining trees
[ ] Jumping on a coal ore block
[ ] Mining coal **(correct)**

Q3: (select all that apply) The following blocks drop an item when mined by hand:
[ ] Wood log **(correct)**
[ ] Wood plank **(correct)**
[ ] Coal ore
[ ] Iron ore
[ ] Stone

(a) Page 1 of Minecraft Qualification Test

Q4: (select all that apply) Which of the following mobs can damage players:

[ ] Skeletons **(correct)**
[ ] Zombies **(correct)**
[ ] Sheep
[ ] Pigs
[ ] Creepers **(correct)**

Q5: (select all that apply) Which of the following items can be eaten by the player:
[ ] Apples **(correct)**
[ ] Dirt
[ ] Beef **(correct)**
[ ] Wheat
[ ] Bread **(correct)**

Q6: (select all that apply) Which of the following are ways that the player can die in vanilla Minecraft:
[ ] Fall damage **(correct)**
[ ] Drowning **(correct)**
[ ] Burning **(correct)**
[ ] Thirst
[ ] Getting hit repeatedly with a stick **(correct)**

(b) Page 2 of Minecraft Qualification Test

Q7: (select all that apply) What is this mob called?

[ ] Creeper **(correct)**
[ ] Beeper
[ ] Leaper
[ ] Reaper
[ ] Peeper

Q8: (select all that apply) What types of items can you make on a crafting table using only this block?

[ ] Planks **(correct)**
[ ] Sticks **(correct)**
[ ] Bone meal
[ ] Apples
[ ] Shield

(c) Page 3 of Minecraft Qualification Test

Q9: (select all that apply) Jumping onto the following block type does what?

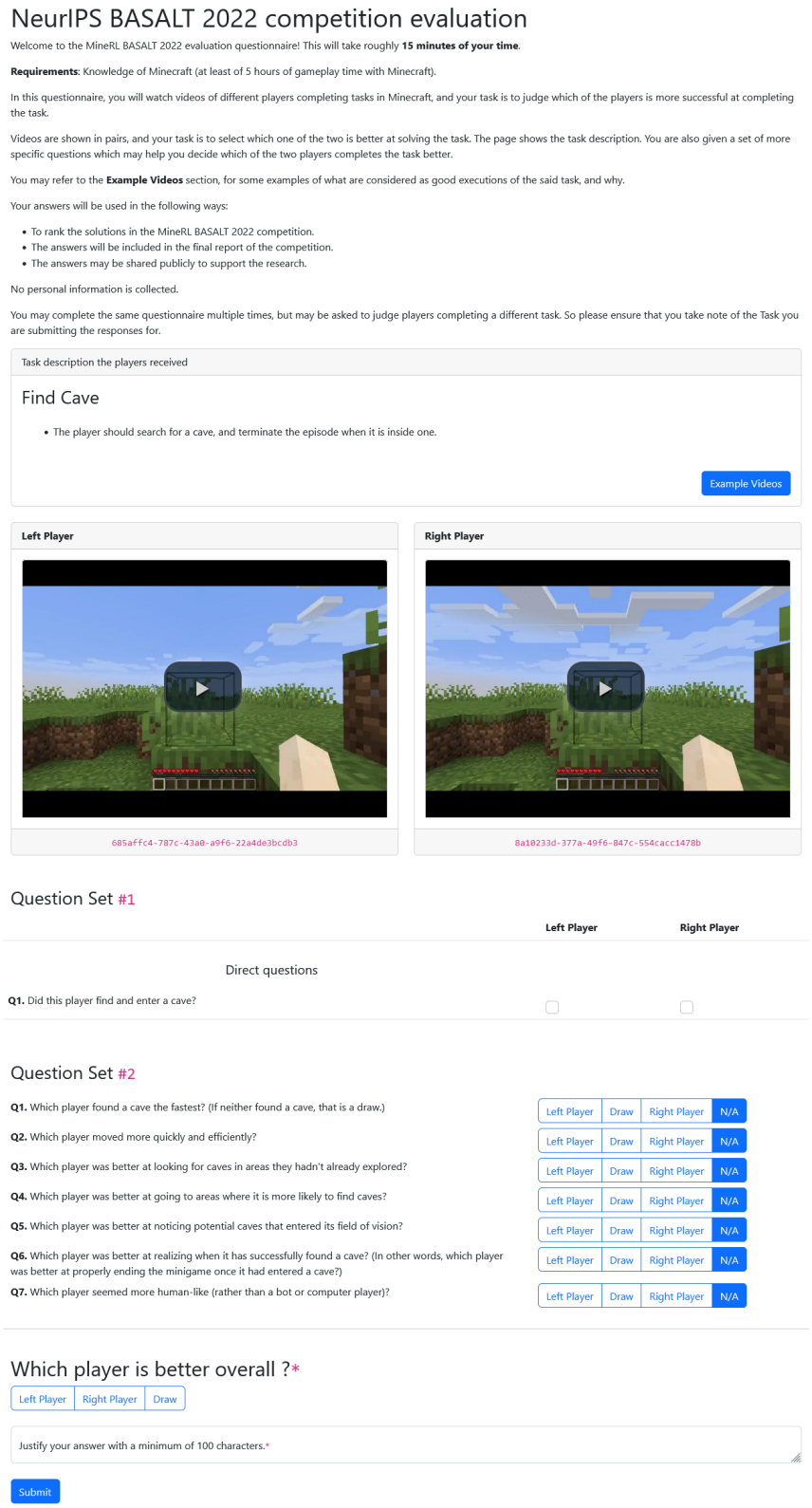
[ ] Makes you drown immediately
[ ] Refreshes your thirst bar
[ ] Heals you
[ ] Removes burning effects **(correct)**
[ ] Stops fall damage **(correct)**

(d) Page 4 of Minecraft Qualification Test

Figure 4: Minecraft Qualification Test, pages 1-4 of 4 total.

> players completes the task better.
>
> You may refer to the Example Videos section, for some examples of what are considered as good executions of the said task, and why.
>
> Your answers will be used in the following ways:
>
> To rank the solutions in the MineRL BASALT 2022 competition. The answers will be included in the final report of the competition. The answers may be shared publicly to support the research. No personal information is collected.
>
> You may complete the same questionnaire multiple times, but may be asked to judge players completing a different task. So please ensure that you take note of the Task you are submitting the responses for.

Task Details Each task contained some common questions and some different questions. For all tasks, the human judges were asked to evaluate which player was better overall and which player appeared more human-like. Some tasks contained more task-specific questions than others. For example, `BuildVillageHouse` contained a single question about whether the players harmed the villagers; in contrast, `CreateVillageAnimalPen` contained six questions to determine proper task completion, such as whether the pen contained at least two animals of the same type. Figures 5 to 8 show screenshots of the form for each task that the human judges saw.



NeurIPS BASALT 2022 competition evaluation

Welcome to the MineRL BASALT 2022 evaluation questionnaire! This will take roughly **15 minutes of your time**.

Requirements: Knowledge of Minecraft (at least of 5 hours of gameplay time with Minecraft).

In this questionnaire, you will watch videos of different players completing tasks in Minecraft, and your task is to judge which of the players is more successful at completing the task.

Videos are shown in pairs, and your task is to select which one of the two is better at solving the task. The page shows the task description. You are also given a set of more specific questions which may help you decide which of the two players completes the task better.

You may refer to the **Example Videos** section, for some examples of what are considered as good executions of the said task, and why.

Your answers will be used in the following ways:

- To rank the solutions in the MineRL BASALT 2022 competition.
- The answers will be included in the final report of the competition.
- The answers may be shared publicly to support the research.

No personal information is collected.

You may complete the same questionnaire multiple times, but may be asked to judge players completing a different task. So please ensure that you take note of the Task you are submitting the responses for.

Task description the players received

Find Cave

- The player should search for a cave, and terminate the episode when it is inside one.

Example Videos

Left Player

685affc4-787c-43a0-a9f6-22a4de3bcdb3

Right Player

8a10233d-377a-49f6-847c-554cacc1478b

Question Set #1

	Left Player	Right Player
Direct questions		
Q1. Did this player find and enter a cave?	☐	☐

Question Set #2

Q1. Which player found a cave the fastest? (If neither found a cave, that is a draw.)	Left Player	Draw	Right Player	N/A
Q2. Which player moved more quickly and efficiently?	Left Player	Draw	Right Player	N/A
Q3. Which player was better at looking for caves in areas they hadn't already explored?	Left Player	Draw	Right Player	N/A
Q4. Which player was better at going to areas where it is more likely to find caves?	Left Player	Draw	Right Player	N/A
Q5. Which player was better at noticing potential caves that entered its field of vision?	Left Player	Draw	Right Player	N/A
Q6. Which player was better at realizing when it has successfully found a cave? (In other words, which player was better at properly ending the minigame once it had entered a cave?)	Left Player	Draw	Right Player	N/A
Q7. Which player seemed more human-like (rather than a bot or computer player)?	Left Player	Draw	Right Player	N/A

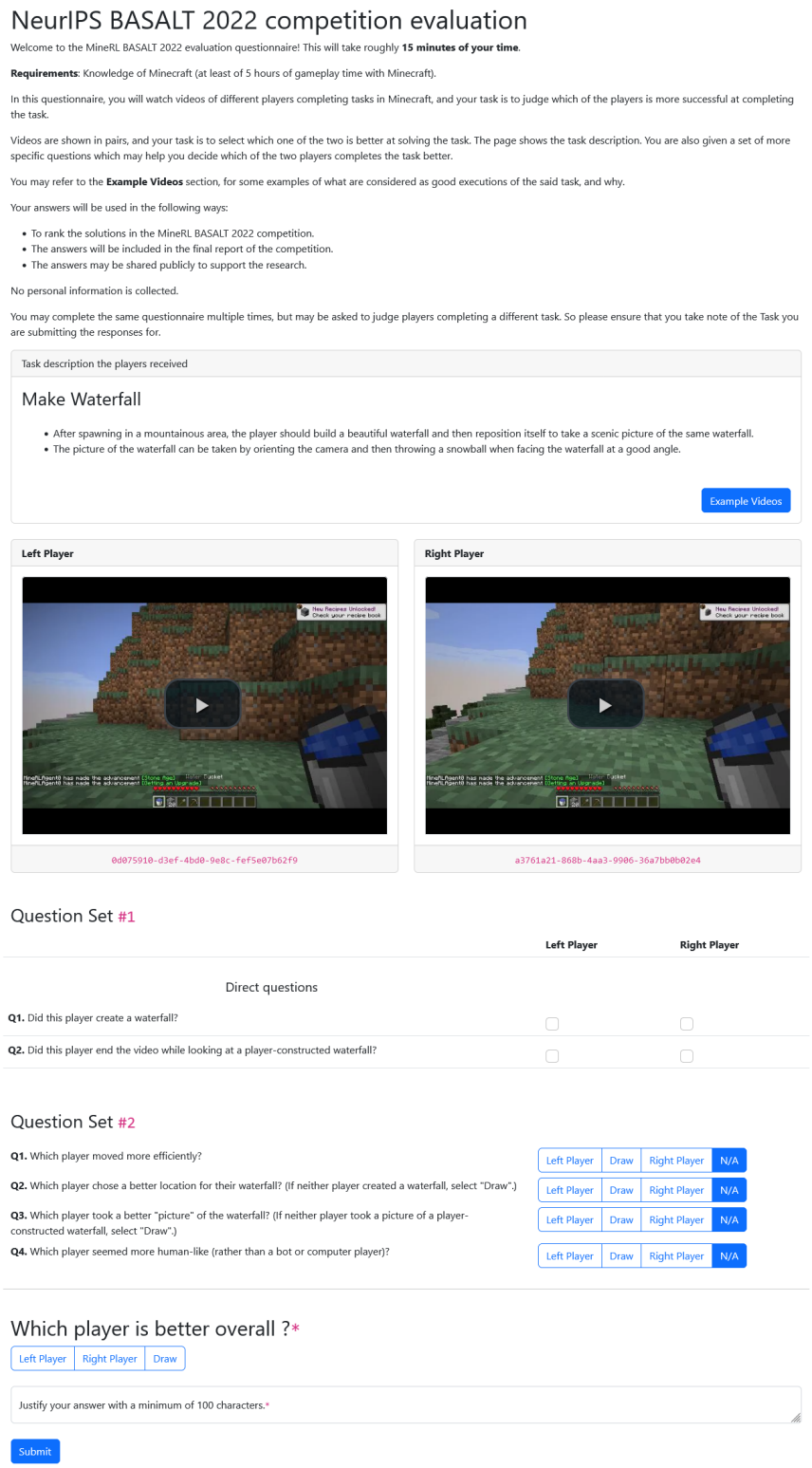
Which player is better overall ?*

Left Player | Right Player | Draw

Justify your answer with a minimum of 100 characters.*

Submit

Figure 5: Screenshot of the page that the human judges viewed when assessing the agent behavior for the `FindCave` task.



NeurIPS BASALT 2022 competition evaluation

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Requirements: Knowledge of Minecraft (at least of 5 hours of gameplay time with Minecraft).

In this questionnaire, you will watch videos of different players completing tasks in Minecraft, and your task is to judge which of the players is more successful at completing the task.

Videos are shown in pairs, and your task is to select which one of the two is better at solving the task. The page shows the task description. You are also given a set of more specific questions which may help you decide which of the two players completes the task better.

You may refer to the **Example Videos** section, for some examples of what are considered as good executions of the said task, and why.

Your answers will be used in the following ways:

- To rank the solutions in the MineRL BASALT 2022 competition.
- The answers will be included in the final report of the competition.
- The answers may be shared publicly to support the research.

No personal information is collected.

You may complete the same questionnaire multiple times, but may be asked to judge players completing a different task. So please ensure that you take note of the Task you are submitting the responses for.

Task description the players received

Make Waterfall

- After spawning in a mountainous area, the player should build a beautiful waterfall and then reposition itself to take a scenic picture of the same waterfall.
- The picture of the waterfall can be taken by orienting the camera and then throwing a snowball when facing the waterfall at a good angle.

Example Videos

Left Player

0d075910-d3ef-4bd0-9e8c-fef5e07b62f9

Right Player

a3761a21-868b-4aa3-9906-36a7bb0b02e4

Question Set #1

	Left Player	Right Player
Direct questions		
Q1. Did this player create a waterfall?	☐	☐
Q2. Did this player end the video while looking at a player-constructed waterfall?	☐	☐

Question Set #2

Q1. Which player moved more efficiently?	Left Player	Draw	Right Player	N/A
Q2. Which player chose a better location for their waterfall? (If neither player created a waterfall, select "Draw".)	Left Player	Draw	Right Player	N/A
Q3. Which player took a better "picture" of the waterfall? (If neither player took a picture of a player-constructed waterfall, select "Draw".)	Left Player	Draw	Right Player	N/A
Q4. Which player seemed more human-like (rather than a bot or computer player)?	Left Player	Draw	Right Player	N/A

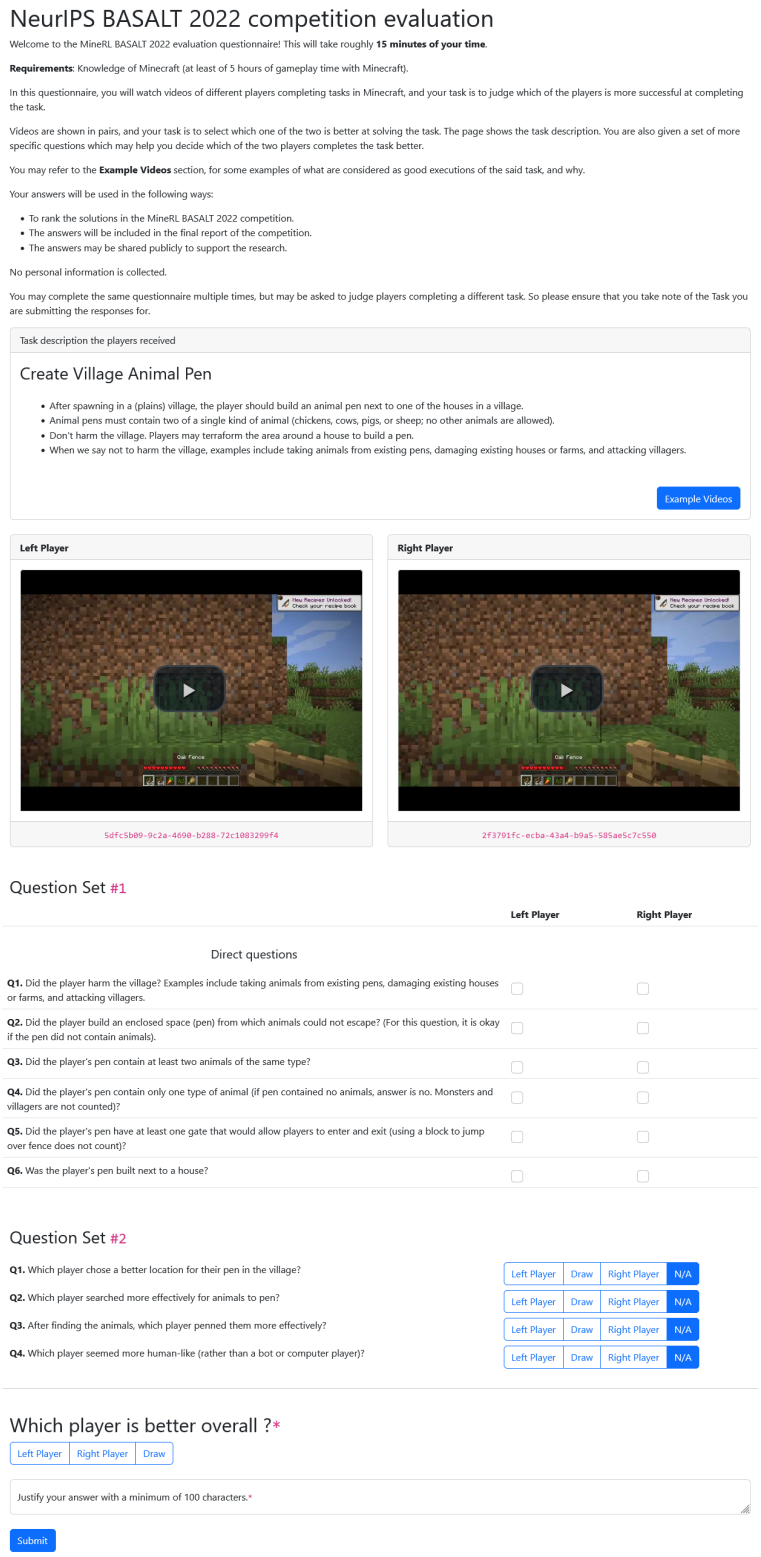
Which player is better overall ?*

Left Player | Right Player | Draw

Justify your answer with a minimum of 100 characters.*

Submit

Figure 6: Screenshot of the page that the human judges viewed when assessing the agent behavior for the `MakeWaterfall` task.



NeurIPS BASALT 2022 competition evaluation

Welcome to the MineRL BASALT 2022 evaluation questionnaire! This will take roughly **15 minutes of your time**.

Requirements: Knowledge of Minecraft (at least of 5 hours of gameplay time with Minecraft).

In this questionnaire, you will watch videos of different players completing tasks in Minecraft, and your task is to judge which of the players is more successful at completing the task.

Videos are shown in pairs, and your task is to select which one of the two is better at solving the task. The page shows the task description. You are also given a set of more specific questions which may help you decide which of the two players completes the task better.

You may refer to the **Example Videos** section, for some examples of what are considered as good executions of the said task, and why.

Your answers will be used in the following ways:

- To rank the solutions in the MineRL BASALT 2022 competition.
- The answers will be included in the final report of the competition.
- The answers may be shared publicly to support the research.

No personal information is collected.

You may complete the same questionnaire multiple times, but may be asked to judge players completing a different task. So please ensure that you take note of the Task you are submitting the responses for.

Task description the players received

Create Village Animal Pen

- After spawning in a (plains) village, the player should build an animal pen next to one of the houses in a village.
- Animal pens must contain two of a single kind of animal (chickens, cows, pigs, or sheep; no other animals are allowed).
- Don't harm the village. Players may terraform the area around a house to build a pen.
- When we say not to harm the village, examples include taking animals from existing pens, damaging existing houses or farms, and attacking villagers.

Example Videos

Left Player

5dfc5b09-9c2a-4690-b288-72c1083299f4

Right Player

2f3791fc-ecba-43a4-b9a5-585aeSc7c550

Question Set #1

	Left Player	Right Player
Direct questions		
Q1. Did the player harm the village? Examples include taking animals from existing pens, damaging existing houses or farms, and attacking villagers.	☐	☐
Q2. Did the player build an enclosed space (pen) from which animals could not escape? (For this question, it is okay if the pen did not contain animals).	☐	☐
Q3. Did the player's pen contain at least two animals of the same type?	☐	☐
Q4. Did the player's pen contain only one type of animal (if pen contained no animals, answer is no. Monsters and villagers are not counted)?	☐	☐
Q5. Did the player's pen have at least one gate that would allow players to enter and exit (using a block to jump over fence does not count)?	☐	☐
Q6. Was the player's pen built next to a house?	☐	☐

Question Set #2

Q1. Which player chose a better location for their pen in the village?	Left Player	Draw	Right Player	N/A
Q2. Which player searched more effectively for animals to pen?	Left Player	Draw	Right Player	N/A
Q3. After finding the animals, which player penned them more effectively?	Left Player	Draw	Right Player	N/A
Q4. Which player seemed more human-like (rather than a bot or computer player)?	Left Player	Draw	Right Player	N/A

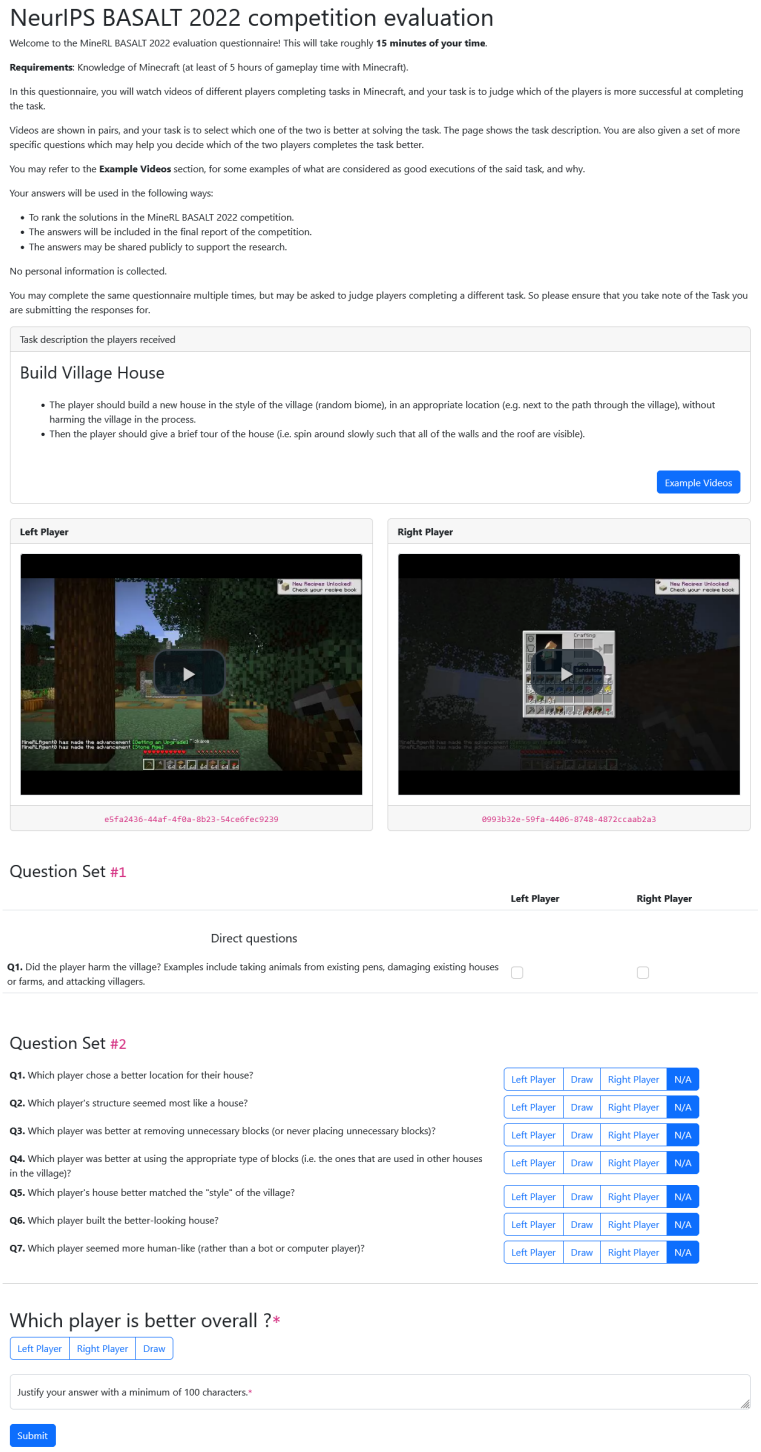
Which player is better overall ?*

Left Player | Right Player | Draw

Justify your answer with a minimum of 100 characters.*

Submit

Figure 7: Screenshot of the page that the human judges viewed when assessing the agent behavior for the `CreateVillageAnimalPen` task.



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- The answers may be shared publicly to support the research.

No personal information is collected.

You may complete the same questionnaire multiple times, but may be asked to judge players completing a different task. So please ensure that you take note of the Task you are submitting the responses for.

Task description the players received

Build Village House

- The player should build a new house in the style of the village (random biome), in an appropriate location (e.g. next to the path through the village), without harming the village in the process.
- Then the player should give a brief tour of the house (i.e. spin around slowly such that all of the walls and the roof are visible).

Example Videos

Left Player

e5fa2436-44af-4f0a-8b23-54ce6fec9239

Right Player

0993b32e-59fa-4406-8748-4872ccaab2a3

Question Set #1

	Left Player	Right Player
Direct questions		
Q1. Did the player harm the village? Examples include taking animals from existing pens, damaging existing houses or farms, and attacking villagers.	☐	☐

Question Set #2

Q1. Which player chose a better location for their house?	Left Player	Draw	Right Player	N/A
Q2. Which player's structure seemed most like a house?	Left Player	Draw	Right Player	N/A
Q3. Which player was better at removing unnecessary blocks (or never placing unnecessary blocks)?	Left Player	Draw	Right Player	N/A
Q4. Which player was better at using the appropriate type of blocks (i.e. the ones that are used in other houses in the village)?	Left Player	Draw	Right Player	N/A
Q5. Which player's house better matched the "style" of the village?	Left Player	Draw	Right Player	N/A
Q6. Which player built the better-looking house?	Left Player	Draw	Right Player	N/A
Q7. Which player seemed more human-like (rather than a bot or computer player)?	Left Player	Draw	Right Player	N/A

Which player is better overall ?*

Left Player | Right Player | Draw

Justify your answer with a minimum of 100 characters.*

Submit

Figure 8: Screenshot of the page that the human judges viewed when assessing the agent behavior for the `BuildVillageHouse` task.

Task	Average Time	Total Time
FindCave	300.47 ± 271.10	$216,941.18$
MakeWaterfall	295.86 ± 270.99	$201,778.77$
CreateVillageAnimalPen	319.52 ± 255.50	$292,041.62$
BuildVillageHouse	375.37 ± 315.20	$274,393.78$

Table 5: More specific timing data of human evaluations in seconds, decomposed per task. Error values are standard error. A total of around 274 human hours were needed for evaluation.

	Length		Sentiment		
Agent	Characters	Words	Positive	Neutral	Negative
FindCave	210.46 ± 3.82	38.71 ± 0.71	79.64%	6.65%	13.71%
MakeWaterfall	217.96 ± 4.18	38.76 ± 0.79	76.10%	7.33%	16.57%
CreateVillageAnimalPen	197.83 ± 3.22	35.85 ± 0.60	56.67%	10.83%	32.49%
BuildVillageHouse	205.73 ± 4.23	36.82 ± 0.77	62.79%	9.58%	27.63%

Table 6: Details about the justification provided for choosing a particular agent as the best one, decomposed per task. We calculate the per-task average length of the response (characters and words) along with the standard error. We also report the percent of positive, neutral, and negative sentiments of these responses.

E. Additional Analyses of `Evaluation Dataset`

This section presents the full results of the analyses performed to supplement the findings discussed in **??**. We decompose the analyses in two ways: task-based and agent-based. Appendix E.1 presents the task-based analyses; Appendix E.2 presents the agent-based analyses.

E.1. Task-Based Decomposition

We first present details about the analysis when we decompose responses by *task*.

Timing Information We present more detailed timing information in Table 5. This is a more detailed view of the Hours column in Table 2 in the main paper. Here, the average time means the average amount of time an evaluator took to complete a single evaluation, in seconds. The total time is computed by adding up the number of seconds taken by all contractors to complete that type of evaluation. On average, the human evaluators took the longest to evaluate the BuildVillageHouse task. However, there is a very high standard error, indicating that the time taken by the MTurk workers was highly variable, regardless of the task. Overall, evaluators spent the most time on the CreateVillageAnimalPen.

Length of Justification We analyzed the length of the justifications provided by the MTurk workers for why they selected an agent as being the best at accomplishing the task. We analyzed both the number of words and characters in the justification. We present the results in Table 6. We observe that, on average, the human judges tended to dedicate the most characters to MakeWaterfall and the least characters to CreateVillageAnimalPen. They also tended to dedicate the most words in their responses about the FindCave and MakeWaterfall and the least number of words to CreateVillageAnimalPen. We note that CreateVillageAnimalPen contains more quantitative additional questions than the other tasks (4 vs. 2, the next highest). For example, the human judges were asked to identify which agent penned the correct amount and type of animals, among other things. These additional questions may have enabled the judges to spend less effort explaining their choice since many of the factors were already captured by other questions.

Sentiment of Justification For completeness, we include the distribution of sentiments in Table 6. We conducted a Chi-square test of independence to examine the relationship between task and sentiment classification. The relation between these variables was found to be significant, $X^2(6, N = 3049) = 132.21, p < .001$. As a result, we conducted Bonferroni-corrected pairwise Chi-square tests to elucidate which of the distributions were significantly different. For completeness,

Comparison	Chi-square	p-value	Significance After Bonferroni Correction
FindCave vs MakeWaterfall	2.69	0.26	No
FindCave vs CreateVillageAnimalPen	98.49	4.10e-22	Yes
FindCave vs BuildVillageHouse	52.31	4.38e-12	Yes
MakeWaterfall vs CreateVillageAnimalPen	66.37	3.87e-15	Yes
MakeWaterfall vs BuildVillageHouse	30.50	2.38e-07	Yes
CreateVillageAnimalPen vs BuildVillageHouse	6.35	0.04	No

Table 7: Results from Chi-square tests between tasks analyzing the sentiment of the free-form responses. Significant differences in sentiment distribution are emphasized with a pink highlight.

the result of these tests is presented in Table 7 for completeness. Perhaps the most interesting takeaway is that the responses for the easier tasks appear to exhibit higher positive sentiments than those for the more challenging tasks. One explanation for this not mentioned in the main text may be that, for more challenging tasks, both agents may have exhibited some issues that were identified by the human judges.

Justification Examples We present an example of justification text provided for each of the tasks. We choose these examples by splitting the data by task, then randomly sampling a response. For `FindCave`, an example justification was,

> They explored a lot, and seemed to go to more new places than before even the water. Left player went AFK.

An example justification response from `MakeWaterfall` was,

> The player on the left couldn't even manage to climb the side of a mountain, the one on the right didn't finish the tasks but at least they seemed to know how to navigate and move around.

An example justification text from `CreateVillageAnimalPen` was,

> the left player completed all the requirements, while the right player did nothing and still behaved like a bot

Finally, an example justification text from `BuildVillageHouse` was,

> The right player was better overall, being able to build a house, but he failed to use the appropriate type of block.

We believe that all of these justifications indicate that human judges were generally familiar with Minecraft and the specific requirements for task completion.

E.2. Agent-Based Decomposition

We now present details about the analysis when we decompose responses by *agent*. Although we release the *full* dataset, which includes the values for all agents, we present here only the specific values for Human1, Human2, BC-Baseline, UniTeam[4], GoUp[5], and Random. We compute these values using only the comparisons with the other presented algorithms, not the full dataset.

Length of Justification We analyzed the length of the justifications provided by MTurk workers. These results are presented in the Length column of Table 8. On average, the MTurk workers used both the most words and characters

[4] https://github.com/fmalato/basalt_2022_submission
[5] https://github.com/gomiss/neurips-2022-minerl-basalt-competition

	Length		Sentiment		
Agent	Characters	Words	Positive	Neutral	Negative
Random	196.80 ± 4.93	35.41 ± 0.92	63.20%	8.31%	28.49%
Human1	207.06 ± 5.66	37.496 ± 1.05	91.55%	2.11%	6.34%
Human2	214.87 ± 6.11	38.86 ± 1.12	91.77%	2.88%	5.35%
BC-Baseline	201.72 ± 5.30	36.25 ± 0.97	64.96%	9.00%	26.03%
GoUp	212.86 ± 5.55	38.67 ± 1.02	73.77%	7.53%	18.70%
UniTeam	201.77 ± 4.85	36.35 ± 0.92	65.68%	9.38%	24.94%

Table 8: Details about the justification provided for choosing a particular agent as the best one. We calculate the per-agent average length of the response (characters and words) along with the standard error. We also report the percent of positive, neutral, and negative sentiments of the responses. This is a more detailed view of the Words in Response and Response Sentiment columns in Table 2 in the main paper.

Comparison	Chi-square	p-value	Significance After Bonferroni Correction
GoUp vs UniTeam	6.37	0.041	No
GoUp vs BC-Baseline	7.50	0.024	No
GoUp vs Random	10.44	0.005	No
GoUp vs Human1	34.10	3.93×10^{-8}	Yes
GoUp vs Human2	31.22	1.66×10^{-7}	Yes
UniTeam vs BC-Baseline	0.15	0.928	No
UniTeam vs Random	1.33	0.515	No
UniTeam vs Human1	62.97	2.12×10^{-14}	Yes
UniTeam vs Human2	56.94	4.31×10^{-13}	Yes
BC-Baseline vs Random	0.60	0.740	No
BC-Baseline vs Human1	64.77	8.64×10^{-15}	Yes
BC-Baseline vs Human2	58.76	1.74×10^{-13}	Yes
Random vs Human1	68.25	1.51×10^{-15}	Yes
Random vs Human2	62.44	2.77×10^{-14}	Yes
Human1 vs Human2	0.53	0.767	No

Table 9: Results from Chi-square tests between teams analyzing the sentiment of the free-form responses. Significant differences in sentiment distribution are emphasized with a pink highlight.

(38.86 words, 214.87 characters) when describing their rationale when Human2 was involved in the pair being compared. In contrast, when the Random agent was involved, the MTurk workers used the least words and characters (35.41 words and 196.80 characters) when explaining their rationale. We believe that this may be due to the relative competency of the agents: because it is easier to identify the Random agent as less skilled and the humans as more skilled, the human judges may require less justification for their selection. However, we note that the difference between these agents for both words and characters (3.45 words and 18.07 characters) is relatively small overall.

Sentiment of Justification We now present the full statistics for our agent-based sentiment analysis. The sentiments are captured in the Sentiment columns of Table 8. As mentioned in the main paper, we conducted Bonferroni-corrected pairwise Chi-square tests to elucidate which of the agent types exhibited different distributions of sentiment. Table 9 shows the result of this analysis. We find that any comparisons that include either of the human agents, except for when they are pitted against one another, exhibit significant differences in sentiment distribution. The responses had the highest positive sentiment for the two human agents and the least positive sentiment for the Random agent. However, the difference in sentiment distribution of sentiment was statistically insignificant when comparing Random with BC-Baseline or UniTeam, meaning that the sentiment was similarly negative.

Task	Question	Factor
`FindCave`	**Quantitative**	
	Did this player find and enter a cave?	Found Cave
	Qualitative	
	Which player found a cave the fastest? (If neither found a cave, that is a draw)	Found Cave Faster
	Which player moved more quickly and efficiently?	More Quick and Efficient Movement
	Which player was better at looking for caves in areas they hadn't already explored?	Better Cave Search in Unknown Areas
	Which player was better at going to areas where it is more likely to find caves?	Better Navigation to Cave Areas
	Which player was better at noticing potential caves that entered its field of vision?	Better Cave Detection
	Which player was better at realizing when it had successfully found a cave? (In other words, which player was better at properly ending the minigame once it had entered a cave?)	Better Cave Perception
	Which player seemed more human-like (rather than a bot or computer player)?	More Human Like

Table 10: Mapping for `FindCave` from question asked of human evaluators to presented attribute.

Task	Question	Factor
`MakeWaterfall`	**Quantitative**	
	Did this player create a waterfall?	Created Waterfall
	Did this player end the video while looking at a player-constructed waterfall?	Looked at Waterfall
	Qualitative	
	Which player moved more efficiently?	More Quick and Efficient Movement
	Which player chose a better location for their waterfall? (If neither player created a waterfall, select "Draw".)	Better Location for Waterfall
	Which player took a better "picture" of the waterfall? (If neither player took a picture of a player-constructed waterfall, select "Draw")	Better Picture of Waterfall
	Which player seemed more human-like (rather than a bot or computer player)?	More Human Like

Table 11: Mapping for `MakeWaterfall` from question asked of human evaluators to presented attribute.

Task	Question	Factor
BuildVillageHouse	**Quantitative**	
	Did the player harm the village? Examples include taking animals from existing pens, damaging existing houses or farms, and attacking villagers.	Least Village Harm
	Qualitative	
	Which player chose a better location for their house?	Better House Location
	Which player's structure seemed most like a house?	More House-Like Structure
	Which player was better at removing unnecessary blocks (or never placing unnecessary blocks)?	Intentional Block Placing
	Which player was better at using the appropriate type of blocks (i.e., the ones that are used in other houses in the village)?	Appropriate Block Placing
	Which player's house better matched the "style" of the village?	Better Style Matching
	Which player built the better-looking house?	More Attractive House
	Which player seemed more human-like (rather than a bot or computer player)?	More Human Like

Table 12: Mapping for BuildVillageHouse from question asked of human evaluators to presented attribute.

Task	Question	Factor
AnimalPen	**Quantitative**	
	Did the player harm the village? Examples include taking animals from existing pens, damaging existing houses or farms, and attacking villagers.	Least Village Harm
	Did the player build an enclosed space (pen) from which animals could not escape? (For this question, it is okay if the pen did not contain animals).	Better Enclosed Space
	Did the player's pen contain at least two animals of the same type?	Correct Number of Animals
	Did the player's pen contain only one type of animal (if pen contained no animals, answer is no. Monsters and villagers are not counted)?	Correct Type of Animals
	Did the player's pen have at least one gate that would allow players to enter and exit (using a block to jump over fence does not count)?	Proper Exit
	Was the player's pen built next to a house?	Next to House
	Qualitative	
	Which player chose a better location for their pen in the village?	Better Location
	Which player searched more effectively for animals to pen?	More Effective Search
	After finding the animals, which player penned them more effectively?	More Effective Penning
	Which player seemed more human-like (rather than a bot or computer player)?	More Human Like

Table 13: Mapping for AnimalPen from question asked of human evaluators to presented attribute.

Factors Here we present the mapping of per-task questions to factors, which were presented in Figure 3 from the main text. We map each question to an attribute. Tables 10 to 13 show this mapping.

F. Related Work and Discussion

Here we provide an extended related work section and a longer discussion about the limitations of our work. We first compare to MineDojo (Appendix F.1). We then suggest future work that stems from the limitations of our work (Appendix F.2) and conclude by discussing the potential societal impacts of this work (Appendix F.3).

F.1. Comparison to MineDojo

Perhaps the most similar benchmark to ours is MineDojo (Fan et al., 2022), which emerged during the BASALT competitions and contributed a large dataset of Minecraft gameplay with the aim of developing generally-capable embodied agents. The focus of MineDojo was to provide a massive dataset scraped from the internet; in contrast, we focus on curating a smaller set of high-quality demonstrations and evaluations. Our demonstration data was produced by experienced Minecraft data collectors using a consistent Minecraft version and settings. In contrast, the MineDojo data, although plentiful, contains many videos with streamer overlays and non-Minecraft parts, different texture packs, mod packs, and more. Although this diversity may be beneficial in some settings, previous work had to filter out such data before it could be useful for training (Baker et al., 2022). Another critical difference is evaluation: MineDojo provides only binary success or failure criterion; instead, our recommended evaluation and resulting `Evaluation Dataset` involves human judgments across a range of quantitative (e.g., Found Cave) and qualitative (e.g., Style Matching) criteria.

F.2. Limitations and Future Work

Low-Level Data Discrepencies As with any dataset, ours is not without issues. We discussed some limitations of the Demonstrations Dataset in a previous section of the appendix. We found that it is often challenging to delineate episode boundaries with data recording tools and splitting methods. In contrast, with games like Atari, episode boundaries are easily provided by the simulator. Furthermore, since the data is temporally-extended and human-generated, there are idiosyncrasies that will necessarily arise. We emphasize that rather than deploying the dataset and making users find these issues, we dedicated time to investigating these issues and proposing solutions.

Demographic Information In both studies, we did not collect any additional demographic information about participants. On one hand, this lack of personally-identifiable information decreases the likelihood of deanonymization of the participants, which is important even in a study with relatively low stakes such as this one. On the other hand, there is a missed opportunity to critically analyze the influence of demographic or other factors on either the produced demonstrations or the assessments. Future work might include some of these demographic details to produce a more in-depth analysis of the assessments.

Fine-Grained Assessment Details In the assessment of the agents, there are still even more fine-grained details that could be assessed. For example, how do we define human likeness? Is the goal to produce agents that behave as though they are controlled by a person or like they are embodied in the real world? What *type* of human are they similar to: a novice Minecraft player? An expert? For many of these comparative questions, we can perform this finer-grained assessment, depending on the factors that are most relevant to the study. Continuing with the human likeness example, future work investigating human likeness may want to substitute some of the non-human-like comparative questions with more detailed questions about human likeness to gain a deeper understanding of assessments of human likeness in this setting. This analysis could also be combined with recent work on the Human Navigation Turing Test (HNTT) and Automated Navigation Turing Test (ANTT) (Devlin et al., 2021) but applied to a much more complex setting: completing fuzzy tasks in Minecraft.

English-Language Focus One aspect of our study that offers both a specific focus and an avenue for exploration is the use of English-language descriptions for tasks. Incorporating multiple languages into the dataset would make the benchmark more globally applicable and uncover new insights about how language and cultural context influence human feedback.

F.3. Societal Impact

We believe that publicly sharing these datasets helps foster a more open and inclusive AI research community in which resources are more broadly accessible. However, there are some potential negative societal impacts that we have considered.

There is a small (but highly unlikely) chance that we missed some inappropriate or harmful symbols or language contained in the dataset. Although the competition-driven nature of the tasks may foster faster progress toward agents that can better learn from human feedback, releasing all data and code may lead to researchers overfitting on the subset of tasks. This may result in a false signal of progress. There is therefore a need to utilize or develop more non-programmatic tasks in Minecraft (Fan et al., 2022) and other domains.