EvalAI:  
Towards Better Evaluation Systems for AI Agents

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Abstract

We introduce EvalAI, an open source platform for evaluating and comparing machine learning (ML) and artificial intelligence algorithms (AI) at scale. EvalAI is built to provide a scalable solution to the research community to fulfill the critical need of evaluating machine learning models and agents acting in an environment against annotations or with a human-in-the-loop. This will help researchers, students, and data scientists to create, collaborate, and participate in AI challenges organized around the globe. By simplifying and standardizing the process of benchmarking these models, EvalAI seeks to lower the barrier to entry for participating in the global scientific effort to push the frontiers of machine learning and artificial intelligence, thereby increasing the rate of measurable progress in this domain.

Our code is available here.

1 Introduction

Time and again across different scientific and engineering fields, the formulation and creation of the right question, task, and dataset to study a problem has coalesced fields around particular challenges – driving scientific progress. Likewise, progress on important problems in the fields of Computer Vision (CV) and Artificial Intelligence (AI) has been driven by the introduction of bold new tasks together with the curation of large, realistic datasets \cite{23,2}.

Not only do these tasks and datasets establish new problems and provide data necessary to address them, but importantly they also establish reliable benchmarks where proposed solutions and hypothesis can be tested which is an essential part of the scientific process. In recent years, the development of centralized evaluation platforms have lowered the barrier to compete and share results on these problems. As a result, a thriving community of data scientists and researchers has grown around these tasks, increasing the pace of progress and technical dissemination.

Historically, the community has focused on traditional AI tasks such as image classification, scene recognition, and sentence parsing that follow a standard input-output paradigm for which models can be evaluated in isolation using simple automatic metrics like accuracy, precision or recall. But with the success of deep learning techniques on a wide variety of tasks and the proliferation of ‘smart’ applications, there is an imminent need to evaluate AI systems in the context of human collaborators and not just in isolation. This is especially true as AI systems become more commonplace and we find ourselves interacting with AI agents on a daily basis. For instance, people frequently interact with virtual assistants like Alexa, Siri, or Google Assistant to get answers to their questions, to book appointments at a restaurant, or to reply to emails and messages automatically. Another such example is the use of AI for recognizing content in images, helping visually impaired users interpret the surrounding scene. To this end, the AI community has introduced several challenging high-level AI tasks ranging from question-answering about multiple modalities (short articles \cite{29}, images \cite{30},

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Figure 1: EvalAI is a new evaluation platform with the overarching goal of providing the right tools, infrastructure and framework to setup exhaustive evaluation protocols for both traditional static evaluation tasks as well as those in dynamic environments hosting multiple agents and/or humans.

As AI improves and takes on these increasingly difficult, high-level tasks that are poorly described by an input-output paradigm, robust evaluation faces a number of challenges. For instance, generating a natural language description for an image, having a conversation with a human, or generating aesthetically pleasing images cannot be evaluated accurately using automatic metrics as performance on these metrics do not correlate well with human-judgment in practice [6]. Such tasks naturally require human-in-the-loop evaluation by connecting the AI system with a human workforce such as Amazon Mechanical Turk (AMT) [1] to quantify performance in a setup which is closest to the one in which they may be eventually deployed. Moreover, human-AI interaction also reveal interesting insights into the true capabilities of machine learning models. For instance, [6] connected human users with AI agents trained to answer questions about images in a 20-questions style image guessing game and then measured the performance of the human-AI team. The authors observed from the experiments that surprisingly, performance gained through AI-AI self-play does not seem to generalize to human-AI teams. These sort of useful insights are increasingly becoming important as more and more of these models reach consumers.

Furthermore, the rise of reinforcement learning based problems in which an agent must interact with an environment introduces additional challenges for benchmarking. In contrast to the supervised learning setting where performance is measured by evaluating on a static test set, it is less straightforward to measure generalization performance of these agents in context of the interactions with the environment. Evaluating these agents involves running the associated code on a collection of unseen environments that constitutes a hidden test set for such a scenario.

To address the aforementioned problems, we introduce a new evaluation platform for AI tasks called EvalAI. It is an extensible open-source platform that fulfills the critical need in the community for (1) human-in-the-loop evaluation of machine learning models and (2) the ability to run user’s code in a dynamic environment to support the evaluation of interactive agents. We have also addressed several limitations of existing platforms by supporting (3) custom evaluation pipelines compatible with any programming language, (4) arbitrary number of challenge phases and dataset splits, and (5) remote evaluation on private worker pool. By providing the functionality to connect agents, environments, and human evaluators in one single platform, EvalAI enables novel research directions to be explored quickly and at scale.
Having outlined the need for an evaluation platform that can properly benchmark increasingly complex AI tasks, in this section we explicitly specify the following **requirements** that a modern evaluation tool should satisfy.

**Human-in-the-loop evaluation of agents.** As discussed in the Sec. 1, the AI community has introduced increasingly bold tasks (goal-oriented dialog, question-answering, GuessWhich, image generation, etc.) some of which require pairing the AI agent with a human to accurately evaluate and benchmark different approaches against each other. A modern evaluation platform should provide a unified framework for benchmarking in scenarios in which agents are not acting in isolation, but are rather interacting with other agents or humans at test-time.

**Environments, not datasets.** As the community becomes more ambitious in the problems they are trying to solve, we have noticed a shift from static datasets to dynamic environments. Now instead of evaluating a model on a single task, agents are deployed in new unseen environments inside a simulation to check for generalization to novel, unseen scenarios [22, 9]. As such, modern evaluation platforms need to be capable of running “submitted” agents within these environments – a significant departure from the standard evaluation paradigm of computing automatic metrics on a set of submitted predictions.

**Extensibility.** Different tasks require different evaluation protocols. An evaluation platform needs to support an arbitrary number of phases and dataset splits to cater to the evaluation scenarios which often use multiple dataset splits, each serving a different purpose. For instance, COCO Challenge [25], VQA [2], and Visual Dialog [10] all use multiple splits such as test-dev for validation, test-std for reporting results in a paper and a separate test-challenge split for announcing the winners of a challenge that may be centered around the task.

## 3 Related Work

Here we survey some of the existing evaluation platforms in light of the requirements highlighted in the previous section. Additionally, for reader’s convenience, we summarize the features offered by EvalAI via head-to-head comparison with the existing platforms in Table. 1.

| Features               | OpenML | Topcoder | Kaggle | CrowdAI | ParllAI | CodaLab | EvalAI |
|------------------------|--------|----------|--------|---------|---------|---------|--------|
| AI Challenge Hosting   | ✔      | ✗        | ✔      | ✔       | ✗       | ✔       | ✔      |
| Custom metrics         | ✗      | ✗        | ✔      | ✔       | ✔       | ✔       | ✔      |
| Multiple phases/splits | ✗      | ✗        | ✗      | ✔       | ✔       | ✔       | ✔      |
| Open Source            | ✔      | ✗        | ✔      | ✔       | ✔       | ✔       | ✔      |
| Remote Evaluation      | ✗      | ✗        | ✔      | ✔       | ✔       | ✔       | ✔      |
| Human Evaluation       | ✗      | ✗        | ✔      | ✔       | ✔       | ✔       | ✔      |
| Environments           | ✗      | ✗        | ✔      | ✗       | ✗       | ✔       | ✔      |

Table 1: Head-to-head comparison of capabilities between existing platforms and EvalAI
provide an evaluation platform on which supports hosting competitions and benchmarking through a public leaderboard. While CodaLab Competitions is very similar to EvalAI and addresses some of the limitations of Kaggle in terms of functionality, it does not support evaluating interactive agents in different environments with or without humans in the loop. As the community introduces more complex tasks in which evaluation requires running an agent inside a simulation or pairing an agent with a human workforce for evaluation, a highly customizable backend like ours connected with existing platforms like Amazon Mechanical Turk become extremely important.

OpenML [34] is an online platform where researchers can automatically log and share machine learning data sets, code, and experiments. As a system, OpenML allows people to organize their experiments online, and build directly on top of the work of others. By readily integrating the online platform with several machine learning tools, large-scale collaboration in real-time is enabled, allowing researchers to share their very latest results while keeping track of their impact and use. While the focus of OpenML is on experiments and datasets, EvalAI focuses more on the end result - models, their predictions and subsequent evaluation. OpenML and EvalAI are complementary to each other and will be useful to the user at different stages of the research.

ParlAI [28] is a recently introduced open-source platform for dialog research implemented in Python. It serves as a unified platform for sharing, training and evaluating models for several dialog tasks. Additionally, ParlAI also supports integration with Amazon Mechanical Turk – to collect dialog data and support human-evaluation. Several popular dialog datasets and tasks are supported off-the-shelf in ParlAI. Note that unlike EvalAI, ParlAI supports only evaluation for dialog models not for any AI task in general. Also, unlike EvalAI – which supports evaluation across multiple-phases and splits to truly test the generalization and robustness of the proposed model, ParlAI only supports evaluation on one test split, as is the norm with most of the existing dialog datasets.

Additionally, reinforcement learning (RL) algorithms also require strong evaluation and good benchmarks. A variety of benchmarks have been released, such as the Arcade Learning Environment (ALE) [3], which exposed a collection of Atari 2600 games as reinforcement learning problems, and recently the RLLab benchmark for continuous control [14]. More recently, OpenAI [5] gym was released as a toolkit to develop and compare RL algorithms on a variety of environments and tasks – ranging from walking to playing pong or pinball. The gym library provides a flexible environment in which agents can be evaluated using existing machine learning frameworks, such as TensorFlow or PyTorch. OpenAI gym has a similar underlying philosophy of encouraging easy accessibility and reproducibility by not restricting to any particular framework. Additionally, environments are versioned in a way to ensure meaningful and reproducible results as the software is updated.

4 EvalAI: Key Features

As discussed in the previous sections, ensuring algorithms are compared fairly in a standard way is a difficult and ultimately distracting task for AI researchers. Establishing fair comparison requires rectifying minor differences in algorithm inputs, implementing complex evaluation metrics, and often ensuring the correct usage of non-standard dataset splits. In the following sub-sections, we describe the key features that address the aforementioned problems.

4.1 Custom Evaluation Protocol

EvalAI is highly customizable since it allows creation of an arbitrary number of evaluation phases and dataset splits, compatibility using any programming language, and organizing results in both public and private leaderboards. All these services are available through an intuitive web-platform and comprehensive REST APIs.

4.2 Human-in-the-loop Evaluation

While standard computer vision tasks such as image classification [31, 20], semantic or instance segmentation [27, 19], object detection [19, 30] are easy to evaluate using the automatic metrics, it is notoriously difficult to evaluate tasks for which automated metrics correlate poorly with human judgement – for instance, natural language generation tasks such as image captioning [8, 24], visual dialog [10, 11] or image generation tasks [17]. Developing measures which correlate well with human judgment remains an open area of research. Automatic evaluation of models for these kind of tasks is further complicated by the huge set of possibly ‘correct’ or ‘plausible’ responses and the relatively sparse set of ground truth annotations, even for large-scale datasets.
Given these difficulties and the interactive nature of tasks, it is clear that the most appropriate way to evaluate these kind of tasks is with a human in the loop, i.e. a Visual Turing Test [16]! Unfortunately, large-scale human-in-the-loop evaluation is still limited by financial and infrastructural challenges that must be overcome by each interested research group independently. Consequently, human evaluations are rarely performed and experimental settings vary widely, limiting the usefulness of these benchmarking studies in human-AI collaborative settings.

We propose to fill this critical need in the community by providing the capability of human-in-the-loop evaluation. To this end, we have developed the infrastructure to pair Amazon Mechanical Turk (AMT) users in real-time with artificial agents – specifically visual dialog as an example.

4.2.1 Challenges

Building a framework to support human-in-the-loop evaluation comes with its own set of challenges:

- **Instructions**: Since the workers do not know their roles before starting a study catered towards evaluating such tasks, they need detailed instructions and a list of Do’s and Don’t’s for the task. Each challenge might have different instructions and therefore we provide challenge organizers the flexibility to provide us with the required instructions in their own HTML templates.

- **Worker pool**: We need to ensure that we have a pool of good quality workers who have prior experience in doing certain tasks and have a history of high acceptance rate(s). We allow organizers to provide us with a list of whitelisted and blocked workers. Additionally, they can also provide a qualification test which the workers need to pass to participate in the evaluation tasks.

- **Uninterrupted back-and-forth communication**: Certain tasks like evaluating dialog agents need uninterrupted back-and-forth communication between agents and workers. However, this is not always possible since turkers might disconnect or close a HIT before finishing it. We do extensive book-keeping to ensure that incompleted HITS are re-evaluated and turkers can reconnect with the same agent if the connection was interrupted only temporarily.

- **Gathering results**: We provide a flexible JSON based schema and APIs to fetch the results from the evaluation tasks once they are completed. These results are automatically updated on the leaderboard for each submission.

4.3 Remote Evaluation

![Remote Evaluation Pipeline](image)

Figure 2: Remote Evaluation Pipeline: Challenge \( C_1 \) and \( C_2 \) are hosted on EvalAI but evaluation for \( C_2 \) happens on an evaluation worker that is running on a private server which is outside EvalAI Virtual Private Cloud (VPC). For two submissions \( S_1 \) and \( S_2 \) made to challenges \( C_1 \) and \( C_2 \) respectively, submission \( S_1 \) will be evaluated on \( W_L \) which is running on EvalAI whereas \( S_2 \) will run on \( W_R \) which is a remote machine.

Certain large-scale challenges need special compute capabilities for evaluation. For instance, running an agent based on some deep reinforcement learning model in a dynamic environment will require powerful clusters with GPUs. If the challenge needs extra computational power, challenge organizers can easily add their own cluster of worker nodes to process participant submissions while we take care of hosting the challenge, handling user submissions and the maintaining the leaderboard. Our remote evaluation pipeline (shown in Fig. 2) decouples the worker nodes from the web servers through via message-queues. On submission, all related metadata is relayed to an external pool of workers through dedicated message queues.

5 System Architecture

The architectural back-end of our system (Fig. 3) was designed with keeping in mind scalability and portability of such a system from the very inception of the idea. Most of the components rely
heavily on open-source technologies – Docker, Django, Node.js, and PostgreSQL. We also rely on certain proprietary services but at the same time we ensure that the protocol is consistent with other open-source alternatives to the best possible extent. The configurations to setup proprietary services are also available through our open-source code. In the following sub-sections, we describe in detail the key pieces of our platform.

**Orchestration** - We rely heavily on Docker [13] containers to run our infrastructure. Additionally, we also deploy all our containers on Amazon Elastic Container Service (ECS) [15] which auto-scales the cluster to meet the computational demands of the platform leading to high operational efficiency.

**Web Servers** - EvalAI uses Django [12] which is a Python based MVC framework that powers our backend. It is responsible for accessing and modifying the database using APIs, and submitting the evaluation requests into a queue. It also exposes certain APIs to serve data and fetch results from Amazon Mechanical Turk [1] during human evaluation. Through these APIs, agents and workers on AMT communicate with each other using JSON blobs. By structuring the communication protocol to JSONs, the challenge organizers are enabled to customize it to support any kind of interaction.

**Message Queue** - The message queue is responsible for routing a user’s submission to the appropriate worker pool based on the unique routing key associated with each challenge. For our message broker, we chose Amazon Simple Queue Service (SQS) [32]. By using SQS, we do not have to worry about consistency and reliability of the queue. An added bonus of using SQS is that it works seamlessly with other AWS services we use.

**Worker Nodes** - For every challenge, there is a different pool of worker nodes dedicated to evaluating submissions specific to the challenge. We spawn worker nodes as docker containers running inside Elastic Container Service (ECS) [15] which results in multiple advantages. First, worker nodes are isolated such that the dependencies for one challenge don’t clash with dependencies of other challenges. Second, pool of worker nodes specific to the challenge can independently scale based on the demands of the challenge. We also worked closely with challenge organizers to optimize their code to leverage the full computational capacity of the worker. For instance, we warm-up the worker nodes at start-up by importing the challenge code and pre-loading the dataset in memory. We also split the dataset into small chunks that are simultaneously evaluated on multiple cores. These simple tricks result in faster evaluation and reduces the evaluation time by an order of magnitude in some cases. Refer to Section 7 for details on speed-up for the VQA Challenge.

6 Lifecycle of a Challenge

We now describe the life-cycle of a challenge starting from creating a challenge, submitting entries to the challenge and finally evaluating the submissions. This process will also elaborate how different components of the platform communicate with each other.
6.1 Challenge Creation

There are two ways to create a challenge on our platform. For challenges like image classification, detection which require simple evaluation metrics (such as precision, recall, accuracy), a user can follow a sequence of prompts on a user-interface to create a challenge. For more complex scenarios which require custom evaluation metrics, multiple dataset splits and phases, users are recommended to create a competition bundle which specifies the challenge configuration, evaluation code, and information about the said data-splits. The associated configuration file provides enough flexibility to configure different phases of the competition, define number of splits for the dataset and specify custom evaluation scripts arbitrarily.

6.2 Submission

EvalAI supports both submitting the model predictions and the model itself for evaluation. Traditional challenges require user to submit their model predictions on a static test set provided by the challenge organizers. On submission, these predictions are handed over to challenge specific workers that compare the predictions against corresponding ground-truth using the custom evaluation script provided by the challenge organizers. As we move towards developing intelligent agents for tasks situated in active environments instead of static datasets, where agents take actions to change the state of the world around them, it is imperative that we build new tools to accurately benchmark agents in environments. In this regard, we have developed an evaluation framework (shown in Fig. 4) where participants upload Docker images with their pretrained models on Elastic Container Registry (ECR) and Amazon S3 respectively, which is then attached and run against test environments and evaluation metrics provided by the challenge organizer. At the time of evaluation, the instantiated worker fetches the image from ECR, assets and configuration for test-environment, model snapshot from Amazon S3 and spins up a new container to perform evaluation. Once the evaluation is complete, the results are sent over to the leaderboard using the message queue described in Section 5.

![Figure 4: EvalAI lets participants submit code for their agent which are eventually evaluated in dynamic environments on the evaluation server. The pipeline involves participants uploading the model snapshot and the code as docker image. Model snapshots are stored in Amazon S3 while the docker images are stored in Amazon Elastic Container Registry (ECR). During evaluation, the worker fetches the image, test environment and the model snapshot and spins up a new container to perform evaluation on this model. The results are then sent over to the leaderboard through a message queue.](image)

6.3 Evaluation

We allow organizers to provide an implementation of their metric and is subsequently used to evaluate all submissions ensuring consistency in evaluation protocols. The by-product of containerizing the evaluation for different challenges in docker containers is that it allows us to package fairly complex pipelines, with all it’s dependencies in an isolated environment. For human-in-the-loop evaluation, the evaluation code first loads up the worker and launches a new HIT on Amazon Mechanical Turk. Once the worker accepts the HIT, the worker is paired with the agent running inside a docker image. Based on the instruction given, the worker will interact with the agent and evaluate it according to certain criteria. This interaction data and the final rating given by the worker is stored by EvalAI which is eventually reflected on the leaderboard. EvalAI takes care of managing a persistent connection between the agent and the worker, error handling, retrying, storing the interaction data corresponding to this HIT and automatically approving or rejecting HIT. We discuss one human-in-the-loop task in the second case study.
7 Case Studies

In this section, we go over two specific past instantiations of challenges organized on our platform to showcase its various capabilities.

7.1 Visual Question Answering.

Visual Question Answering (VQA) is a multi-modal task where given an image and a free-form open-ended natural language question about the image, the AI agent’s task is to answer the question accurately. The Visual Question Answering Challenge (VQA) 2016 was organized on the VQAv1 [2] dataset and was hosted on another platform, where mean evaluation time per dataset instance was \(\sim 10\) minutes. In the following years, VQA Challenge 2017 and 2018 (on the VQAv2 [18] dataset) were hosted on EvalAI. Even with twice the dataset size (VQAv2 vs VQAv1), our parallelized implementation offered a significant reduction in per-instance evaluation time (\(\sim 130\) seconds) – an approximately 12x speedup. This was made possible by leveraging map-reduce techniques to distribute smaller chunks of the test-split on multiple cores and eventually combining the individual results to compute overall performance. Execution time is further reduced by making sure that the evaluation program is not loaded in memory (preloaded earlier) everytime a new submission arrives. The above instance of the challenge also utilized several other features of our platform – namely, supporting multiple challenge phases for continued evaluation beyond the challenge; multiple data-splits for debugging submissions and reporting public benchmarks and privacy levels for leaderboards associated with different data-split evaluations.

7.2 Visual Dialog.

As mentioned before, it is notoriously difficult to evaluate free-form multimodal tasks such as image captioning [8, 24], visual dialog [10, 11, 26] etc using automatic metrics and as such they inherently require human-in-the-loop evaluation. Recall that Visual Dialog, where given an image, an associated dialog history and a follow-up question about the image, an agent is required to answer the question while inferring relevant context from history – evaluation is further complicated by the huge set of possibly ‘correct’ answers and the relatively sparse sampling of this space, even in large-scale datasets – making human-in-the-loop evaluation imperative. As part of a demonstration at CVPR 2018, EvalAI hosted a visual dialog challenge where each submission was connected with a human subject (Fig. 5) on Amazon Mechanical Turk tasked with rating a response generated by participating model along.
several axes – correctness, fluency, consistency, etc. After 10 such rounds of human-agent interaction, the human’s rating of the agent was reflected as a score on the leaderboard immediately.

7.3 Embodied Question Answering.

Finally, as we move towards developing intelligent agents for tasks situated in active environments instead of static datasets, where agents take actions to change the state of the world around them, it is imperative that we build new tools to accurately benchmark agents in environments. One example of such a task is Embodied Question Answering [9] – an agent is spawned at a random location in a simulated environment (say in a kitchen) and is asked a natural language question (“What color is the car?”). The agent perceives its environment through first-person vision and can perform a few actions: \{move-forward, turn-left, turn-right, stop\}. The agent’s objective is to explore the environment and gather visual information necessary to answer the question (“orange”). Evaluating agents for EmbodiedQA presents a key challenge – instead of a hidden test dataset, there are hidden test environments, so participants have to submit pretrained models and inference code, which has to be reliably executed in these environments to benchmark them. In ongoing work, we have developed an evaluation framework for EmbodiedQA – wherein participants upload Docker images with their pretrained models on Amazon S3, which is then attached and run against test environments and evaluation metrics provided by the challenge organizer. We will be using this to host a CVPR 2019 challenge on EmbodiedQA, and aim to extend this to support a wide range of reinforcement learning task evaluations in future.

7.4 fastMRI.

fastMRI [35] is a collaborative research project between Facebook AI Research (FAIR) and NYU Langone Health to investigate the use of AI to make MRI scans up to 10 times faster. By focusing on the reconstruction capabilities of several AI algorithms, the goal is to enable faster scanning and subsequently making MRIs accessible to more people. This collaborative effort to accelerate Magnetic Resonance Imaging (MRI) by taking fewer measurements was recently structured as a challenge organized around a large-scale open dataset for both raw MR measurements and clinical MR images. EvalAI currently hosts the first iteration of the fastMRI challenge. Ensuring proper benchmarking on such a medical dataset comes with its own set of challenges – primarily centered around privacy and storage. Firstly, since proposed algorithms for fastMRI have a direct real-world impact, any leakage of test-annotations compromises generalization and can subsequently have drastic consequences. Secondly, in addition to privacy, it is important to note that the dataset itself consumes a lot of storage space as it consists of clinical MR images. As such, supporting decentralized evaluation in addition to a centralized leaderboard to benchmark solutions seems desirable from the organizer's perspective. EvalAI fulfills both of these requirements – as a platform, we do not have access to the test-annotations for fastMRI but still support efficient evaluation on a remote server (belonging to the organizer). The evaluation metrics are sent from the remote servers to EvalAI via an API format provided by EvalAI. The metrics are then displayed on a centralized leaderboard hosted on EvalAI.

8 Conclusion

While traditional platforms were adequate for evaluation of tasks using automatic metrics, there is a critical need to support human-in-the-loop evaluation for more free-form multimodal tasks like (visual) dialog, question-answering, etc. To this end, we have developed a new evaluation platform that supports the same on a large-scale. Effectively, EvalAI supports pairing an AI agent with thousands of workers so as to rate or evaluate the former over multiple rounds of interaction. By providing a scalable platform that supports such evaluations will eventually encourage the community to benchmark performance on tasks extensively, leading to better understanding of a model’s performance both in isolation and in human-AI teams.

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