The last decade has seen a significant increase of interest in deep learning research, with many public successes that have demonstrated its potential. As such, these systems are now being incorporated into commercial products. With this comes an additional challenge: how can we build AI systems that solve tasks where there is not a crisp, well-defined specification? While multiple solutions have been proposed, in this competition we focus on one in particular: learning from human feedback. Rather than training AI systems using a predefined reward function or using a labeled dataset with a predefined set of categories, we instead train the AI system using a learning signal derived from some form of human feedback, which can evolve over time as the understanding of the task changes, or as the capabilities of the AI system improve.

The MineRL BASALT competition aims to spur forward research on this important class of techniques. We design a suite of four tasks in Minecraft for which we expect it will be hard to write down hardcoded reward functions. These tasks are defined by a paragraph of natural language: for example, “create a waterfall and take a scenic picture of it”, with additional clarifying details. Participants must train a separate agent for each task, using any method they want. Agents are then evaluated by humans who have read the task description. To help participants get started, we provide a dataset of human demonstrations on each of the four tasks, as well as an imitation learning baseline that leverages these demonstrations.
Figure 1: An illustration of the MineRL BASALT competition procedure. We provide tasks consisting of a simple English language description alongside a Gym environment, without any associated reward function. Participants will train agents for these tasks using their preferred methods. Submitted agents will be evaluated based on how well they complete the tasks, as judged by humans given the same task descriptions.

Our hope is that this competition will improve our ability to build AI systems that do what their designers intend them to do, even when the intent cannot be easily formalized. Besides allowing AI to solve more tasks, this can also enable more effective regulation of AI systems, as well as making progress on the value alignment problem.

Keywords
Learning from humans, Reward modeling, Imitation learning, Preference learning.

Competition type
Regular.

1 Competition description
The MineRL Benchmark for Agents that Solve Almost-Lifelike Tasks (MineRL BASALT) competition aims to promote research in the area of learning from human feedback in order to enable agents that can pursue tasks that do not have crisp, easily defined reward functions. As illustrated in Figure 1, we ask participants to train agents that perform a specific task described only in English and have humans evaluate how well the agents perform the task.
1.1 Background and impact

It is becoming common knowledge that specifying reward functions by hand is challenging: typically, there will be some method for the agent to achieve high reward that is not what the designer intended [Krakovna 2018, Lehman et al. 2018, Kerr 1975]. Even in video games, optimizing for a high score may not produce the desired behavior. In an infamous example, an agent trained to play the boat racing game CoastRunners discovers it can loop forever collecting power-ups that give it bonus points: significantly increasing the score, but never finishing the race [Clark and Amodei 2016].

The fundamental problem is that a reward function is effectively interpreted as the single source of truth that defines the optimal behavior of the agent in any circumstance that can possibly arise, rather than as a source of evidence about what task designers want, which may be flawed or incomplete [Hadfield-Menell et al., 2017]. We thus aim to incorporate additional channels for communicating information about what designers want to our AI agents. We call the class of techniques for this problem “learning from human feedback” (LfHF). Reward functions are just one type of feedback that the designer can provide to an AI system. Jeon et al. [2020] provide a survey of other possible feedback modalities, including demonstrations [Ng and Russell 2000, Ziebart et al., 2010], comparisons [Christiano et al., 2017, Wirth et al., 2017], the state of the world [Shah et al., 2019], and many more.

In recent work, many LfHF techniques have been adapted to use function approximation in order to scale to high-dimensional state spaces [Ho and Ermon 2016, Fu et al., 2017, Christiano et al., 2017, Warnell et al., 2018]. These techniques are typically evaluated within a deep reinforcement learning (RL) benchmark by testing whether LfHF agents generate high ground-truth reward. However, deep RL benchmarks are often designed to be challenging for reinforcement learning, and need not be good benchmarks for LfHF techniques, since the environment may by itself provide information about the desired behavior. For example, in many Atari games, if the agent fails to take the actions that lead to winning, the agent will get stuck or die (terminating the episode). As a result, even pure curiosity-based agents that never get a reward signal tend to get high ground-truth reward in Atari [Burda et al., 2018]. Similarly, Kostrikov et al. [2018] show that when initializing the GAIL discriminator to a constant value that implies the constant reward \( r(s,a) = \log 2 \), they reach 1000 reward on Hopper (corresponding to about a third of expert performance), since surviving correlates well with obtaining reward.

Due to these issues, our goal is to test LfHF techniques in an open world designed with many possible goals in mind. Open worlds are more complex, making for a more challenging benchmark, and help to avoid biases where the environment itself provides information about the goal.

In the MineRL BASALT competition, we choose Minecraft as our environment because

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1 We are using “feedback” in a broader sense than the colloquial usage. In our usage, it refers to any form of information about the designer’s intent, not just corrective information about the agent’s policy.
of how open-ended the game is: humans pursue a wide variety of goals within the game, thus providing a rich space of tasks that agents can be trained to perform. We select four tasks in particular and challenge participants to build agents that can perform these tasks well. We expect that good performance will require participants to use and improve existing LfHF techniques.

Our hope is that this is just the first step along a path to general, capable agents in Minecraft. Over time, we want this competition to incorporate increasingly challenging tasks. We envision eventually building agents that can be instructed to perform arbitrary Minecraft tasks in natural language on public multiplayer servers, or inferring what large scale project humans are working on and assisting with those projects, while adhering to the norms and customs followed on that server.

The goal of this competition is to promote research using LfHF techniques, rather than reward functions, to solve sequential decision-making tasks. We see the impact as coming from three main sources. First, such techniques can enable us to build AI systems for tasks without formal specifications. Second, LfHF methods greatly expand the set of properties we can incorporate into our AI systems, allowing more effective governance of AI systems. Finally, by learning from human feedback, we can train AI systems that optimize for our goals, making progress on the value alignment problem.

1.1.1 Performing fuzzy tasks

Recent research has had a number of major successes when using deep RL, such as in Go [Silver et al., 2016], Dota [OpenAI, 2018], and StarCraft [Vinyals et al., 2019]. However, all of these occurred in domains where there was a well-defined, procedurally-specified reward function. In realistic settings, any automated, hard-coded reward function will likely be, at best, a rough proxy for what we actually want. And, unfortunately, confidently optimizing for a proxy can have undesirable outcomes, resulting not just in a less-than-optimal solution to your true intention, but in solutions actively at odds with that intention [Kerr, 1975, Krakovna, 2018].

LfHF allows us to widen the “communication channel” used to convey intentions to an agent. For example, whether a summary of an article is good depends on a strong understanding of what details in the article are most important and salient, which will necessarily be very context-dependent and not amenable to formalization. Nonetheless, Stiennon et al. [2020] achieve strong summarization results through a combination of imitating human summaries and learning from human comparisons between summaries.

Taking a more futuristic example, we might want our virtual assistants to follow instructions given to them by their users. However, an assistant should not be perfectly obedient. Suppose Alice asks her AI assistant to buy a diamond necklace on her behalf, but doesn’t realize that this would make her unable to pay rent. A human assistant in this situation would likely point out this fact, and ask for explicit confirmation before going ahead, or perhaps even refuse to follow the instructions; presumably an AI assistant should...
do something similar as well. We cannot specify ahead of time the exact set of situations in which the assistant should not immediately execute an instruction. With LfHF, we can instead have the assistant clarify whenever a human in its place would do so.

### 1.1.2 Making AI governable

One major challenge in the governance of AI is that we cannot simply legislate that AI be “beneficial”, “fair” or “safe”, since we do not how to define these terms, or how to make AI systems that meet them. LfHF offers an alternative: rather than legislating that AI systems must satisfy some property P by formalizing what P means, we can instead legislate that AI systems must be trained to match the conception of P that a “reasonable person” would agree with. LfHF techniques would then be used to transfer the human concept of P into the AI system. This opens up hugely important affordances [Graber, 2020] or algorithmic social contracts [Rahwan, 2018] to be used in the governance of AI.

For example, some argue that recommender systems cause harm, such as by exacerbating political polarization and promoting extremist content [Milano et al., 2020] (though such concerns have been disputed [Orben and Przybylski, 2019]). These concerns persist despite efforts by companies to change recommender systems to optimize subjective well-being [Stray, 2020, Milli et al., 2020], suggesting that the issue is that we do not know how to optimize for subjective wellbeing. LfHF offers the alternative of training recommender systems to promote content that humans would predict would improve the user’s well-being. If companies choose not to implement such solutions, legislators can demand that they do so. Note that recommender systems operate in a sequential decision-making setting (where the “environment” consists of the user’s mental state), similarly to this competition.

We are not married to the particular example of recommender alignment; indeed it would not surprise us if we found some alternative solution besides LfHF. Our point is that many problems with AI systems, even ones that we do not yet know about, could be addressed if we had significantly improved LfHF techniques.

### 1.1.3 Value alignment

It has been argued that sufficiently powerful agents pursuing incorrectly specified objectives could cause an existential catastrophe [Russell, 2019, Bostrom, 2014]. One possible solution is value alignment: rather than have agents that are optimizing for their objectives, we would like to have agents that learn and optimize our objectives [Shapiro and Shachter, 2002]. Learning objectives from human feedback is a natural approach to this problem.

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2Of course, humans may not agree on what would and would not improve user well-being. LfHF would only allow us to match some particular person’s predictions; it does not solve the issue that different people may reasonably disagree about such predictions.
1.1.4 Malicious use

A discussion of impact would not be complete without an analysis of possible negative impacts. We do not currently see concrete, probable negative impacts of promoting research on LfHF. However, like most fundamental AI techniques, LfHF is omni-use: it can conceivably enable both good and harmful applications of AI. Just as language models can be finetuned from human feedback to summarize well [Stiennon et al., 2020], they could also be finetuned to, say, produce hate speech targeted against specific groups. Inevitably, there will be some negative effects of this sort, even if we cannot predict exactly what they will be ahead of time. Nonetheless, we expect that the positive impacts will be significantly larger, and thus justify the research.

1.2 Novelty

To our knowledge, MineRL BASALT is the first competition to test LfHF techniques in a sequential decision-making setting. We hope to turn it into an annual competition, with the difficulty of tasks increasing in tandem with the capabilities of our algorithms.

The most similar competition we know of is our sister competition, MineRL Diamond [Guss et al., 2019]. MineRL Diamond provides tasks with known reward functions in Minecraft, and challenges participants to train agents to perform these tasks using a fixed, limited budget of compute and environment interactions. They also provide a dataset of human demonstrations for the tasks, with the result that many participants use imitation learning algorithms in their solutions. The competition thus has led to research on imitation learning (a specific LfHF technique). However, there are several differences between the two competitions:

1. The MineRL Diamond challenge focuses on environment sample efficiency, whereas we focus on solving tasks and sample efficiency of human feedback.

2. The MineRL Diamond challenge specifies tasks that include reward functions for all tasks, whereas our tasks are explicitly designed to not include them.

3. The MineRL Diamond challenge restricts the approaches participants can take, in order to prevent participants from baking in domain knowledge. In contrast, we take a “no-holds-barred” approach[^3] where participants may use any techniques they want to solve our tasks.

4. The MineRL Diamond challenge only allows participants to use a specific set of human demonstrations, whereas we allow participants to use any type of human feedback that could be given by contractors with knowledge of Minecraft and optionally a small amount (<30m) of additional instruction.

[^3]: The only restriction is that participants may not extract data from the Minecraft simulator beyond what we provide, since this strategy would not be applicable in a real-world setting.
While the competitions are working towards different goals, the goals themselves are complementary, and the techniques used to achieve the goals are similar. As a result, we plan to share resources, including a website, a community forum, a technical stack, and outreach efforts, which should make both competitions more effective at their individual goals.

Besides MineRL Diamond, there have been other benchmarks that use Minecraft as a platform, such as MARLÖ [Perez-Liebana et al., 2019], CraftAssist [Gray et al., 2019], Malmö [Johnson et al., 2016], and Generative Design in Minecraft (GDMC) [Salge et al., 2018], but none are particularly relevant to LfHF.

1.3 Data

For each task (described in Section 1.4), we provide a dataset of human demonstrations of that task, using the same infrastructure as in MineRL Diamond [Guss et al., 2019]. Each demonstration is a sequence of state-action pairs—a trajectory—contiguously sampled at every Minecraft game tick (20 game ticks per second). Each state is comprised of an RGB video frame from the player’s point of view and a comprehensive set of features from the game state at that tick: player inventory, item collection events, distances to objectives, player attributes (health, level, achievements), and details about the current GUI the player has open. The action recorded at each tick consists of all the keyboard presses, the change in view, pitch and yaw (mouse movements), a representation of player GUI interactions, and agglomerative actions such as item crafting. The publicly released version of this dataset has been postprocessed to simplify its use: for example, since agents do not use the GUI, the GUI data in the demonstrations has been converted to a format compatible with the agent’s action space.

Note that participants are not required to use the dataset: they are free to completely ignore the demonstrations and use an alternative form of feedback to train agents. However, we expect that the winning submissions will make use of the collected datasets.

In addition to collecting demonstrations, we will also use human-generated data during evaluation. In particular, to score agents, we will show videos of agent behavior to humans and have them determine which of two agents performed the task better. This process is explained in more detail in Section 1.5.

The procedures for collecting demonstrations and for evaluation of agents have been approved under IRB 2021-01-13955 from UC Berkeley.

1.4 Tasks and application scenarios

Our goal is to promote work on LfHF, to design algorithms that can eventually be applied to hard-to-specify problems of interest in the real world. Since we want algorithms to transfer to real-world settings, we want to incentivize general solutions rather than algorithms that are specific to a given task. So, we design a suite of four tasks that participants must perform well on. Training code does not need to be identical across all four tasks, but
we hope that having performance on all tasks count towards final competition score will encourage the use of general-purpose techniques rather than task-specific hard-coding.

**FindCave.** The agent spawns in a plains biome, and must explore the surrounding area to find a naturally generated cave.

**MakeWaterfall.** The agent spawns in an extreme hills biome. The task is to create a waterfall, and take a scenic photograph of the waterfall. To implement the photograph, we have the agent throw a snowball, which we then interpret as the moment which the agent captures as its “photograph”. Agents will be judged both on whether they created a waterfall at all and how aesthetically pleasing their photograph is. The agent is provided with the tools needed to efficiently move around the extreme hills biome, a snowball for taking a picture, and two buckets of water for creating the waterfall. (Minecraft physics is such that a single bucket of water is sufficient to create large waterfalls, and two buckets of water allow for an agent to get infinite amounts of water.)

**CreateVillageAnimalPen.** The agent spawns in a village. It must build an animal pen next to one of the houses in the village, and then corral a pair of animals (chickens, cows, sheep, or pigs) into the pen such that they could then be bred. The agent is provided with materials that it can use to build the pen, as well as the types of food necessary to lure animals.

**BuildVillageHouse.** The agent spawns in a village. It must build a new house for itself in the same style as the other village houses, without damaging the village in any way. The agent is provided with the materials needed to build a house in a variety of different types of villages.

### 1.5 Metrics

Participants will submit a separate trained agent for each of the four tasks. We will score these agents using human judgments, as illustrated in Figure 2.

**Method.** We will execute the agents on test environments4 to produce multiple videos of agent behavior. For each task, we will then play agents against each other in “matches”. In a single match, we choose two agents and one test environment, and show the two corresponding videos to a human rater, and ask the rater to determine which agent better completed the task. Given a dataset of such comparisons, we will use the TrueSkill system [Herbrich et al., 2006] to compute scores for each agent. Matches will be selected so that the test environments will be generated in the same way as the training environments, but with different seeds during the generation of the Minecraft world.
Figure 2: Evaluation workflow. Human workers are first shown the description of the task as well as calibration examples of how good particular trajectories are. They are then shown two agent trajectories, and are asked which agent performed the task better. From these comparisons, we compute scores using the TrueSkill system, and compute final scores by averaging the normalized TrueSkill scores across tasks.

as to maximize the expected increase in information, and will be run until the TrueSkill scores are sufficiently confident to produce a reasonably stable ranking of agents.

To aggregate TrueSkill scores across tasks, we first normalize scores within a task to have mean 0 and standard deviation 1. A participant’s final score is then given by the average of their normalized scores across all tasks. The normalization ensures that no one task will unduly drive the final scores, while still remaining sensitive to the magnitude of the differences in scores between different agents on a task.

Challenges. Any human evaluation comes with significant challenges. We view this as an unavoidable evil: it seems necessary to use human evaluation in order to scale to tasks that are hard to formally specify, since any metric other than human evaluation would probably require some sort of formal specification. We try to address the problems as well as possible, but some remain:

- **Replicability**: By replicability, we mean that the final scores can be recreated exactly by rerunning the evaluation. Our method is obviously not perfectly replicable, since we have no way of ensuring that different humans give exactly the same judgments in their evaluations of the same matches. However, the videos that human raters are shown are replicable, at least to the extent that participants’ training procedures are replicable. In addition, the human evaluations should still be repro-
ducible: redoing the evaluation should give similar and consistent results, even if not the exact same numbers.

- **Bias:** It is possible that the human evaluators will fail to account for the factors that we care about, or overweight features that aren’t actually very important. We don’t see this as a major problem for this competition: participants should be optimizing for how the raters will judge their agents, rather than what the competition organizers do or don’t care about. In real-world applications, it would also be important to ensure that rater judgments are correlated with real-world value, but this does not matter for the purposes of this competition. Section 2.1.2 explains how we ensure that participants can learn how raters will judge their agents.

- **Explanations:** With human evaluations, it can be opaque why a particular agent got a low score. To combat this, we ask raters to answer additional questions about specific features of how the agent performed, which can then be provided as an explanation for the score. However, this only ameliorates the problem rather than fixing it entirely, since raters may also be making judgments based on implicit features that we fail to ask about.

- **Variance:** Human evaluations can have relatively high variance. We hope to minimize this by having an initial calibration phase (see Figure 2), but in any case, we plan to overcome the variance through sufficiently large sample sizes (i.e. playing enough matches).

### 1.6 Baselines, code, and material provided

**Baselines.** We have provided a behavioral cloning [Pomerleau 1991] baseline. There is significant room for improvement: for example, on the MakeWaterfall task, the agent has learned to go near waterfalls (presumably to take pictures of them), but does not typically create waterfalls, presumably since the “place water” action needed to create a waterfall is a tiny fraction of the actions taken in the human demonstrations.

**Starting kit.** The starter kit contains the following:

1. A Gym environment (without reward) for each of the four tasks.

2. Code to download the dataset of demonstrations for each of the above tasks, described in more detail in Section 1.3.

3. A submission template that provides the boilerplate code needed for submission.

4. An instantiation of the submission template that contains the behavioral cloning baseline, that could be submitted as is.
Since we build upon the MineRL framework, participants automatically get access to the environments defined in the MineRL Diamond challenge [Guss et al., 2019]. Participants may use these environments for quick iteration: since these environments provide a reward signal, it is possible to simulate human feedback in order to quickly test human-in-the-loop algorithms without requiring an actual human. For example, when learning from human comparisons, participants could use the MineRL TreeChop environment and simulate human comparisons between two trajectories \( \tau_1 \) and \( \tau_2 \) via the Boltzmann rational model:

\[
P(\tau_1 > \tau_2) = \frac{\exp(\beta R(\tau_1))}{\exp(\beta R(\tau_1)) + \exp(\beta R(\tau_2))}.
\]

1.7 Tutorial and documentation

We provide a website that contains instructions, documentation, and updates to the competition. We have also provided references to prior LfHF approaches that participants can read for ideas on how to tackle the competition.

2 Organizational aspects

2.1 Protocol

2.1.1 Submission protocol

Participants are asked to submit trained agents along with the training code for these agents, following the pipeline developed for the MineRL Diamond challenge. Specifically, participants will submit a git repository through the use of tags, and use the aicrowd-repo2docker\(^5\) tool to specify their runtime using Anaconda environment exports, requirements.txt, or a traditional Dockerfile.

To the extent that training procedures make use of live human feedback, we require that the training code exposes an English-language interface - either via the command line, or some more complex GUI, if desired - where humans with minimal training (<30m) can provide that feedback. Participants must specify training instructions for their feedback mechanism, as well as an expected amount of human labor their training process requires, with a to-be-determined cap on the amount we will support.

For the majority of submissions, we will never run the training code, as it is only used to validate that participants followed the rules.

\(^5\)https://pypi.org/project/aicrowd-repo2docker/
2.1.2 Evaluating submissions

As described in Section 1.5, our core evaluation mechanism is to run the submitted agents on test seeds to produce videos of agent behavior and then have human raters compare different videos against each other. Since this evaluation scheme relies on human labor, it is relatively expensive (about $100 per submission), and so we do not plan to run it throughout the competition. Instead, we will only pay contractors for evaluations at the end of the competition in order to compute final scores for qualifying submissions.

In order to provide participants with useful feedback during the submission phase, we plan to maintain a public leaderboard in which anyone can provide pairwise comparisons between the trajectories of two agents. For every submission after their first one, participants are required to compare other submitted agents, in order to get the necessary comparisons for calculating scores. Submitting new agents for each of the tasks should require around one or two hours of comparisons in total, and so should not be too onerous for participants. We will also advertise the leaderboard and evaluation mechanism publicly to induce interested Minecraft players in providing some comparisons as well.

It is possible that even with only one tabulation of final results, it would still be prohibitively expensive to evaluate every submission. In this case, we will only evaluate the top submissions, as determined by the public leaderboard.

2.1.3 Preventing cheating

Once final results are computed, we will validate the top submissions. We will inspect the submitted training code for any rule violations, and then rerun the submitted training code, working with participants to ensure that the code runs smoothly. We will hire contractors to provide any online feedback needed by the training process. Once agents have been trained, we will check that the resulting agents behave similarly to the ones that were submitted for evaluation.

Note that winners are determined by the scores of submitted agents rather than the scores of retrained agents. The only purpose of the retraining stage is to catch any cheating and disqualify those entries. In particular, the retraining will catch cases where participants broke a rule while creating their submitted agents (for example, by using excessive amounts of computational resources, or extracting information from the Minecraft simulator), and tried to hide it by submitting an entirely different piece of training code that does follow the rules and claiming that the submitted agent was trained using that code.

If any issues come up during this process, we will contact the corresponding team for appeal. In the case of an unsuccessful appeal, the team will be removed from consideration for final results.
2.2 Rules

Our goal is to promote research into techniques that allow us to train agents for tasks without well-specified rewards, as is the default in the real world. The real world does not impose any restrictions on how AI systems must be built, and we seek to match that as closely as possible. We thus choose a “no-holds-barred” approach, where participants may take any approach they like to build their agents. The only restriction we place is that participants may not extract additional information from within the Minecraft simulator beyond what we provide, since this does not have any analog in real world applications (where we usually do not have a perfect simulator). The remaining rules are chosen to enable accurate evaluation of submissions and to encourage openness and scientific progress. This leads to the rules draft below:

1. Participants must not extract any additional information from the Minecraft simulator beyond what is provided by the Gym environment. Note that this also prohibits the use of Minecraft internals during training, even if the resulting agent uses only pixels as input. For example, it is not allowed to extract an indicator of whether the agent is in a village, in order to define a reward signal during training in ObtainStone, even though such a reward signal would not be needed at test time. We will retrain the top submissions in order to ensure compliance with this rule.

2. Except where prohibited by rule 1, participants are encouraged to use additional resources and sources of human feedback beyond those provided by the competition organizers.

3. Participants must adhere to the limits on compute and online human feedback when training their agent.\(^6\)

4. Submissions may re-use open-source code with proper attribution. At the end of the competition, submissions must be open-sourced to enable reproducibility.

Since we adopt a “no-holds-barred” approach, cheating is not a significant concern. We need only verify that rule 1 is followed, which we will do by inspecting the training code for the winning submissions and re-running it to ensure that it does produce an agent of similar quality as the submitted agent. To enable this, we are working with AIcrowd, who have already developed a similar pipeline for our sister competition, MineRL Diamond.

The third rule, on adhering to compute and human feedback limits, serves three purposes. First, it ensures that we will be able to retrain participants’ submissions at reasonable cost in order to validate their second stage submission. Second, it ensures that the competition remains accessible to all, and is not just won by the team that trains the

\(^6\)These limits have not yet been determined, but a rough version would be $100 of compute and 5 hours of human feedback for each task.
largest network with the most human feedback. And, third, it promotes solutions that make *efficient* use of human feedback.

### 2.3 Schedule

The planned schedule for the competition is as follows:

- **Jul 7**  **Competition begins:** Participants are invited to download the starting kit and begin developing their submission.
- **Oct 15**  **Submission deadline:** Submissions are closed and organizers begin the evaluation process.
- **Oct 29**  **Evaluation complete:** Evaluation scores have been calculated. The top teams proceed to the validation stage.
- **Nov 12**  **Validation complete:** Winners are announced and are invited to contribute to the competition writeup.
- **Dec 13**  **Presentation at NeurIPS 2021.**

### 2.4 Competition promotion

We have coordinated our competition promotion with that of MineRL Diamond, allowing for a greater reach on the part of both competitions.

**Website.** Our competition is promoted on the general MineRL website[^7] which is already well known to previous participants in the MineRL Diamond challenge.

**Partnership with affinity groups.** We hope to partner with affinity groups to promote the participation of groups who are traditionally underrepresented. We plan to reach out to organizers of Women in Machine Learning (WiML[^8]), LatinX in AI (LXAI[^9]), Black in AI (BAI[^10]), and Queer in AI[^11]. We will also reach out to organizations, such as Deep Learning Indaba[^12] and Data Science Africa[^13] to determine how to increase the participation of more diverse teams.

[^7]: https://minerl.io/basalt/
[^8]: https://wimlworkshop.org/
[^9]: https://www.latinxinai.org/
[^10]: https://blackinai.github.io/
[^11]: https://sites.google.com/view/queer-in-ai/
[^12]: http://www.deeplearningindaba.com/
[^13]: http://www.datascienceafrica.org/
Promotion through mailing lists. To promote participation in the competition, we plan to distribute the call to general technical mailing lists, such as Robotics Worldwide and Machine Learning News; company mailing lists, such as DeepMind’s internal mailing list; and institutional mailing lists. We plan to promote participation of underrepresented groups in the competition by distributing the call to affinity group mailing lists, including, but not limited to Women in Machine Learning, LatinX in AI, Black in AI, and Queer in AI. Furthermore, we will reach out to individuals at historically black or all-female universities and colleges to encourage the participation of these students and/or researchers in the competition. By doing so, we will promote the competition to individuals who are not on any of the aforementioned mailing lists, but are still members of underrepresented groups.

Media coverage. To increase general interest and excitement surrounding the competition, we will reach out to the media coordinator at Carnegie Mellon University. By doing so, our competition will be promoted by popular online magazines and websites, such as Wired. We will also post about the competition on relevant popular subreddits, such as [r/machinelearning](https://www.reddit.com/r/machinelearning) and [r/datascience](https://www.reddit.com/r/datascience), and promote it through social media. We will utilize our industry and academic partners to post on their various social media platforms, such as the Berkeley AI Research (BAIR) blog, the OpenAI Blog, and the Carnegie Mellon University Twitter.

3 Resources

3.1 Organizing team

3.1.1 Organizers

Rohin Shah. Rohin Shah is a Research Scientist at DeepMind. He completed his PhD at the Center for Human-Compatible AI at UC Berkeley, advised by Anca Dragan, Stuart Russell, and Pieter Abbeel. His research has focused on the application of preference learning to the value alignment problem, and has been supported by the NSF Fellowship and the Berkeley Fellowship. He was inspired to create this competition through frustration at the lack of good benchmarks for preference learning algorithms. He is particularly interested in improving education and has created the Alignment Newsletter, a weekly publication rounding up recent research in AI alignment with thousands of subscribers.

Cody Wild. Cody Wild is a research engineer at the Center for Human-Compatible AI at Berkeley. She has previously collaborated on implementation, tooling, and experiment design for research into representation pretraining for imitation learning and adversarial attacks on reinforcement learning policies. Outside of her formal engineering work, she
has done extensive technical writing explaining and clarifying aspects of modern machine learning research, and has published over 100,000 words in the form of either single-paper summaries or more in-depth blog posts.

Steven Wang. Steven Wang is a research engineer at the Center for Human-Compatible AI at UC Berkeley, where he also completed a Bachelor’s of Science in EECS. He is interested in robust machine learning and learning from human feedback. In previous research projects, he has open-sourced modular implementations of imitation learning algorithms and developed robust pedestrian tracking systems for quadcopter navigation.

Neel Alex. Neel Alex is a recent graduate from UC Berkeley where he worked with the Center for Human-Compatible AI. He is interested in learning from human feedback, and hopes that this competition improves the efficacy of such methods. His past research has studied the importance of understanding which questions are relevant to ask in an active learning context.

Brandon Houghton. Brandon Houghton is a Machine Learning Engineer at OpenAI and co-creator of the original MineRL dataset. Graduating from the School of Computer Science at Carnegie Mellon University, Brandon’s work focuses on developing techniques to enable agents to interact with the real world through virtual sandbox worlds such as Minecraft. He has worked on many machine learning projects, such as discovering model invariants in physical systems as well as learning lane boundaries for autonomous driving.

William H. Guss. William Guss is a research scientist at OpenAI and Ph.D. student in the Machine Learning Department at CMU. William co-created the original MineRL dataset and lead the original MineRL Diamond competition at NeurIPS 2019. He is advised by Dr. Ruslan Salakhutdinov and his research spans sample-efficient reinforcement learning and deep learning theory. William completed his bachelors in Pure Mathematics at UC Berkeley where he was awarded the Regents’ and Chancellor’s Scholarship, the highest honor awarded to incoming undergraduates. During his time at Berkeley, William received the Amazon Alexa Prize Grant for the development of conversational AI and co-founded Machine Learning at Berkeley.

Sharada Mohanty. Sharada Mohanty is the CEO and Co-founder of AIcrowd, a community of AI researchers built around a platform encouraging open and reproducible artificial intelligence research. He was the co-organizer of many large-scale machine learning competitions, such as NeurIPS 2017: Learning to Run Challenge, NeurIPS 2018: AI for Prosthetics Challenge, NeurIPS 2018: Adversarial Vision Challenge, NeurIPS 2019: MineRL Competition, NeurIPS 2019: Disentanglement Challenge, NeurIPS 2019: REAL Robots Challenge, NeurIPS 2020: Flatland Competition, NeurIPS 2020: Procgen Competition. He is extremely passionate about benchmarks and building communities. During
his Ph.D. at EPFL, he worked on numerous problems at the intersection of AI and health, with a strong interest in reinforcement learning. In his previous roles, he has worked at the Theoretical Physics department at CERN on crowdsourcing compute for Monte-Carlo simulations using Pythia; he has had a brief stint at UNOSAT building GeoTag-X - a platform for crowdsourcing analysis of media coming out of disasters to assist in disaster relief efforts. In his current role, he focuses on building better engineering tools for AI researchers and making research in AI accessible to a larger community of engineers.

**Stephanie Milani.** Stephanie Milani is a Ph.D. student in the Machine Learning Department at Carnegie Mellon University, where she is advised by Dr. Fei Fang. Her research interests include sequential decision-making problems, with an emphasis on reinforcement learning. In 2019, she completed her B.S. in Computer Science and her B.A. in Psychology at the University of Maryland, Baltimore County. She co-organized the 2019 and 2020 MineRL competitions. Since 2016, she has worked to increase the participation of under-represented groups in CS and AI at the local and state level. For these efforts, she has been nationally recognized through a Newman Civic Fellowship.

**Nicholay Topin.** Nicholay Topin is a Machine Learning Ph.D. student advised by Dr. Manuela Veloso at Carnegie Mellon University. He co-created the original MineRL dataset and co-organized the 2019 and 2020 MineRL competitions. His current research focus is explainable deep reinforcement learning systems. Previously, he has worked on knowledge transfer for reinforcement learning and learning acceleration for residual networks.

**Pieter Abbeel.** Professor Pieter Abbeel is Director of the Berkeley Robot Learning Lab and Co-Director of the Berkeley Artificial Intelligence (BAIR) Lab. Abbeel's research strives to build ever more intelligent systems, which has his lab push the frontiers of deep reinforcement learning, deep imitation learning, deep unsupervised learning, transfer learning, meta-learning, and learning to learn, as well as study the influence of AI on society. His lab also investigates how AI could advance other science and engineering disciplines. Abbeel's Intro to AI class has been taken by over 100K students through edX, and his Deep RL and Deep Unsupervised Learning materials are standard references for AI researchers. He has organized the NeurIPS Deep RL Workshop, which has consistently been one of the most highly attended NeurIPS workshops for the past 6 years. Abbeel has founded three companies: Gradescope (AI to help teachers with grading homework and exams), Co-variant (AI for robotic automation of warehouses and factories), and Berkeley Open Arms (low-cost, highly capable 7-dof robot arms), advises many AI and robotics start-ups, and is a frequently sought after speaker worldwide for C-suite sessions on AI future and strategy. Abbeel has received many awards and honors, including the PECASE, NSF-CAREER, ONR-YIP, Darpa-YFA, TR35. His work is frequently featured in the press, including the New York Times, Wall Street Journal, BBC, Rolling Stone, Wired, and Tech Review.
Stuart Russell. Stuart Russell is a Professor of Computer Science at the University of California at Berkeley, holder of the Smith-Zadeh Chair in Engineering, and Director of the Center for Human-Compatible AI. He is a recipient of the IJCAI Computers and Thought Award and from 2012 to 2014 held the Chaire Blaise Pascal in Paris. He is an Honorary Fellow of Wadham College, Oxford, an Andrew Carnegie Fellow, and a Fellow of the American Association for Artificial Intelligence, the Association for Computing Machinery, and the American Association for the Advancement of Science. His book “Artificial Intelligence: A Modern Approach” (with Peter Norvig) is the standard text in AI, used in 1500 universities in 135 countries. His research covers a wide range of topics in artificial intelligence, with an emphasis on the long-term future of artificial intelligence and its relation to humanity. He has developed a new global seismic monitoring system for the nuclear-test-ban treaty and is currently working to ban lethal autonomous weapons. His current concerns include the threat of autonomous weapons and the long-term future of artificial intelligence and its relation to humanity. The latter topic is the subject of his book, “Human Compatible: AI and the Problem of Control” (Viking/Penguin, 2019).

Anca Dragan. Anca Dragan is an Assistant Professor in the EECS Department at UC Berkeley. Her goal is to enable robots to work with, around, and in support of people. She runs the InterACT Lab, where the focus is on algorithms for human-robot interaction - algorithms that move beyond the robot’s function in isolation, and generate robot behavior that also accounts for interaction and coordination with end-users. The lab works across different applications, from assistive robots, to manufacturing, to autonomous cars, and draw from optimal control, planning, estimation, learning, and cognitive science. She also helped found and serve on the steering committee for the Berkeley AI Research (BAIR) Lab, and is a co-PI of the Center for Human-Compatible AI. She was also honored by the Sloan Fellowship, MIT TR35, the Okawa award, and an NSF CAREER award.

3.1.2 Advisors

Sergio Guadarrama. Sergio Guadarrama is a Staff Software Engineer in the Google Brain team, where he works in Reinforcement Learning and Deep Learning. His research focus is on reliable, scalable and efficient Reinforcement Learning. Currently he is the lead of TF-Agents project and a core developer of TensorFlow (co-creator of TF-Slim). Before joining Google he was a Research Scientist at the University of California, Berkeley where he worked with Prof. Lotfi Zadeh and Prof. Trevor Darrell. He received his Bachelor and PhD degrees from the Technical University of Madrid. He earned the 2017 Everingham Prize for providing the open-source deep learning framework Caffe to the research community. He was part of the winning team of the COCO 2016 Detection Challenge, won the ACM Multimedia Open-Source Software Competition in 2014, and received the Best Doctoral Dissertation Award by the Technical University of Madrid (advisor: Prof. Enric
Katja Hofmann. Katja Hofmann is a Senior Researcher at the Machine Intelligence and Perception group at Microsoft Research Cambridge. Her research focuses on reinforcement learning with applications in video games, as she believes that games will drive a transformation of how people interact with AI technology. She is the research lead of Project Malmo, which uses the popular game Minecraft as an experimentation platform for developing intelligent technology, and has previously co-organized two competitions based on the Malmo platform. Her long-term goal is to develop AI systems that learn to collaborate with people, to empower their users and help solve complex real-world problems.

3.1.3 Partners and sponsors

As mentioned previously, we are working with AIcrowd for the purposes of evaluation, and are sponsored by Microsoft and OpenAI. We are also currently in conversation with other potential partners as well, one of which has provided a soft commitment to sponsor the competition. We are confident that we will have the resources needed to run the competition.

3.2 Resources provided by organizers

Mentorship. Previous MineRL competitions have set up an online community forum through a public Discord server. This has been very helpful in increasing participant engagement and helping solve any issues that arise. Both MineRL BASALT and MineRL Diamond are using this Discord server again this year in order to create an active community to work on the competition problems.

Computing and evaluation resources. We hope to provide compute grants to teams that self identify as lacking access to the necessary resources to take part in this competition. We are currently in conversation with some potential sponsors for the necessary compute credits.

Prizes. We already have at least $12,000 worth of prizes, and may increase this depending on funding availability.

3.3 Support requested

We do not request any support, beyond a time slot at which to present the results of the competition.
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