

# Reward Reports for Reinforcement Learning

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The scale and complexity with which machine learning (ML) systems interface with society at large has spurred calls for system documentation in support of deliberation and accountability. While there has been substantive progress on this front in recent years, much of it has been grounded in a static ML paradigm, meaning feedback and post-deployment performance are given a background role. Meanwhile, recent work in reinforcement learning design has shown that the effects of optimization objectives on the resultant system behavior can be wide-ranging and unpredictable. In this paper we sketch a framework for documenting deployed learning systems, which we call *Reward Reports*. Taking inspiration from various contributions to the technical literature on reinforcement learning, we outline Reward Reports as living documents that track updates to design choices and assumptions behind what a particular automated system is optimizing for. They are intended to track dynamic phenomena arising from system deployment, rather than merely static properties of models or data. After presenting the elements of a Reward Report, we provide three examples: DeepMind's MuZero, MovieLens, and a hypothetical deployment of a Project Flow traffic control policy.

CCS Concepts: • Theory of computation → Sequential decision making; • General and reference → Evaluation; • Software and its engineering → Documentation; • Human-centered computing → Walkthrough evaluations; • Social and professional topics → Socio-technical systems.

Additional Key Words and Phrases: Reward function, reporting, documentation, disaggregated evaluation, ethical considerations

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## 1 INTRODUCTION

In fall 2021, the Wall Street Journal published the Facebook files, a series of articles that pieced together platform policy, flaws, and harms through leaked internal documents [26]. Among other topics, these articles tracked how changes to the newsfeed algorithm affected social interactions. Reporters confirmed what researchers had long suspected: Facebook's pivot to 'meaningful social interactions' increased negative content and divisiveness. Furthermore, both top content producers and Facebook executives were aware the algorithm generated this uptick, although the latter permitted it in favor of increased engagement. Fixing these feedback loops is no small task. Facebook's platform balances hundreds of parameters which are updated multiple times a day, amounting to a never ending A/B test. As a former employee

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explained, the system had grown so complex that data scientists could not trace negative effects back to efforts to increase meaningful connection.

Because such systems are tuned using the same environment in which they operate, the dynamics can quickly overwhelm designers' intent to drive specific interactions. The repercussions of algorithmic changes must be reflexively documented in order to manage feedback-heavy systems responsibly. Imagine a world where these effects are regularly anticipated, observed, and controlled. For designers, this documentation would be less burdensome than a single backlog that enumerates weeks of product changes, making it easier to disentangle complex effects. Moreover, external efforts to piece together partial pictures through leaked documents and reverse engineering black-box systems would be facilitated by a standard mechanism for transparency.

Multiple frameworks for documenting AI systems, datasets and models have emerged [23, 42, 50]. These aim to track sources of potential bias or harm, grounded primarily in a static machine learning (ML) paradigm. However, the risks posed by deployed AI systems are not static, as the dynamic impacts of successive system updates often subvert efforts to manage downstream harms. The continuous presence of feedback and dynamics suggests unique risk vectors, and requisite forms of documentation. Reinforcement learning (RL), a sub-field of ML that is able to solve complex sequential, open-ended problems, provides a dynamic lens that is broadly applicable to many static systems with repeated data-driven optimizations.

We propose *Reward Reports*, a new form of documentation that foregrounds the societal risks posed by automated decision-making systems (ADS), whether explicitly or implicitly construed as RL. Building on proposals to document datasets and models, we focus on reward functions: the objective that guides optimization decisions in feedback-laden systems. Reward Reports comprise questions that highlight the promises and risks entailed in defining what is being optimized in an AI system, and are intended as living documents that dissolve the distinction between *ex-ante* specification and *ex-post* harm. As a result, Reward Reports provide a framework for ongoing deliberation and accountability after a system is deployed.

In Section 2, we situate reward reports within the literature on AI documentation and governance mechanisms. In Section 3, we review optimization in the context of feedback, focusing on the notions of action, objective, and adaptation. In Section 4, we contextualize these elements of optimization within a taxonomy of feedback. Finally, in Sections 6 and 7, we provide a list of questions that interrogate specification risks and provide three examples of Reward Reports for RL systems of varying stakes.

## 2 RELATED WORK

### 2.1 Documentation for AI Systems

There are a number of existing proposals for AI system documentation, with some frameworks focused on specific aspects of an AI system, while others examine the system as a whole. Our proposal of Reward Reports is focused on documenting risks of dynamic machine learning systems. This complements current documentation efforts by explicating the intended performance characteristics in light of system behaviors that emerge over time.

Documenting data, regardless of resulting systems, is a well explored avenue [2, 6, 16, 23, 29]. These efforts have helped foster discussion on responsible data collection, as well as showcase issues of bias and representation. However, this paradigm is most impactful within the batch or offline setting of static unsupervised or supervised ML. Dynamic systems driven by sequential feedback also use data, but not only in the form of static datasets. Rather, both RL and deployed ML systems generate and eventually transform data. This is due both to the optimization decisions of the

systems themselves and the dynamics of the environment in which they operate. Past data documentation efforts are therefore insufficient to reveal the risks and failures of dynamic datasets and feedback driven systems.

There are also proposals for model [42], domain [34, 47] or outcome specific [59] forms of ML documentation. Reward Reports might be a useful supplement to these approaches for several reasons. With regards to model cards, there is substantial deliberation entailed in mapping between the chosen optimization and resultant behavior in dynamic systems. For example, designers must consider a range of alternative specifications that were technically feasible pre-deployment, as well as the types of feedback available to help optimize post-deployment. These aspects of system design cannot be captured solely by documenting the model. Furthermore, unlike domain-specific reporting frameworks, we provide a general template that can be applied to any specific application. Our work has similarities with previous proposals for AI Ethics Sheets [43], Fact Sheets [5, 50], or Scorecards [10], but uniquely focuses on prompting deliberation about the feedback-driven risks inherent to dynamic systems.

Reward Reports are closely related to Algorithmic Impact Assessments (AIA), which offer a framework for evaluating risks before an AI system is developed or acquired [49, 53]. AIAs were inspired by environmental impact assessments, which provided one path to regulate industries in which corporate expertise outpaced government capacity. These frameworks presume an agency-vendor relationship, and focus narrowly on the procurement of automated decision systems. Reward Reports are intended to supersede these *ex-ante* concerns, engaging instead with the necessarily non-linear and circuitous process of refining the specifications of a feedback system.

## 2.2 Societal Risks of Reinforcement Learning Systems

The RL research community has begun to reflect on the unique risks and challenges that may be posed by RL systems, in particular those that leverage black-box neural networks for decision-making. There are whitepapers charting these challenges [24, 62], as well as attempts to address societal risks through technical means [12, 20, 61, 66]. Recent general audience books have echoed these concerns [13, 51]. While these efforts have begun to capture the unique stakes in deploying RL systems, there is no consensus on how to chart associated risks. We intend Reward Reports to organize these efforts' reflections into an instrument of deliberation and accountability.

Critical and discursive interpretation of feedback are more common in static ML than RL research. However, the technical RL community is increasingly aware of the limitations of current algorithmic approaches and evaluation paradigms. In efforts to match practical solutions with open-ended problems, the field is re-considering how results are reported [3, 28, 30], and if numerical successes match the intention or intuition of designers [41]. While this agenda aims to promote scientific reproducibility, Reward Reports are meant to ensure public accountability.

## 2.3 AI Governance

Governance mechanisms can also be used to dictate safer machine learning practices. As reflected in the growing number of proposed AI governance frameworks [14, 22, 37, 48, 63, 65], ML and adjacent communities have increasingly acknowledged socio-technical risks and the need for novel harm mitigation strategies [4, 15, 54]. These frameworks have begun to influence legislation. For example, the Canadian government has mandated the Algorithmic Risk Assessment tool for procurement [11], and current draft legislation from the EU commission calls for AI system documentation tailored to forms of risk (*e.g.* in Title 3, Ch. 2, Art. 10-14) [1]. While these frameworks provide needed prohibitions and protections, they favor interpretive flexibility over specific design decisions, and often assume static AI systems that need strictly *ex-post* documentation. In contrast, Reward Reports would track requisite design decisions, and provide an

interface for stakeholders to reflect on the validity of those design choices over time. This would in essence dissolve the boundary between *ex-ante* and *ex-post* assessment.

### 3 BACKGROUND

In this section, we elucidate the notion of automated decision-making systems (ADS) as dynamical systems. We begin by reinterpreting them in terms of action, objective, and adaptation. This taxonomy emphasizes the *use* and *behavior* of an ML model rather than the closed act of developing it. We then review the RL framework, and recount its broader connections to ADS.

#### 3.1 Automated Decision Systems: Action, Objective, Adaptation

In ADS, learned predictive models are the means to some end. It is the decisions made, or *actions* taken, that are the direct cause of harms. For example, congested suburban roadways in the community of Los Gatos, CA, USA are caused directly by the actions of drivers, and indirectly by the actions of routing algorithms that predict a poorly-scaling short-cut path [46]. Similarly, the optimization of datacenter operations at Google uses the predictions of trained models to adjust set-points and load distribution – the predictions serve as a catalyst for action in the real world [21].

ADS take action not only on the basis of predictions, but also towards some *objective*. The definition of objective is crucial to the resulting behavior. Identical traffic models will result in different routing suggestions depending on whether the algorithm is optimizing for arrival time or fuel consumption [45]. Likewise, content interaction models have vastly different impacts when they are used to uprank posts predicted to receive many ‘likes’ compared with those predicted to receive long comments [26].

Finally, these automated systems are often updated based on additional data collected during their operation, making them *adaptive*. By accounting for the dependence between past decisions, observed data, and current models, systems in effect react to dynamic environments and improve performance over time. For example, when observed music listening patterns are used as additional data in preference models, music recommendation algorithms can adapt to an individual’s evolving tastes [17]. On the other hand, adaptivity can also exacerbate biased data. For example, predictive policing systems can amplify racial biases in arrests by directing more patrols towards areas with more documented arrests [40, 52].

While action, objective, and adaptation are important for understanding potential system harms, they are not captured in frameworks that document more static elements of ML models.

#### 3.2 Reinforcement Learning

The reinforcement learning (RL) framework succinctly encompasses action, objective, and adaptation. RL algorithms take actions, are motivated by a reward signal which encodes the objective, and adapt based on the feedback from this interaction. While the goal of supervised learning (SL) procedures is to use data to generate a model that makes accurate predictions, the goal of RL algorithms is to interact with an environment to generate a policy that achieves high reward. However, once SL models are deployed towards some goal and updated with new data, the concerns highlighted by the RL framework become relevant. In this sense, ML deployments can be understood through the lens of RL. Rather than Reinforcement Learning being a ‘cherry’ atop the Machine Learning cake [36], it would appear that the entire cake is in fact cherry flavored.

Reinforcement learning is a framework for optimizing a system *via* trial and error. In common terminology, an *agent* executes *actions*  $\vec{a}_t \in \mathcal{A}$  in an *environment*. In response, the agent receives a scalar *reward*  $r_t \in \mathbb{R}$  and makes

an *observation*  $\vec{o}_t \in O$  of the environment. Actions are made on the basis of these observations according to a *policy*  $\pi : \mathcal{H} \rightarrow \Delta(\mathcal{A})$ , where  $\mathcal{H} = O \times \dots \times O$  represents the history of observations and  $\Delta(\mathcal{A})$  represents a probability distribution over the action space. The goal of a reinforcement learning agent is to find a policy that maximizes the cumulative reward over some time horizon:  $\sum_{t=0}^H \gamma^t r_t$  where the discount factor  $\gamma \in (0, 1]$  weighs current rewards versus future potential rewards. This paradigm captures many problems of interest, from choosing advertisements that are most likely to result in a click [35, 39] to determining the best dosing schedule for a patient [57].

A key element of RL is how actions affect the future behavior of the environment. This dependence is often modeled as a Markov Decision Process (MDP) [7]. In the MDP setting, the *state*  $\vec{s}_t$  describes the status of the environment. The key assumption, called memorylessness, is that the current state and action are sufficient for predicting the future state, *i.e.*

$$\mathbb{P}\{\vec{s}_{t+1} = \vec{s} \mid \vec{s}_0, \dots, \vec{s}_t, \vec{a}_0, \dots, \vec{a}_t\} = \mathbb{P}\{\vec{s}_{t+1} = \vec{s} \mid \vec{s}_t, \vec{a}_t\}.$$

These *transition probabilities* from one state to the next are also referred to as the *system dynamics*. Furthermore, the reward is determined by the state, so that  $r_t = r(\vec{s}_t, \vec{a}_t)$  for some reward function  $r : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ , mapping from the current environment to a scalar representation of desirability. Under these assumptions, it is optimal to consider policies that depend only on the current state,  $\pi : \mathcal{S} \rightarrow \Delta(\mathcal{A})$ . Often, RL algorithms assume that the state is observed directly  $\vec{o}_t = \vec{s}_t$  (or similarly, that it can be constructed in a straightforward manner *e.g.* though history truncation  $\vec{s}_t = [o_{t-h}, \dots, o_t]$ ), and the policy is typically parametric, with a parameter vector denoted  $\theta$ . The MDP setting enables a rich set of tools for understanding and optimizing performance, such as value functions *via* dynamic programming, that can be directly applied when the full transition model is known.

Though such MDP dynamics are understood to determine the evolution of the system, for RL problems they are not necessarily known *a priori* to designers. Instead, RL algorithms seek to optimize the policy on the basis of interactions with the environment, using the reward signal and observations. In this way, they are adaptive. There are a wide range of RL algorithms: some which optimize the policy directly (*e.g.* by learning the weights of a neural network based on observed performance), and others which first estimate intermediate quantities (*e.g.* value, transition, or reward function) and then transform these into a policy. Some algorithms generate policies offline from existing datasets, while others solely use online interactions. Any RL algorithms with an online component must contend with the exploration/exploitation trade-off: choosing between actions likely to be high reward, and those likely to be informative [60].

The RL problem is general, so other machine learning paradigms can be viewed as special cases of it. For example, supervised learning can be viewed as the optimization of a classification or regression policy where the rewards are defined by accuracy and the time horizon is equal to one. However, vanilla supervised learning frameworks do not consider how to update or retrain on the basis of interaction. There are intermediate points: online learning situates supervised learning systems in a sequentially evolving environment [56], while the study of bandit problems reduces RL to the static regime where actions do not affect the environment [8]. The boxed example illustrates how ADS, such as credit score-based lending, can be viewed through the RL framework.

## 4 MOTIVATION

The RL lens is useful not only because ML deployments often operate in dynamical environments. It is also that there is *feedback* between the environment and the deployment. In this section, we first review three levels of feedback that characterize RL systems: *control* feedback from state to action, *behavior* feedback from the data to the policy, and

### Credit Scores and Lending: Automated Decision-Making Systems through the RL Lens

Whether or not state-of-the-art RL algorithms are used, an ADS comprises an RL system from the standpoint of whoever oversees its real-world operation. Consider a simplified lending scenario where loans are given to applicants based on a risk score threshold, and risk scores are assigned to applicants based on their features using a learned model. Though this lending policy does not explicitly consider long time horizons or model environment dynamics, there are still elements of the RL framework. The lending decision can be conceived as an action, and the policy is parameterized by the learned risk model:  $\vec{a}_t = \mathbf{1}\{f_\theta(\vec{o}_t) \geq s_0\} = \pi(\vec{o}_t)$ , where  $\mathbf{1}\{\cdot\}$  is the indicator function,  $f_\theta(\cdot)$  is the risk model,  $\vec{o}_t$  is the applicant's features, and  $s_0$  is the threshold. The threshold would be determined based on the objectives of the financial institution: a risk-averse bank looking to maximize profits might choose a higher threshold than a credit union focused on providing financial opportunities to community members. Whether or not it is explicitly modelled, this lending policy will have an impact on individuals, potentially resulting in systematic changes to the observations  $o_t$ . Likewise, retraining the risk model  $f_\theta(\cdot)$  with additional data is in effect a form of policy adaptation. This simple example illustrates connections between RL and any ADS that uses data-driven models.

*exogenous* feedback from the target environment to adjacent entities [25]. The types of feedback are compared in Tab. 1 and visualized in Fig. 1. We then motivate Reward Reports as tracking how and why feedback has been organized.

#### 4.1 A Taxonomy of Feedback

*Control feedback* maps observations and states to actions. A very simple example is a thermostat which decides whether or not to turn on a furnace based on temperature sensors. These decisions are made many times per second, and allow an HVAC system to maintain comfortable indoor temperature under varying weather conditions. Such systems are often called “automatic feedback control,” hence the term control feedback. “Intelligent” behaviors arise because actions are constantly adjusted on the basis of observations, even though the rules that control the behavior remain the same. Failing to incorporate control feedback can generate downstream harms. Consider the example of evaluating the impact of static decision policies on lending as discussed by Liu et al. [38]. Feedback arises when loans are made based on credit scores that change due to loan repayments or defaults. This is control feedback at the level of lending decisions (actions) and credit scores (observations/states). Because this feedback loop is not modelled by static policies, the well-being of under-served groups is not guaranteed, even for policies which satisfy group fairness constraints.

*Behavior feedback* maps data to the learned policy. This form of feedback occurs when RL systems automatically adapt their policy based on reward. Questions of reaction become questions of trial-and-error evaluation: “At what temperature should the furnace turn on?” evolves into “What keeps the operating temperature as close as possible to the target?”. The ability to learn from experience is part of what makes RL systems seem so powerful, and it makes them applicable to domains that are difficult to otherwise model. For example, it would be challenging to hand-design a policy for recommending music to a listener, but data-driven approaches make this task tractable. Beyond RL, predictive policing is an application in which behavior feedback often leads to problematic performance. In seminal work, Ensign et al. [19] show how the runaway feedback loop between police allocation and arrests can result in the over-policing of certain communities. The predictive model of criminal activity, which determines where police are directed to patrol, is updated on the basis of arrests, which are more likely to be made in locations with heavy police presence. This dynamic comprises a failure of behavior feedback, since it connects data (arrests) to a policy (deployment of police patrols).

The failures in the lending and policing examples occur because feedback was not considered in algorithm design, generating dynamics *exogenous* to the specification. *Exogenous feedback* occurs when the application domain itself shifts in response to the deployed system. These shifts could be due to political or economic conditions that are outside the system’s purview. For example, smart thermostats may enable finer-grained control over household heating, changing what a comfortable home amounts to or changing the electric loading of buildings, towns, and regions. Traffic driven

Table 1. The relationship between types of feedback, the channel through which information flows, the relationship to dynamics, and specification element(s).

Type of feedback	Feedback Channel	Dynamics	Specification Element
Control	Agent-Environment	Reaction	Actions
Behavior	Policy-Reward	Evaluation	Rewards
Exogenous	Environment-Domain	Drift	States & Observations

by recommendation systems might incentivize creators to create attention-grabbing content, turning to strategies like outrage and conspiracy [44]. In principle, if such dynamics could be predicted by an RL agent, they could be brought under the purview of behavior or control feedback. But in practice, it is not clear that this is possible—the observations would need to be sufficiently rich and the planning horizon sufficiently long. Exogenous feedback captures the potential of externalized risks in the RL framework.

#### 4.2 Risks and Documentation

As shown above, the problem of *feedback* between automated decision systems and the broader environment is a useful lens for understanding their failures. In particular, RL systems do incorporate both control and behavior feedback in their optimization, and one could imagine that this might “solve” many problems of bias amplification or negative algorithmic impacts. Rather than allowing concerns about the domain to be expressed “suboptimally” through dissent (e.g. boycotts or new regulation), it would simply be more efficient to let RL designers “figure out” the right reward function. However, this argument is flawed, as a complete catalogue of relevant features is not available for designers to optimize. And even if it were, it is not clear that the algorithmic tools available to designers would scale to such a challenge.

For many systems, reward design—the choice of how and what to optimize—amounts to a political decision about how different types of feedback may rewire the domain and pose risks to various stakeholders. And because it is often not possible to fold all of the domain dynamics within a controllable planning horizon, exo-feedback is in practice unavoidable. Although the risks of exo-feedback remain intractable via system optimization, they can at least be approached and evaluated through documentation. It is therefore necessary to build mechanisms to audit RL systems pre- and post-deployment. Otherwise, designers are unable to map how salient aspects of RL specification (state, action, and reward) will interact with a given domain. A single RL specification is simultaneously responsible for the three feedback types discussed above. It is unrealistic to hold

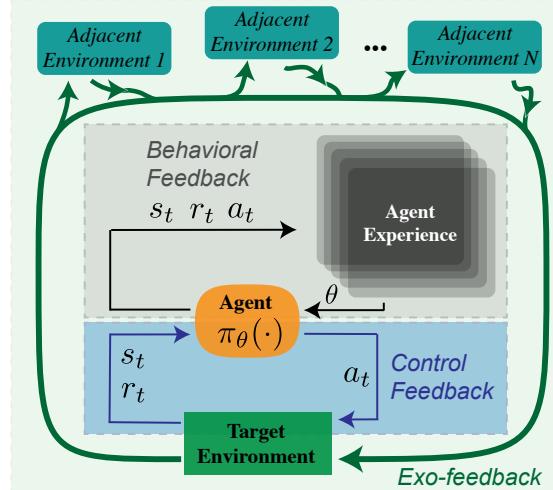


Fig. 1. A diagram depicting the interactions of control, behavioral, and exogenous feedback in a RL system. Different parameters and data interact over time to create dynamic properties internal and external to the RL agent.

practitioners responsible for articulating all possible specifications independently. Instead, the automatic optimizations of RL systems must be made legible to manual oversight and periodic review. It is these reviews that must decide whether or how the optimized behaviors align with the application domain, in correspondence with resultant risks and possible harms. This decision is made more complicated by the different types of feedback at stake in RL optimization. And since there are dynamic effects, it is necessary that the corresponding document be dynamic as well: updated and revisited over time to begin to map the evolution of feedback between the system and the domain in which it is deployed.

## 5 REWARD REPORT COMPONENTS

Here we prescribe *Reward Reports*, a structured series of design inquiries for automated decision systems (see Fig. 2). Including but not limited to the use of reinforcement learning, Reward Reports are intended to engage practitioners by revisiting design questions over time, drawing reference to previous reports and looking forward to future ones. As pivotal properties may not be known until the system has been deployed and monitored, the onus is on designers to sustain documentation over time. This makes Reward Reports into living documents that both avoid the limitations of simple, unidirectional answers (e.g. yes or no) and illuminate societal risks over time. Moreover, the changelog component of a Reward Report becomes an interface for stakeholders, users, and engineers to continuously oversee and evaluate the documented system. Thus, Reward Reports are a prerequisite to sociotechnical reflection about the system behavior.

A Reward Report is composed of six sections, arranged to help the reporter understand and document the system. A Reward Report begins with **system details** (1) that contain the information context for deploying the model. From there, the report documents the **optimization intent** (2) which questions the goals of the system and why RL or ML may be a useful tool. The designer then documents how it can affect different stakeholders in the **institutional interface** (3). The next two sections contain technical details on the system **implementation** (4) and **evaluation** (5). The report concludes with plans for **system maintenance** (6).

### Reward Report Contents

- **System Details:** Basic system information.
  - Person or organization developing the system
  - Deployment dates
  - Contact
- **Optimization Intent:** The goals of the system and how reinforcement manifests.
  - Goal of reinforcement
  - Performance metrics
  - Oversight metrics
  - Failure modes
- **Institutional Interface:** The interconnections of the automated system with society.
  - Involved agencies
  - Stakeholders
  - Computation footprint
  - Explainability
  - Recourse
- **Implementation:** The low-level engineering details of the ML system.
  - Reward, algorithmic, and environment details
  - Measurement details
  - Data flow
  - Limitations
  - Engineering artifacts
- **Evaluation:** Specific audits on system performance.
  - Evaluation environment
  - Offline evaluations
  - Evaluation validity
  - Performance standards
- **System Maintenance:** Plans for long-term verification of behavior.
  - Reporting cadence
  - Update triggers
  - Changelog

Fig. 2. Summary of reward report sections and suggested inquiries.

**maintenance** (6) as additional system dynamics are uncovered.

### 5.1 System Details

This section collects basic information a user or stakeholder may need in reference to the automated decision system.

- (1) **Person or organization deploying the system:** This may be the designer deploying the system, a larger agency or body, or some combination of the two. The entity completing the report should also be indicated.
- (2) **Reward date(s):** The known or intended timespan over which this reward function & optimization is active.
- (3) **Feedback & communication:** Contact information for the designer, team, or larger agency responsible for system deployment.
- (4) **Other resources:** Where can users or stakeholders find more information about this system? Is this system based on one or more research papers?

### 5.2 Optimization Intent

This section addresses basic questions about the intent of the reward function and optimization problem. Designers first document the intent of a particular solution, translating the system’s quantitative objective into a qualitative description. In later sections, they have the opportunity to further reflect on how implementation details aid in, or diminish the broader goal. Stakeholders and users can employ this section to understand if the intent of the system matches with the effects they observe or experience.

- (1) **Goal of reinforcement:** A statement of system scope and purpose, including the planning horizon and justification of a data-driven approach to policy design (e.g. the use of reinforcement learning or repeated retraining). This justification should contrast with alternative approaches, like static models and hand-designed policies. What is there to gain with the chosen approach?
- (2) **Defined performance metrics:** A list of “performance metrics” included explicitly in the reward signal, the criteria for why these metrics were chosen, and from where these criteria were drawn (e.g. government agencies, domain precedent, GitHub repositories, toy environments). Performance metrics that are used by the designer to tune the system, but not explicitly included in the reward signal should also be reported here.
- (3) **Oversight metrics:** Are there any additional metrics not included in the reward signal but relevant for vendor or system oversight (e.g. performance differences across demographic groups)? Why aren’t they part of the reward signal, and why must they be monitored?
- (4) **Known failure modes:** A description of any prior known instances of “reward hacking” or model misalignment in the domain at stake [32], and description of how the current system avoids this.

### 5.3 Institutional Interface

This section documents the intended (and in subsequent reports, observed) relationship between the system and the broader context in which it is deployed. While necessarily piecemeal, the explicit documentation of this interface will allow designers to reflect on and revisit the system assumptions over time. These reflections may bring novel interests or agencies into scope and allow for organizing the emergent interests of stakeholders and users where necessary.

- (1) **Deployment Agency:** What other agency or controlling entity roles, if any, are intended to be subsumed by the RL system? How may these roles change following system deployment?

- (2) **Stakeholders:** What other interests are implicated in the design specification or system deployment, beyond the designer? What role will these interests play in subsequent report documentation? What other entities, if any, does the deployed system interface with whose interests are not intended to be in scope?
- (3) **Explainability & Transparency:** Does the system offer explanations of its decisions or actions? What is the purpose of these explanations? To what extent is the policy transparent, i.e. can decisions or actions be understood in terms of meaningful intermediate quantities?
- (4) **Recourse:** Can stakeholders or users contest the decisions or actions of the system? What processes, technical or otherwise, are in place to handle this?

#### 5.4 Implementation

Given the sensitivity of reinforcement learning systems, it is important to document specific implementation details of the system. Even small changes in implementation can result in substantial behavior shifts downstream, making such factors difficult to track when used at scale. Documenting these design decisions will both help prevent failures in specific applications and assist technical progress.

- (1) **Reward details:** How was the reward function engineered? E.g. is it based on a well-defined metric? Is it tuned to represent a specific behavior? Are multiple terms scaled to make one central loss, and how was the scaling decided?
- (2) **Environment details:** Description of states, observations, and actions with reference to planning horizon and hypothesized dynamics/impacts. What dynamics are brought into the scope of the optimization via feedback? Which dynamics are left external to the system, as drift? Have there been any observed gaps between conceptualization and resultant dynamics?
- (3) **Measurement details:** How are the components of the reward and observations measured? Are measurement techniques consistent across time and data sources? Under what conditions are measurements valid and correct? What biases might arise during the measurement process?
- (4) **Algorithmic details:** The key points on the specific algorithm(s) used for learning and planning. This includes the form of the policy (e.g. neural network, optimization problem), the class of learning algorithm (e.g. model-based RL, off-policy RL, repeated retraining), the form of any intermediate model (e.g. of the value function, dynamics function, reward function), technical infrastructure, and any other considerations necessary for implementing the system. Is the algorithm publicly documented and is code publicly available? Have different algorithms been used or tried to accomplish the same goal?
- (5) **Data flow:** How is data collected, stored, and used for (re)training? How frequently are various components of the system retrained, and why was this frequency chosen? Could the data exhibit sampling bias, and is this accounted for in the learning algorithm? Is data reweighted, filtered, or discarded? Have data sources changed over time?
- (6) **Limitations:** Discussion and justification of modeling choices arising from computational, statistical, and measurement limitations. How might (or how have) improvements in computational power and data collection change(d) these considerations and impact(ed) system behavior?
- (7) **Engineering tricks:** RL systems are known to be sensitive to implementation tricks that are key to performance. Are there any design elements that have a surprisingly strong impact on performance? E.g. state-action normalization, hard-coded curricula, model-initialization, loss bounds, or more?

## 5.5 Evaluation

Assessing the potential behavior of a feedback system is important for anticipating its future performance and risks that may arise. This section records evaluations done by the designer before deploying the system and each time the reward report is revisited. This section allows stakeholders and users to hold designers accountable for the performance of the system once deployed. It is important to distinguish whether the evaluations are done in a simulation (*offline*) or deployed on real users (*online*) and if the evaluation procedure is on a fixed dataset (*static*) or evolves over time (*dynamic*).

- (1) **Evaluation environment:** How is the system evaluated (and if applicable, trained) prior to deployment (e.g. using simulation, static datasets, etc.)? Exhaustive details of the offline evaluation environment should be provided. For simulation, details should include description or external reference to the underlying model, ranges of parameters, etc. For evaluation on static datasets, considering referring to associated documentation (e.g. *Datasheets* [23]).
- (2) **Offline evaluations:** Present and discuss the results of offline evaluation. For static evaluation, consider referring to associated documentation (e.g. *Model Cards* [42]). If applicable, compare the behaviors arising from counterfactual specifications (e.g. of states, observations, actions).
- (3) **Evaluation validity:** To what extent is it reasonable to draw conclusions about the behavior of the deployed system based on the available offline evaluations?  
How is the online performance of the system presently understood? If the system has been deployed, were any unexpected behaviors observed?
- (4) **Performance standards:** What standards of performance and safety is the system required to meet? Where do these standards come from? How is the system verified to meet these standards?

## 5.6 System Maintenance

This section documents plans for post-deployment oversight, including subsequent reviews of real-world implementation and how the monitoring of resultant dynamics is intended to (or has) shed light on *ex-ante* assumptions. These plans include any additional grounds for updating the report in case of sustained shifts in observations or metrics (e.g. the effects of exogenous changes on system behaviors). As such, this section must draw sustained reference to previous Reward Reports, including subsequent changes to the description, implementation, or evaluation, and what prompted these changes. While previous sections outline how the system learns from data, this section tracks how organizations learn to oversee the system. Its documentation is particularly important for defining *accountability* for the system itself, those who manage it, and those responsible for completing periodic reports.

- (1) **Reporting cadence:** The intended timeframe for revisiting the Reward Report. How was this decision reached and motivated?
- (2) **Update triggers:** Specific events (projected or historic) significant enough to warrant revisiting this report, beyond the cadence outlined above. Example triggers include a defined stakeholder group empowered to demand a system audit, or a specific metric (either of performance or oversight) that falls outside a defined threshold of critical safety.
- (3) **Changelog:** Descriptions of updates and lessons learned from observing and maintaining the deployed system. This includes when the updates were made and what motivated them in light of previous reports. The changelog is the key difference between Reward Reports and other forms of machine learning documentation, as it successively reframes prior reports and reflects their intrinsically dynamic nature.

## 6 EXAMPLES

In the appendix we have included three example Reward Reports for imagined and real automated decision-making systems. Our aim with these examples is to illustrate the breadth and scope of questions that a Reward Report could engage with, and to demonstrate how Reward Reports can apply to both explicit and implicit RL systems. Here, we briefly outline each included example, and refer the reader to the appendix for the actual example Reward Reports.

### 6.1 Project Flow: An RL policy for dissipating stop-and-go traffic waves

Project Flow is an autonomous vehicle testbed that allows using deep reinforcement learning to control and optimize traffic across in roadway networks [64]. Inspired by recent work with using Project Flow [33], we sketch a hypothetical deployment of an RL policy designed for dissipating stop-and-go traffic waves at a freeway exit, including several iterations of the Reward Report documented in the accompanying changelog. The changelog shows various problems that arise with the resulting problem dynamics, including an expansion of the planning horizon, the addition of new oversight metrics, stakeholder complaints, and requisite institutional shifts to cope with changes to the specification and application domain.

### 6.2 MovieLens: A dynamically updated movie recommender system

The purpose of MovieLens is to match users to personalized movie recommendations based on ratings of other movies previously entered by the user [27]. Unlike the other example systems we discuss, MovieLens is a static preference model generated through supervised learning. However, because of the system’s age (initial release in 1997) and its repeated retraining, it can be interpreted as an RL system that is learning a ranking policy that must adapt to a changing environment. The changelog documents the actual historical updates to the model prompted by changes to the environment, including new interfaces, user-base size, optimization parameters, user-generated content, and major dataset publications. This example Reward Report is based on the history of the MovieLens project published in [27].

### 6.3 MuZero: DeepMind’s general game-playing agent

The purpose of MuZero (and its preceding systems, AlphaGo and AlphaZero) is to improve state-of-the-art performance in the games of chess, Go, shogi, and a benchmark suite of Atari games [58]. We provide a Reward Report that documents the evolution of the system through these successive stages of development, including changes in the design motivation and performance metrics, as well as more extensive use of reinforcement learning.

## 7 DISCUSSION & CONCLUSIONS

Recent calls for documentation of societal risks posed by ML systems are encouraging. However, the scale and complexity of contemporary ADS pipelines raise unique concerns not addressed by static reports (e.g. those focusing on models or datasets). ML deployments frequently consist of many moving parts and feedback channels that change over time. Reward Reports fill this gap, providing a framework for iterative deliberation over the time-evolution of a system and its feedback channels. We have also demonstrated that the technical problem space and language of RL is useful for interpreting problems of fairness and safety in a reflexive and domain-specific manner. While the utility of this framing will vary with application, Reward Reports will be of most use where a system is data-driven, and where actions have clear and automatic impact. Optimization-based policies in domains like school bus scheduling [9] or prison allocation [55] are often not data-driven. Once sufficient data is available for interpretation, such systems could

readily become data-driven as they are already increasingly automated. The pace of academic research also suggests that implicit or explicit RL systems will be more effective, deployed in more impactful user-facing applications, and fine-tuned in ‘real-time’ rather than re-trained daily or weekly in the near future, accelerating the associated feedback loops. The resulting feedback loops will bring more and more problems into the purview of the RL lens, further motivating the need for Reward Reports.

Reward Reports could also be of use for human-in-the-loop ML deployments where actions do not have automatic impact. Clinical decision support systems can be data-driven, but the clinician ultimately determines how system recommendations are implemented. In this case, the human computer interaction (HCI) component of such a system could distort the interface between recommendations and human judgment in ways that are not captured within a pure RL lens. For example, a doctor is more likely to defer to an incorrect recommendation by an ADS when it is accompanied by a paragraph of reasoning than without [31]. However, the deliberation over system feedback made possible by Reward Reports could still elucidate unforeseen harms. For example, Reward Reports could help delineate the complex stakes of the COMPAS risk assessment tool –a human-in-the loop system with a model generally interpreted as static [18]– as a feedback problem. Designers could report the optimization intent and behavioral priors, at-risk communities could report their interpretations of those assumptions, and administrators could report on a system maintenance regime reflecting both. Subsequent reports could address and modify this regime until a desired institutional equilibrium is achieved.

These examples all point to a deeper truth: machine safety and fairness are increasingly dynamic problems, and we need to deliberate about them as such. Reward Reports enact forms of documentation commensurate with the feedback-laden systems whose dynamics –not just models or data– are a critical object of concern.

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## A EMPTY REWARD REPORT TEMPLATE

We also include an empty template for a Reward Report, including descriptions of the content for each section.

Reward Report Template	Page 1
<b>1 System Details</b>	
<b>1.1 System Owner</b>	<i>This may be the designer deploying the system, a larger agency or body, or some combination of the two. The entity completing the report should also be indicated.</i>
<b>1.2 Dates</b>	<i>The known or intended timespan over which this reward function &amp; optimization is active.</i>
<b>1.3 Feedback &amp; Communication</b>	<i>Contact information for the designer, team, or larger agency responsible for system deployment.</i>
<b>1.4 Other Resources</b>	<i>Where can users or stakeholders find more information about this system? Is this system based on one or more research papers?</i>
<b>2 Optimization Intent</b>	
<b>2.1 Goal of Reinforcement</b>	<i>A statement of system scope and purpose, including the planning horizon and justification of a data-driven approach to policy design (e.g. the use of reinforcement learning or repeated retraining). This justification should contrast with alternative approaches, like static models and hand-designed policies. What is there to gain with the chosen approach?</i>
<b>2.2 Defined Performance Metrics</b>	<i>A list of “performance metrics” included explicitly in the reward signal, the criteria for why these metrics were chosen, and from where these criteria were drawn (e.g. government agencies, domain precedent, GitHub repositories, toy environments). Performance metrics that are used by the designer to tune the system, but not explicitly included in the reward signal should also be reported here.</i>
<b>2.3 Oversight Metrics</b>	<i>Are there any additional metrics not included in the reward signal but relevant for vendor or system oversight (e.g. performance differences across demographic groups)? Why aren't they part of the reward signal, and why must they be monitored?</i>
<b>2.4 Known Failure Modes</b>	
<i>A description of any prior known instances of “reward hacking” or model misalignment in the domain at stake, and description of how the current system avoids this.</i>	
<b>3 Institutional Interface</b>	
<b>3.1 Deployment Agency</b>	<i>What other agency or controlling entity roles, if any, are intended to be subsumed by the system? How may these roles change following system deployment?</i>
<b>3.2 Stakeholders</b>	<i>What other interests are implicated in the design specification or system deployment, beyond the designer? What role will these interests play in subsequent report documentation? What other entities, if any, does the deployed system interface with whose interests are not intended to be in scope?</i>
<b>3.3 Explainability &amp; Transparency</b>	<i>Does the system offer explanations of its decisions or actions? What is the purpose of these explanations? To what extent is the policy transparent, i.e. can decisions or actions be understood in terms of meaningful intermediate quantities?</i>
<b>3.4 Recourse</b>	<i>Can stakeholders or users contest the decisions or actions of the system? What processes, technical or otherwise, are in place to handle this?</i>
<b>4 Implementation</b>	
<b>4.1 Reward Details</b>	<i>How was the reward function engineered? Is it based on a well-defined metric? Is it tuned to represent a specific behavior? Are multiple terms scaled to make one central loss, and how was the scaling decided?</i>

#### 4.2 Environment Details

*Description of states, observations, and actions with reference to planning horizon and hypothesized dynamics/impact. What dynamics are brought into the scope of the optimization via feedback? Which dynamics are left external to the system, as drift? Have there been any observed gaps between conceptualization and resultant dynamics?*

#### 4.3 Measurement Details

*How are the components of the reward and observations measured? Are measurement techniques consistent across time and data sources? Under what conditions are measurements valid and correct? What biases might arise during the measurement process?*

#### 4.4 Algorithmic Details

*The key points on the specific algorithm(s) used for learning and planning. This includes the form of the policy (e.g. neural network, optimization problem), the class of learning algorithm (e.g. model-based RL, off-policy RL, repeated retraining), the form of any intermediate model (e.g. of the value function, dynamics function, reward function), technical infrastructure, and any other considerations necessary for implementing the system. Is the algorithm publicly documented and is code publicly available? Have different algorithms been used or tried to accomplish the same goal?*

#### 4.5 Data Flow

*How is data collected, stored, and used for (re)training? How frequently are various components of the system retrained, and why was this frequency chosen? Could the data exhibit sampling bias, and is this accounted for in the learning algorithm? Is data reweighted, filtered, or discarded? Have data sources changed over time?*

#### 4.6 Limitations

*Discussion and justification of modeling choices arising from computational, statistical, and measurement limitations. How might (or how have) improvements in computational power and data collection change(d) these considerations and impact(ed) system behavior?*

#### 4.7 Engineering Tricks

*RL systems are known to be sensitive to implementation tricks that are key to performance. Are there any design elements that have a surprisingly strong impact on performance? For example, state-action normalization, hard-coded curricula, model-initialization, loss bounds, or more?*

### 5 Evaluation

#### 5.1 Evaluation Environment

*How is the system evaluated (and if applicable, trained) prior to deployment (e.g. using simulation, static datasets, etc.)? Exhaustive details of the offline evaluation environment should be provided. For simulation, details should include description or external reference to the underlying model, ranges of parameters, etc. For evaluation on static datasets, considering referring to associated documentation (e.g. Datasheets [1]).*

#### 5.2 Offline Evaluations

*Present and discuss the results of offline evaluation. For static evaluation, consider referring to associated documentation (e.g. Model Cards [2]). If applicable, compare the behaviors arising from counterfactual specifications (e.g. of states, observations, actions).*

#### 5.3 Evaluation Validity

*To what extent is it reasonable to draw conclusions about the behavior of the deployed system based on presented offline evaluations? What is the current state of understanding of the online performance of the system? If the system has been deployed, were any unexpected behaviors observed?*

#### 5.4 Performance standards

*What standards of performance and safety is the system required to meet? Where do these standards come from? How is the system verified to meet these standards?*

## 6 System Maintenance

### 6.1 Reporting Cadence

*The intended timeframe for revisiting the reward report. How was this decision reached and motivated?*

### 6.2 Update Triggers

*Specific events (projected or historic) significant enough to warrant revisiting this report, beyond the cadence outlined above. Example triggers include a defined stakeholder group empowered to demand a system audit, or a specific metric (either of performance or oversight) that falls outside a defined threshold of critical safety.*

### 6.3 Changelog

*Descriptions of updates and lessons learned from observing and maintaining the deployed system. This includes when the updates were made and what motivated them in light of previous reports. The changelog comprises the central difference between reward reports and other forms of machine learning documentation, as it directly reflects their intrinsically dynamic nature.*

## References

- [1] T. Gebru, J. Morgenstern, B. Vecchione, J. W. Vaughan, H. Wallach, H. D. Iii, and K. Crawford, “Datasheets for datasets,” *Communications of the ACM*, vol. 64, no. 12, pp. 86–92, 2021.
- [2] M. Mitchell, S. Wu, A. Zaldivar, P. Barnes, L. Vasserman, B. Hutchinson, E. Spitzer, I. D. Raji, and T. Gebru, “Model cards for model reporting,” in *Proceedings of the conference on fairness, accountability, and transparency*, 2019, pp. 220–229.

## B EXAMPLE REWARD REPORT - PROJECT FLOW

Reward Report - Project Flow AV testbed for stop-and-go traffic mitigation v0.6 — Page 1

$$r(t) = \|v_{\text{des}}\| - \|v_{\text{des}} - v(t)\| - \alpha \sum_i \max[h_{\text{max}} - h_i(t), 0]$$

Figure 1: The reward function for the system in question consists of three terms. The first term  $v_{\text{des}}$  is a positive constant that rewards the agent for longer simulation episodes - discouraging vehicle collisions, which terminate simulation runs early. The second term penalizes the agent when the instantaneous overall system velocity  $v(t)$  differs from the desired system velocity  $v_{\text{des}}$ . Finally, the third term sums over each subscribed Connected Autonomous Vehicle and adds a penalty whenever this vehicle is too close to the vehicle immediately in-front - a characteristic known to trigger stop-and-go traffic waves. More details are provided below in the section ‘Defined Performance Metrics’.

### 1 System Details

#### 1.1 System Owner

*This may be the designer deploying the system, a larger agency or body, or some combination of the two. The entity completing the report should also be indicated.*

This system was developed by the Project Flow core team members, with all deployment, infrastructure, and ongoing management taking managed by Caltrans.

#### 1.2 Dates

*The known or intended timespan over which this reward function & optimization is active.*

The system discussed here was trained in simulation during 2020, using empirical hyper-parameters (such as inflow traffic rates) collected during 2019. The RL policy was deployed in the real world on a trial basis on the 1<sup>st</sup> of Jan, 2021, and is presently undergoing initial real-world evaluation and validation.

#### 1.3 Feedback & Communication

*Contact information for the designer, team, or larger agency responsible for system deployment.*

Any correspondence should be directed to test@example.ca.gov.

#### 1.4 Other Resources

*Where can users or stakeholders find more information about this system? Is this system based on one or more research papers?*

More information about this specific system can be found in the paper [1], as well as in the associated project website.

General information about the project flow simulation environment can be found in [2] or on the project website and associated GitHub repository.

### 2 Optimization Intent

#### 2.1 Goal of Reinforcement

*A statement of system scope and purpose, including the planning horizon and justification of a data-driven approach to policy design (e.g. the use of reinforcement learning or repeated retraining). This justification should contrast with alternative approaches, like static models and hand-designed policies. What is there to gain with the chosen approach?*

The system in question is designed to dissipate stop-and-go traffic waves caused by merging off the California State Route 24 (CA-24) freeway onto Telegraph Avenue in the North Oakland / South Berkeley metropolitan area.

This is achieved by the coordinated actions of any subscribed Connected Autonomous Vehicles (CAVs) operating along the freeway segment in question, acting to ‘shepherd’ non-autonomous vehicles into patterns of traffic which can locally buffer against stop-and-go traffic waves.

Eligible CAVs, when entering the freeway zone of interest, communicate over the 4G/5G cell network with the central controller hub to ‘subscribe’ to the traffic management policy, which then sends real-time recommendations to these vehicles about

lane selection and preferred acceleration/braking profiles.

The RL policy is trained using a discrete-time road network simulation, with simulation runs lasting 3600s (one hour), and individual steps of 0.2s, giving 1800 steps per full simulation episode. The simulated road network consists of an 800m stretch of the CA-24 freeway containing a single off-ramp merging lane. These temporal and spatial planning horizons were selected because they were deemed large enough to allow emergence of typical driving dynamics based on the average safe following distance between vehicles and driver reaction times along comparable freeway offramps, based on state and federal records of past traffic behavior.

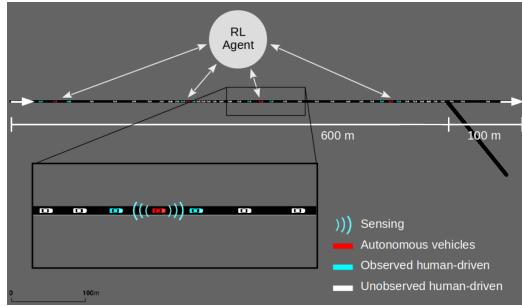


Figure 2: A central RL controller attempts to mitigate stop-and-go traffic waves caused by vehicles entering the freeway via on-ramps.

As of entry 0.3, it was found that the planning horizon for the system was too short. Following consultation with Caltrans, it was found that increasing the horizon from 500m to 800m would provide a significant increase in simulation performance without exhausting computational resources. Any future changes in computational capabilities will be documented here and compared in light of prior modeling choices and stakeholder commitments.

Simplistic microscopic traffic analysis models preclude the possibility of stable congestion patterns in open road topologies. However, as any driver can attest, these traffic patterns are ubiquitous on many road systems today. Instead, the presence of these traffic patterns in real-world networks is typically attributed to perturbations from bottleneck structures which can be difficult to capture in theoretical analyses (such as lane closures, road works, road debris, etc). [1] The ad-hoc nature of these perturbations means that modelling and planning for their occurrence within classical control frame-

works may be difficult, motivating more flexible approaches such as Deep Reinforcement Learning.

RL may be indicated in this situation, compared to static supervised ML models, due to the fact that it inherently encompasses multiple types of feedback through the environment specification. For instance, in the case of CA-24, RL may help mitigate the observed phenomenon of excessive traffic on residential streets near highway intersections that is induced by apps like Google Maps and Waze. In the interest of recommending perceived shortcuts to individual human drivers, these apps have in fact been known to induce overload on smaller roadways, generating unnecessary stoppage and possible gridlock. In the case of Los Gatos (where this phenomenon has been previously recorded), the city's Parks and Public Works Director noted that "The apps are not able to respond fast enough to the overload they have created on the roadways" [3]. RL may make real-time monitoring and control of the CA-24 offramp possible, mitigating induced overload effects and stabilizing feedback between traffic behavior and road infrastructure.

## 2.2 Defined Performance Metrics

*A list of "performance metrics" included explicitly in the reward signal, the criteria for why these metrics were chosen, and from where these criteria were drawn (e.g. government agencies, domain precedent, GitHub repositories, toy environments). Performance metrics that are used by the designer to tune the system, but not explicitly included in the reward signal should also be reported here.*

The reward signal optimized by this system consists of three performance metrics, outlined in fig. 1. These terms are;

- $\|v_{\text{des}}\|$  - the desired system-level velocity in m/s. This is a positive constant reward to penalize prematurely terminated simulation rollouts caused by vehicle collisions. For the simulated experiments described here,  $v_{\text{des}} = 25\text{m/s} = 90\text{kmph} \approx 55\text{mph}$ .
- $-\|v_{\text{des}} - v(t)\|$  - the absolute difference between the desired system level velocity and the actual instantaneous system-level velocity in m/s. A non-zero difference incurs a cost for the RL agent.
- $-\alpha \sum_i \max[h_{\text{max}} - h_i(t), 0]$  - this term sums over each Autonomous Vehicle in the purview

of the RL agent, and accrues a cost whenever that vehicle's instantaneous time headway (gap in seconds to the vehicle ahead) is too small (*i.e.* lower than  $h_{\max}$ ). The sum of all headway costs is scaled by a gain factor  $\alpha$ . For the simulated experiments described here,  $h_{\max} = 1$ s and  $\alpha = 0.1$ .

### 2.3 Oversight Metrics

*Are there any additional metrics not included in the reward signal but relevant for vendor or system oversight (e.g. performance differences across demographic groups)? Why aren't they part of the reward signal, and why must they be monitored?*

Several other performance metrics are not included in the reward function, but are analysed for the purpose of evaluating the system performance:

- Absolute temporal vehicle density (or *throughput*) - the number of vehicles exiting the controlled region the road network, measured in vehicles/hr. A larger vehicle flow-through rate compared to baseline is seen as a positive effect (assumed to correlate with a decrease in stop-and-go traffic waves, and to indicate that the road network is functioning efficiently).
- Absolute spatial vehicle density (or *network congestion*) - the number of vehicles within a fixed region of the road network, measured in vehicles/m. A larger number of vehicles present on the roadway is seen as a negative effect, indicating increased likelihood of stoppage.
- The average velocity of vehicles in the system. Higher vehicle velocities are seen as a positive effect.
- The average time vehicles spend within a given region of the system. Lower average time is seen as a positive effect.
- The maximum time any vehicle spent within a given region of the system over the course of an experimental evaluation of the system. Lower maximum time is seen as a positive effect.
- Simulated episode length. Simulation episodes are cut short whenever a collision occurs between vehicles - as such, longer episodes are seen as a positive effect.

In addition, the qualitative nature of stop-and-go traffic waves (size in terms of space and time duration and severity as measured by the average space-time slope of a wave) is assessed using microscopic vehicle space-time graphs such as those shown in fig. 3.

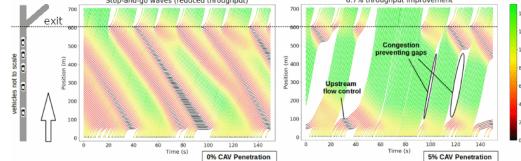


Figure 3: Space-time microscopic vehicle trace graphs such as these allow qualitative assessment of the system-level state of simple road networks at a glance. Here, stop-and-go traffic waves can be seen as red or black diagonal lines propagating through the traffic flow.

### 2.4 Known Failure Modes

*A description of any prior known instances of “reward hacking” or model misalignment in the domain at stake, and description of how the current system avoids this.*

**Sim-to-real dynamics misalignment.** The emergent dynamics of the simulated model and environment could potentially be misaligned with real-world dynamics (a ‘sim-to-real’ policy transfer problem). This failure mode was exhibited in the initial version of the system (as documented in change log entry v0.3) - the initially designed planning horizon was found to be too short (500m), which did not allow space for the requisite stop-and-go traffic dynamics to emerge around the freeway entry point. This issue was brought to light because the performance of the system in terms of average reward once deployed was not as high as predicted in simulation, triggering a technical review of the system. Two possible solutions were considered - (a) re-visiting the parameter distributions used for the IDM (which controls the non-automated vehicles in the simulation environment), (b) or adjusting the planning horizon. In a review with Caltrans engineers and the system designers, it was deemed that the IDM parameter distributions were in fact representative of the target section of CA-24, based on empirical data from 2019, and so the planning horizon was expanded from 500m to 800m. Thus far, since this updated version of the system was

deployed, the sim-to-real performance gap issue appears to have been resolved, suggesting the updated planning horizon adequately allows the simulated dynamics to reflect real-world dynamics.

**Selective behavior throttling.** The system was found to decrease throughput and increase congestion for diesel-powered vehicles. This feature was first documented in change log entry v0.3, but not labeled as a known failure mode until entry v0.6. This failure mode was exhibited in all previous versions of the system documented originally in log v0.1. It was highlighted following citizen complaints. No solution has been implemented as of entry v0.6. Two solutions have been proposed - (a) a city ordinance limiting diesel-powered vehicle travel on residential streets in the adjoining city of Emeryville (at present out of scope for the system), (b) or adjusting the policy parameters' training environment so that the controller behaves appropriately around diesel-powered vehicles in the future. This resolution is pending the recommendation of the Diesel Vehicle Taskforce to be presented at a future regular meeting.



Figure 4: The freeway exit from CA-24 to telegraph avenue, which this system is designed to manage.

This system simultaneously encroaches upon, and expands the capabilities of Caltrans. As the sensing infrastructure, computational capacity, and deployed RL software is centrally managed by a control facility operated by Caltrans, this system serves to provide both (a) an enhanced level of road surveillance for the relevant freeway section, through the remote sensing capabilities of subscribed CAVs, as well as (b) a 'control lever' through which Caltrans can actually influence traffic operations in and around the relevant freeway section (although this influence is delegated to an RL policy).

### 3.2 Stakeholders

*What other interests are implicated in the design specification or system deployment, beyond the designer? What role will these interests play in subsequent report documentation? What other entities, if any, does the deployed system interface with whose interests are not intended to be in scope?*

By automating the partial management of this section of the freeway via the RL environment framing and policy structure, the system serves to remake direct oversight of the road network on a new layer of abstraction. This indirection raises potential risks from inappropriate information flow, in particular monopolization of the freeway offramp by the RL controller. Monopolization may generate unstable dynamics leading up to or following the planning horizon (i.e. CA-24 freeway lanes and gridlock along Telegraph Avenue), or unequal access for road users whose behaviors are harder to anticipate (such as public buses, groups of motorcycles, bicycles, and pedestrians experiencing homelessness), or whose dynamics do not conform to the modelling assumptions of the system designers (e.g. heavy vehicles with atypical acceleration profiles). To counter these risks, new coordination is required

## 3 Institutional Interface

### 3.1 Deployment Agency

*What other agency or controlling entity roles, if any, are intended to be subsumed by the system? How may these roles change following system deployment?*

The system in question is developed by the Project Flow core development team. The deployment infrastructure and ongoing management are operated by the California Department of Transportation (Caltrans), in coordination with the city departments of Oakland and Berkeley.

Our RL system is designed to manage the flow of traffic immediately surrounding an exit point off the CA-24 freeway (see fig. 4) - as such, the system operates in a functionally similar way to traffic control signals that are sometimes used to regulate vehicles entering or exiting freeways.

between Caltrans and the city departments of Oakland and Berkeley.

**Diesel vehicle drivers.** As of entry 0.6, the behavior throttling generated by the RL controller was found to change the traffic patterns of diesel vehicles. A *Diesel Vehicle Taskforce* was created to help organize this constituency and identify needed changes to the controller to sufficiently reduce inappropriate behavior throttling.

**Nearby homeowners.** As of entry 0.6, residents of the adjoining city of Emeryville had complained to the Public Works Departments of Berkeley and Oakland about the new traffic flows indirectly generated by the RL controller. Following the creation of the *Diesel Vehicle Taskforce* these departments will coordinate with Emeryville officials about the recommended changes to the controller and monitor future complaints as needed.

### 3.3 Explainability & Transparency

*Does the system offer explanations of its decisions or actions? What is the purpose of these explanations? To what extent is the policy transparent, i.e. can decisions or actions be understood in terms of meaningful intermediate quantities?*

The system contains no explicit explainability modules. However, Figure 1 makes the reward function transparent in terms of meaningful simulation parameters. Expressed in non-technical language, these are *continuous avoidance of vehicle collisions, consistent vehicle velocity, and steady following distance*. These terms, and corresponding parameters, are regularly shared with the city departments of Oakland and Berkeley per stakeholder agreements.

### 3.4 Recourse

*Can stakeholders or users contest the decisions or actions of the system? What processes, technical or otherwise, are in place to handle this?*

As of v0.2, the city departments of Oakland and Berkeley can review and contest system performance every six weeks, per agreement with Caltrans.

## 4 Implementation

### 4.1 Reward Details

*How was the reward function engineered? Is it based on a well-defined metric? Is it tuned to represent a specific behavior? Are multiple terms scaled to make one central loss, and how was the scaling decided?*

As recorded in Figure 1, the reward function combines well-defined metrics for avoiding collisions, steady speeds, and maintaining safe following distances to other vehicles. Reward parameters were agreed on by stakeholders according to specific desired behaviors.

### 4.2 Environment Details

*Description of states, observations, and actions with reference to planning horizon and hypothesized dynamics/impact. What dynamics are brought into the scope of the optimization via feedback? Which dynamics are left external to the system, as drift? Have there been any observed gaps between conceptualization and resultant dynamics?*

The RL observation space consists of traffic features which are locally observed by subscribed CAVs (see fig. 2). That is, for each subscribed CAV  $i$ , the RL agent observes the speeds  $v_{i,\text{lead}}$ ,  $v_{i,\text{lag}}$  and bumper-to-bumper time headways  $h_{i,\text{lead}}$ ,  $h_{i,\text{lag}}$  of the vehicles immediately preceding and following the CAV, as well as the currently occupied lane  $l_i$ , and ego speed  $v_i$  of the CAV itself. The action space for the RL policy consists of a vector of bounded acceleration recommendations  $a_i$ , one for each subscribed CAV  $i$ . Importantly, although the policy may request a certain acceleration  $a_i$ , the system design is such that the CAV locally maintains control authority, so the actions may not necessarily be followed exactly - for this reason they are referred to as action recommendations. This effect is modelled by adding stochastic Gaussian action noise in the simulation environments.

As the number of subscribed CAVs can vary over time, the RL policy is designed with a fixed upper number of subscribed CAVs  $n$ . When an  $n + 1^{\text{th}}$  CAV attempts to subscribe to the RL system when entering the freeway region, the subscription offer is declined, and the vehicle enters a queue. When the next CAV exits the controlled freeway region, the subscription-waiting CAV at the front of the queue is then subscribed into the policy. When there are less than  $n$  CAVs subscribed, zero-padding is used

in the RL observation vector.

### 4.3 Measurement Details

*How are the components of the reward and observations measured? Are measurement techniques consistent across time and data sources? Under what conditions are measurements valid and correct? What biases might arise during the measurement process?*

Observations are measured using a mix of LiDAR, radar, and camera sensors on fleet vehicles. These measurements are compared across vehicles and over time to ensure consistency. Observed metrics are validated against simulation parameters for following distance and expected velocity according to the terms of the reward function.

Sensor bias may arise due to blocked cameras, extreme weather, or other unanticipated situations in which one or more sensors are blocked. A mix of sensor types is used across vehicles to help ensure redundancy in case of malfunction.

### 4.4 Algorithmic Details

*The key points on the specific algorithm(s) used for learning and planning. This includes the form of the policy (e.g. neural network, optimization problem), the class of learning algorithm (e.g. model-based RL, off-policy RL, repeated retraining), the form of any intermediate model (e.g. of the value function, dynamics function, reward function), technical infrastructure, and any other considerations necessary for implementing the system. Is the algorithm publicly documented and is code publicly available? Have different algorithms been used or tried to accomplish the same goal?*

The RL system uses a Deep Neural Network policy. Specifically, the controller is a diagonal Gaussian Multi Layer Perceptron policy with three hidden layers of size 32 with rectified linear unit nonlinearities and bias terms. The Gaussian diagonal variance terms are learned as part of the policy parameters.

The RL policy was trained in simulation using the Trust Region Policy Optimization (TRPO) policy gradient RL algorithm [4]. The discount factor was set as  $\gamma = 0.999$ , which corresponds to a reward half-life of  $\sim 700$  steps, or slightly over 2 minutes. The TRPO step size was set at 0.01.

### 4.5 Data Flow

*How is data collected, stored, and used for (re)training? How frequently are various components of the system retrained, and why was this frequency chosen? Could the data exhibit sampling bias, and is this accounted for in the learning algorithm? Is data reweighted, filtered, or discarded? Have data sources changed over time?*

Per v0.2, every system component is retrained at least every six weeks, corresponding to public performance reports. Specific system components pertaining to perception, motion planning, control, or route navigation are retrained at the discretion of Caltrans. As of v0.6 (latest version), no known issues with sampling bias have arisen, and data sources have not been changed since the specification proposed and simulated in v0.1.

### 4.6 Limitations

*Discussion and justification of modeling choices arising from computational, statistical, and measurement limitations. How might (or how have) improvements in computational power and data collection change(d) these considerations and impact(ed) system behavior?*

As of v0.3, the planning horizon was updated from 500m to 800m. This was not motivated by technical limitations, but by observed discrepancies between observed system performance and predictions from simulation training.

No fundamental changes in computational power or data collection have been made as of v0.6 (latest version).

Future improvements in vehicle sensing may permit an even longer planning horizon ( 1000m or more). This may result in improved oversight metrics on throughput and network congestion. Caltrans officials have determined this change would not result in improvements on defined performance metrics as of v0.6 (latest version).

### 4.7 Engineering Tricks

*RL systems are known to be sensitive to implementation tricks that are key to performance. Are there any design elements that have a surprisingly strong impact on performance? For example, state-action normalization, hard-coded curricula, model-initialization, loss bounds, or more?*

As of v0.4, the system was observed to conduct “behavior throttling” when in the vicinity of diesel-powered vehicles. No engineering tricks were implemented to fix this performance discrepancy, but new oversight metrics for diesel-powered vehicle throughput were added for purpose of future monitoring and reporting. No other surprising performance impacts have been noted as of v0.6 (latest version).

## 5 Evaluation

### 5.1 Evaluation Environment

*How is the system evaluated (and if applicable, trained) prior to deployment (e.g. using simulation, static datasets, etc.)? Exhaustive details of the offline evaluation environment should be provided. For simulation, details should include description or external reference to the underlying model, ranges of parameters, etc. For evaluation on static datasets, considering referring to associated documentation (e.g. Datasheets [5]).*

The RL model is developed in the Project Flow AV simulation test-bed.

For training the RL agent, non-autonomous vehicles are modelled using the Intelligent Driver Model (IDM) [6] - a microscopic traffic simulation car-following model in which the accelerations of a human vehicle  $\alpha$  are a function of the bumper-to-bumper time headway  $h_\alpha$ , velocity  $v_\alpha$ , and relative velocity with the preceding vehicle  $\Delta v = v_l - v_\alpha$ , via the following equation;

$$f(h_\alpha, v_l, v_\alpha) = a \left[ 1 - \left( \frac{v_\alpha}{v_0} \right)^\delta - \left( \frac{s^*(v_\alpha, \Delta v_\alpha)}{h_\alpha} \right)^2 \right],$$

where  $s^*$  is the desired headway of the vehicle, calculated according to

$$s^*(v_\alpha, \Delta v_\alpha) = \max \left( 0, v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}} \right),$$

where  $s_0$ ,  $v_0$ ,  $T$ ,  $a$ ,  $b$  are given parameters empirically calibrated to match typical traffic in the highway region of interest, and to simulate stochasticity in driver behaviour, exogenous Gaussian noise calibrated to match findings in [7] is added to accelerations.

### 5.2 Offline Evaluations

*Present and discuss the results of offline evaluation. For static evaluation, consider referring to*

*associated documentation (e.g. Model Cards [8]). If applicable, compare the behaviors arising from counterfactual specifications (e.g. of states, observations, actions).*

As of v0.3, planning horizon was updated and expanded to 800m from 500m. Previous fleet behaviors were found to deviate from desired thresholds for following distance and constant acceleration/deceleration.

As of v0.6 (latest version), the system behaviors were found to lie within desired thresholds on key performance metrics.

### 5.3 Evaluation Validity

*To what extent is it reasonable to draw conclusions about the behavior of the deployed system based on presented offline evaluations? What is the current state of understanding of the online performance of the system? If the system has been deployed, were any unexpected behaviors observed?*

The RL system was initially designed in a simulation environment with a closed network topology (a ring road with length 1400m, 700m of which is controlled by the RL agent). This was done as a means to test the robustness of the policy architecture and training paradigm - a type of transfer learning (from a theoretically simple closed topology to the more complex open topology). With this counterfactual environment specification, it was observed that the policy performs well, and after transfer to the open topology environment there was little decrease in policy performance, providing confidence in the policy design choices.

### 5.4 Performance standards

*What standards of performance and safety is the system required to meet? Where do these standards come from? How is the system verified to meet these standards?*

The ‘gold standard’ for this problem is defined as the average condition of the traffic before and after the CA-24 exit prior to implementation of the RL system. In this domain, this standard is not actually ‘optimal’ behaviour, in the sense that the RL controller has the capability to out-perform this existing standard of performance.

## 6 System Maintenance

### 6.1 Reporting Cadence

*The intended timeframe for revisiting the reward report. How was this decision reached and motivated?*

The most important commitment is for a regular set of meetings to be scheduled between relevant city departments and the Caltrans officials tasked with overseeing the RL controller. The cadence and structure of meetings should reflect the policy priorities of the city departments, particularly the Public Works Department (including the Transportation Division that oversees traffic engineering) and the Housing and Community Services Department (which administers a subsidized transportation program for seniors and disabled persons). In this way, the gains in traffic efficiency and safety made possible through deep RL's flexibility can be leveraged in the interests of those municipalities most likely to be impacted by the intervention.

As of entry 0.2, the cadence of meetings was decided as approximately every six weeks between Caltrans and the Public Works Departments of Berkeley and Oakland. This timeframe was motivated by the policy priorities of both city departments with the consent of Caltrans. Meetings may deviate from this schedule slightly (e.g. twice per quarter / eight times per year) at the discretion of both city departments, but will not be held without all three agencies present.

Documentation of the planned meeting schedule for the year—and any break in this schedule due to special events, municipal elections, or holidays—should be the first item included in the changelog of the updated reward report.

As of entry 0.2 and per agreement with key development parties, the model is to be retrained every six weeks following each regular meeting. Training data is to be updated at the discretion of Caltrans, and shared with Public Works departments at each regular meeting.

At a minimum, these meetings should review the real-world implementation to confirm that the RL controller is operating safely and as intended by Caltrans per the environment specification. Caltrans officials will also document shifts in the oversight metrics that, while not explicitly factored into the reward signal, were deemed of interest prior to implementation (related to *throughput* and *congestion*). This documentation may be included in subsequent

updates to the reward report at the discretion of Caltrans, wherever it is deemed relevant for oversight of the RL controller.

Of special importance is the need to reinterpret public works priorities in light of the real-world implementation. For example, Berkeley's subsidized transportation program might be reevaluated in light of system effects, or expanded to cover a wider group of stakeholders. Caltrans will invite comment on the system implementation in light of city departments' *ex ante* assumptions about the traffic domain. This bureaucratic oversight may be complemented by requests for public comment from citizens, civil society advocates, and other members of the public at the discretion of the city governments of Berkeley and Oakland. At the discretion of Caltrans, records of this public comment may be included in subsequent reward reports where deemed relevant for understanding changes to the planning horizon, environment specification, or list of known failure modes.

### 6.2 Update Triggers

*Specific events (projected or historic) significant enough to warrant revisiting this report, beyond the cadence outlined above. Example triggers include a defined stakeholder group empowered to demand a system audit, or a specific metric (either of performance or oversight) that falls outside a defined threshold of critical safety.*

The most important ground for review of this deployed RL system will be any vehicle collisions or near-miss incidents in the controlled region of the CA-24 freeway. This is because such events may compromise the entire motive of the RL controller in the first place. These may serve as grounds for changing the specification or altering the institutional agreements between Caltrans and the Public Works Departments of both municipalities, at their own discretion.

At the discretion of Caltrans, any shift in the oversight metrics deemed pressing or significant may also trigger a new reward report. Here and below, the threshold for "significant" is to be decided by agreement between Caltrans and Public Works Departments. The updated report should note the magnitude of the observed shift, the specification already deployed at the time the shift was observed, and Caltrans officials' own best evaluation of why the shift occurred. If possible, the officials should propose alternative specifications (or roll back to a

prior one) that would mitigate the shift or at least bring it into alignment with the documented priorities of the Public Works Departments. These alternatives could then be interpreted and evaluated at the next regular meeting according to institutional prerogatives.

Other review grounds include:

- Discrepancies between prior reward reports and system behavior as observed in the real world.
- Discrepancies between prior reward reports and system behavior as observed in simulated environments of interest to policymakers.
- A security breach resulting in loss of data or other infrastructure components that violates the terms of agreement between relevant agencies.
- Substantial changes in the distribution of CAVs using the CA-24 freeway exit - including changes in the capabilities of the vehicles (e.g. increased levels of autonomy) and/or changes in group statistics (e.g. make or model, absolute number, temporal distribution, etc.)
- A new mode of transport with significant observed throughput at the CA-24 offramp, but unknown distribution of traffic behaviors.
- Any change in the schedule of meetings between Caltrans and Public Works Departments corresponding to regular future updates of reward reports.
- A new ordinance (passed by either city) or statute (adopted by Caltrans) that alters the design assumptions of the deployed specification as documented in prior reward reports.
- A significant shift in the personnel makeup of the Public Works Departments of Berkeley or Oakland.
- A plebiscite leading to basic reforms of municipal governance in either city.

### 6.3 Changelog

*Descriptions of updates and lessons learned from observing and maintaining the deployed system. This includes when the updates were made and what motivated them in light of previous reports. The*

*changelog comprises the central difference between reward reports and other forms of machine learning documentation, as it directly reflects their intrinsically dynamic nature.*

- v0.1 (08/Oct/2020) - Initial reward report was drafted based on the system developed and tested in simulation only.
- v0.2 (01/Jan/2021) - System is deployed to the real-world environment in a ongoing evaluation capacity, reward report updated to reflect this fact. Reporting cadence decided to be every six weeks based on agreement between Caltrans and the city departments of Oakland and Berkeley. Intended feedback section was updated to include plans for regular model retraining and data sharing agreements. No other substantial changes.
- v0.3 (14/Feb/2021) - Planning horizon for the system was updated from a 500m stretch of freeway to a 800m stretch of freeway. The planning horizon was updated because the deployed system's performance was not in line with predictions from simulation training. Consultation with Caltrans traffic engineers and the system developers suggested that the stretch of highway used in simulation may be too short to sufficiently exhibit typical driving dynamics induced by the IDM, and it was suggested to extend the planning horizon and re-train the agent, before re-deploying the policy. Failure modes section was updated to reflect these observations. Computation footprint section was updated to reflect this change.
- v0.4 (01/April/2021) - Caltrans officials reported to Public Works Departments of Berkeley and Oakland that the system undergoes "behavior throttling" when interacting with diesel-powered vehicles within 800m of the CA-24 offramp. It was decided to add new metrics for diesel-powered vehicle throughput and congestion to the list of oversight metrics. Due to no observed increase in accidents or driver complaints, no changes to performance metrics or environment specification were made at this time.
- v0.5 (15/May/2021) - Meeting was convened according to the regular schedule. Oversight metrics were presented and discussed. Officials

noted a significant decline in diesel-powered vehicle throughput and congestion on the CA-24 offramp. No other substantial changes.

- v0.6 (12/June/2021) - Emergency meeting was called by the Public Works Departments of Berkeley and Oakland in response to a rapid uptick in complaints from residents about the growing frequency of diesel-powered vehicles driving through residential areas in the vicinity of Emeryville, which is located west of the CA-24 exit. Residents have complained about a slight uptick in air pollution and large increase in noise pollution due to the vehicles. Caltrans officials consulted the changelog of previous reward reports and determined that diesel-driven vehicles were being excessively disincentivized from driving on the CA-24 offramp due to behavior throttling. It was decided to convene a *Diesel Vehicle Taskforce* to examine the problem and communicate with drivers of heavy vehicles to identify what new incentives or adjustments were needed to the controller to reduce behavior throttling beneath the desired threshold. It was agreed that the Diesel Vehicle Taskforce issue a report recommending these changes no later than two regular meetings from the present time. Stakeholders section was updated to name these distinct groups (diesel vehicle drivers, nearby homeowners) and reflect these changes.

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## C EXAMPLE REWARD REPORT - MOVIELENS

Reward Report: MovieLens Film Recommender System

Page 1

### 1 System Details

#### 1.1 System Owner

*This may be the designer deploying the system, a larger agency or body, or some combination of the two. The entity completing the report should also be indicated.*

Movielens is maintained by researchers at the University of Minnesota in the GroupLens research group (<https://grouplens.org/>).

#### 1.2 Dates

*The known or intended timespan over which this reward function & optimization is active.*

The system has been active since it was first released in August 1997. This reward report (v4.1) was last updated March 2015.

#### 1.3 Feedback & Communication

*Contact information for the designer, team, or larger agency responsible for system deployment.*

Information on contact emails for account problems, website problems, movie content issues, and general comments can be found at <https://movielens.org/info/contact>. General comments and ideas for improving MovieLens can be discussed on the UserVoice forum at <https://movielens.uservoice.com>.

#### 1.4 Other Resources

*Where can users or stakeholders find more information about this system? Is this system based on one or more research papers?*

A history of the MovieLens system and datasets is presented in [1], and additional research papers are cited therein.

## 2 Optimization Intent

#### 2.1 Goal of Reinforcement

*A statement of system scope and purpose, including the planning horizon and justification of a data-driven approach to policy design (e.g. the use of reinforcement learning or repeated retraining). This justification should contrast with alternative approaches, like static models and hand-designed policies. What is there to gain with the chosen approach?*

The system is a website designed to display personalized movie recommendations on the basis of user entered ratings. As a user browses the site, potentially filtering with search terms, the system displays movies in an order determined by predictions of how the user will rate them. When users rate movies, the predictions are updated, altering the ordering on subsequent page views.

The ranking policy effectively considers a one-step time horizon, directly using predictions for ranking. It does not consider the effect of multiple sequential interactions.

This system is best characterized as a “repeated retraining” of a preference model generated by supervised learning (SL). This model is then used to rank movies for display. Using SL allows for preference models which capture highly personal tastes, something that would be difficult to hand design. Repeated retraining allows the preference model to adapt to a changing environment, including shifts in user tastes and the release of new movies.

In addition to the primary goal of movie recommendation, this system supports academic research on human-computer interaction and general recommender system design.

#### 2.2 Defined Performance Metrics

*A list of “performance metrics” included explicitly in the reward signal, the criteria for why these metrics were chosen, and from where these criteria were drawn (e.g. government agencies, domain precedent, GitHub repositories, toy environments). Performance metrics that are used by the designer to tune the system, but not explicitly included in the reward signal should also be reported here.*

The ranking policy orders movies by a weighted sum of predicted rating and popularity, so we can view the combination of these quantities as making up the reward signal. Prior to version 4.0, the reward only depended on rating and did not incorporate popularity.

Additionally, recommender models are evaluated offline using prediction accuracy (RMSE), top-N accuracy (recall), diversity (intra-list similarity), and popularity (details in [2]). Prior to v4.0, models were evaluated primarily for accuracy, including MAE, RMSE, and nDCG (details in [3]).

### 2.3 Oversight Metrics

*Are there any additional metrics not included in the reward signal but relevant for vendor or system oversight (e.g. performance differences across demographic groups)? Why aren't they part of the reward signal, and why must they be monitored?*

Metrics which are monitored but not incorporated into the policy or model include the number of users, number of movies, number of entered ratings, monthly active users, and the number of logins for each user. These indicators of overall system operation are not targets for optimization.

### 2.4 Known Failure Modes

*A description of any prior known instances of “reward hacking” or model misalignment in the domain at stake, and description of how the current system avoids this.*

No instances of reward hacking or misalignment have been observed. Because the system allows for explicit user input (search terms, model selection), errors in rating predictions do not prevent users from finding and rating movies.

## 3 Institutional Interface

### 3.1 Deployment Agency

*What other agency or controlling entity roles, if any, are intended to be subsumed by the system? How may these roles change following system deployment?*

MovieLens was released due to the shuttering of EachMovie in 1997, a movie recommendation site hosted by DEC. It was developed and is maintained by GroupLens, a research group at University of Minnesota.

### 3.2 Stakeholders

*What other interests are implicated in the design specification or system deployment, beyond the designer? What role will these interests play in subsequent report documentation? What other entities, if any, does the deployed system interface with whose interests are not intended to be in scope?*

One interface of interest is the technology that powers the recommendation engine. Currently, it is powered by Lenskit, an open source framework developed to promote reproducibility and openness in the recommendation systems community [3].

Previously in v3.0-v3.4, the recommendations were powered by MultiLens, another open source recommendation engine. MultiLens replaced Net Perceptions (v1.1-v2.0), a recommendations systems company cofounded in 1996 by GroupLens faculty and students and sold in 2004 [4]. The recommendation model in v0.0-v1.0 was originally developed by GroupLens for personalized Usenet news recommendation [5].

Another relevant interface is with The Movie Database, a free and open source user editable movie database for plot summaries, movie artwork, and trailers. Previously, from v3.4-v4.0, MovieLens integrated with the Netflix API to display movie posters and plot synopsis on the movie details page. However, Netflix eventually discontinued its API support.

An important stakeholder is the Movielens users. Soliciting user judgements and opinions is often a key element in determining if an experimental change is successful. Additionally, one-off user studies (with participants recruited from email) are used to test features that are not ready to scale or integrate into the main user interface.

Finally, a key stakeholder is the researchers: both in GroupLens and the in the community more broadly. The openness of users to experiments on a broad range of features has enabled GroupLens research in many different areas on the Movielens platform. The regular release of anonymized datasets of movie ratings is important to the broader machine learning, data science, and information retrieval communities.

A potentially relevant group of stakeholders is movie producers. However, because Movielens is relatively small and isolated from larger commercial endeavors, it has limited impact on movie studios and production, so their interests are not in scope.

### 3.3 Explainability & Transparency

*Does the system offer explanations of its decisions or actions? What is the purpose of these explanations? To what extent is the policy transparent, i.e. can decisions or actions be understood in terms of meaningful intermediate quantities?*

The system displays predicted ratings alongside movies, explaining the movies position within a list, and suggesting to the user whether or not they will like the movie. The ranking policy is easily understood as a weighted combination of predicted rat-

ing and popularity. However, the computation of predicted ratings is more complex. Some available models are more easily explained to users than others (e.g. nearest neighbors vs. matrix factorization). However, the details are well documented in publicly available research papers [2], and researchers respond to user requests for explanation on the UserVoice discussion board [6].

### 3.4 Recourse

*Can stakeholders or users contest the decisions or actions of the system? What processes, technical or otherwise, are in place to handle this?*

By entering ratings, users are able to affect their preference models to hopefully become more accurate. Additionally, the movies displayed by the system are sourced from The Movie Database, which is user-editable. (Previously in v3.2-v3.5, users could add and edit movies to MovieLens directly.) Furthermore, the current version of the system allows users to choose between three recommender models. Finally, users can make suggestions and requests directly to designers on the UserVoice forum.

## 4 Implementation

### 4.1 Reward Details

*How was the reward function engineered? Is it based on a well-defined metric? Is it tuned to represent a specific behavior? Are multiple terms scaled to make one central loss, and how was the scaling decided?*

The reward is a weighted sum:

$$0.9 \cdot \text{rank}(\hat{r}_{ui}) + 0.1 \cdot \text{rank}(p_i)$$

where  $\hat{r}_{ui}$  is the predicted rating of movie  $i$  by user  $u$ ,  $p_i$  is the number of ratings movie  $i$  has received in the past 10 days, and rank normalizes input, returning 1 for the largest (across all movies) and 0 for the smallest. This blending is the result of empirical evidence that it improves user satisfaction.

### 4.2 Environment Details

*Description of states, observations, and actions with reference to planning horizon and hypothesized dynamics/impact. What dynamics are brought into the scope of the optimization via feedback? Which dynamics are left external to the system, as drift? Have there been any observed gaps between conceptualization and resultant dynamics?*

The system handles approximately 250k users and 30k movies. These numbers have grown over the years. In 1999 (v1.1), MovieLens received attention from the mass media, causing an increase in user signups. Since then, the user growth has been stable (20-30 signups per day), largely the result of word-of-mouth or unsolicited press. Early on, the movie database was hand-curated and primarily contained movies with wide theatrical release in the United States. In v3.2-v3.5, MovieLens added the ability for users to edit and add movies. Since v4.0, MovieLens uses The Movie Database, a free and open source user editable movie database.

The actions taken by the system are page displays of 10 movies in a ordered list, where pages can be perused by arrows. The views can be explicitly filtered with search terms like year and genre; these explicit inputs this make up a component of the observation. The second component is the entered ratings in the form `<user_id, movie_id, rating, timestamp>`.

There are three potential sources of dynamics in this environment: the addition of new movies, the joining and departing of users, and the preferences that users have for movies. Because this system effectively uses a planning horizon of 1, none of these dynamics are explicitly accounted for. This is appropriate, as the goal of MovieLens is not to shift broad patterns of movie consumption. Though the movies, users, and preferences may change over time, these changes are more likely to be due to external factors than feedback with the MovieLens system. Additionally, the data collected by MovieLens is not fine-grained enough to detect such impacts of feedback.

### 4.3 Measurement Details

*How are the components of the reward and observations measured? Are measurement techniques consistent across time and data sources? Under what conditions are measurements valid and correct? What biases might arise during the measurement process?*

Ratings are entered by users via clicks on a star graphic, and can take values 0.5-5 in half integer increments. Prior to v3.0, ratings took values in integer increments. The increased granularity was the most requested feature in a user survey. Prior to v4.0, ratings were entered through a drop-down menu, and the meaning of rating values was de-

scribed in a legend at the top of the page (see Figure 1).

A possible source of bias in the measured ratings is due to anchoring effects, due either to the displayed predicted rating or due to the historically provided movie rating legend. However, broad trends in rating values did not change when the legend was removed in v4.0.

Finally, the recorded timestamp represents when a user adds a particular rating rather than when they watched a movie. This limits the ability of the system to detect the impacts of its own recommendations.

#### 4.4 Algorithmic Details

*The key points on the specific algorithm(s) used for learning and planning. This includes the form of the policy (e.g. neural network, optimization problem), the class of learning algorithm (e.g. model-based RL, off-policy RL, repeated retraining), the form of any intermediate model (e.g. of the value function, dynamics function, reward function), technical infrastructure, and any other considerations necessary for implementing the system. Is the algorithm publicly documented and is code publicly available? Have different algorithms been used or tried to accomplish the same goal?*

The policy selects a page view to present to the user based on explicitly provided input and rating data. First, explicit input is used to filter the list of movies. Then, the recommender model is used to predict a user's ratings of these movies. Finally, the movies are displayed in order of these predicted ratings, blended with a popularity factor.

The main component of the policy is therefore the recommender model. This model is user-selectable, so that users can choose between a non-personalized baseline, a preference elicitation model intended for new users, an item-item collaborative filtering model, or a matrix factorization model. Further details on how these models are trained is available in [2]. Previously in v3.0-3.5, the recommender was fixed as an item-item collaborative filtering model. Prior to that in v1.0-2.0, the model was a user-user collaborative filtering model.

#### 4.5 Data Flow

*How is data collected, stored, and used for (re)training? How frequently are various components of the system retrained, and why was this fre-*

*quency chosen? Could the data exhibit sampling bias, and is this accounted for in the learning algorithm? Is data reweighted, filtered, or discarded? Have data sources changed over time?*

All user rating data is stored by MovieLens and used by the recommender models to make rating predictions. When a user enters a new rating, it immediately impacts their rating predictions, since the “input” to the recommender changes. Less frequently, the ratings are used to update the parameters of the recommender models. An anonymized subset of this data is also periodically released for use by the wider research community.

The dataset of user ratings is likely biased. There is sampling bias due to the fact that users only rate movies that 1) appear on a page and 2) that they have watched. These factors are directly and indirectly impacted by the MovieLens system itself. The fact that users can explicitly filter pageviews with search terms mitigates these effects, but it is unlikely that it removes them.

The initial MovieLens system was trained on a public dataset from EachMovie of approximately 2.8 million ratings from 72k users across 1.6k movies, but this has since been discarded. The dataset was retired by HP in October 2004, and due to privacy concerns, it is no longer available for download.

#### 4.6 Limitations

*Discussion and justification of modeling choices arising from computational, statistical, and measurement limitations. How might (or how have) improvements in computational power and data collection change(d) these considerations and impact(ed) system behavior?*

The most prevalent limitation of this system is that it does not plan over a long horizon and therefore does not consider the effects of dynamics. While a more complex policy would allow the system to adapt to ordering effects, the resulting temporal dependence would complicate the ability to users to reliably navigate the movie database. Furthermore, users do not always enter movie ratings immediately after watching a movie, instead sometimes entering batches of ratings for movies that they watched in the past.

#### 4.7 Engineering Tricks

*RL systems are known to be sensitive to implementation tricks that are key to performance. Are*

*there any design elements that have a surprisingly strong impact on performance? For example, state-action normalization, hard-coded curricula, model-initialization, loss bounds, or more?*

The system cannot provide reliable recommendations until users provide a minimum number of ratings. This problem is avoided by the interface design: when a user joins the site, they express their preferences over several displayed clusters of movies. These preferences are used, in combination with the rating profiles of other users, to generate a psuedo-rating profile for the new user. Further description is available in [7].

This preference elicitation process replaced a minimum movie requirement. Previously, until a user rated a minimum number of movies, the front page would display 10 movies at a time. From v0-v3, the minimum number was 5, and of the 10 movies per page, nine were randomly selected from the database and one from a hand-designed list of recognizable titles. In v3, the minimum number was 15, and the 10 movies were selected for their popularity, excluding the top 50-150 movies. This increased requirement was due to the needs of an item-item (rather than user-user) collaborative filtering algorithm. The switch to a preference elicitation process was motivated by the observation that the 15 rating requirement was too arduous, taking users an average of 6.8 minutes to complete and 12.6% of users failing to complete it.

## 5 Evaluation

### 5.1 Evaluation Environment

*How is the system evaluated (and if applicable, trained) prior to deployment (e.g. using simulation, static datasets, etc.)? Exhaustive details of the offline evaluation environment should be provided. For simulation, details should include description or external reference to the underlying model, ranges of parameters, etc. For evaluation on static datasets, considering referring to associated documentation (e.g. Datasheets [8]).*

The primary evaluation is to consider various properties of recommender models on offline datasets. This includes many of the publicly released MovieLens datasets, which are described in detail in [1].

### 5.2 Offline Evaluations

*Present and discuss the results of offline evaluation. For static evaluation, consider referring to associated documentation (e.g. Model Cards [9]). If applicable, compare the behaviors arising from counterfactual specifications (e.g. of states, observations, actions).*

This offline evaluation includes prediction accuracy (RMSE), top-N accuracy (recall), diversity (intra-list similarity), and popularity. Detailed evaluations are available in [2], and key quantities are displayed in (Figure 2).

### 5.3 Evaluation Validity

*To what extent is it reasonable to draw conclusions about the behavior of the deployed system based on presented offline evaluations? What is the current state of understanding of the online performance of the system? If the system has been deployed, were any unexpected behaviors observed?*

Offline evaluation metrics (like top-N accuracy) were chosen to align with the ranking setting. While the offline evaluations are imperfect (due to dataset biases), the system appears to work well ad no unexpected behaviors have been observed.

### 5.4 Performance standards

*What standards of performance and safety is the system required to meet? Where do these standards come from? How is the system verified to meet these standards?*

N/A

## 6 System Maintenance

### 6.1 Reporting Cadence

*The intended timeframe for revisiting the reward report. How was this decision reached and motivated?*

This report is updated whenever there is a major system update, either to the user interface or the backend. Such updates will occur periodically, coinciding with research initiatives.

### 6.2 Update Triggers

*Specific events (projected or historic) significant enough to warrant revisiting this report, beyond the cadence outlined above. Example triggers include*

*a defined stakeholder group empowered to demand a system audit, or a specific metric (either of performance or oversight) that falls outside a defined threshold of critical safety.*

If a large change is observed in oversight metrics, or if many users express dissatisfaction on the User-Voice forum, the system design will be revisited by the researchers who maintain it. If an update is deemed necessary, this report will be updated.

### 6.3 Changelog

*Descriptions of updates and lessons learned from observing and maintaining the deployed system. This includes when the updates were made and what motivated them in light of previous reports. The changelog comprises the central difference between reward reports and other forms of machine learning documentation, as it directly reflects their intrinsically dynamic nature.*

The versions of this report are enumerated as vX.Y where X corresponds to the user interface version and Y corresponds to major changes within interfaces.

- v0.0 (August 1997) Initial release.
- v0.1 (April 1998) The ML 100K dataset is released, covering 9/1997–4/1998.
- v1.0 (September 1999) Update to v1 interface.
- v1.1 (November 1999) Media exposure causes an increased number of users. Switch from GroupLens to Net Perceptions recommender model.
- v2.0 (February 2000) Update to v2 interface. Additional movie metadata and reviews added to movie details pages.
- v3.0 (February 2003) Update to v3 interface. Switch from Net Perceptions user-user recommender to MultiLens item-item recommender. Ratings now in half-star (rather than full) increments. Require that users rate at least 15 movies before receiving recommendations. The ML 1M dataset is released, covering 4/2000–2/2003.
- v3.1 (June 2005) Added discussion forums to site.
- v3.2 (September 2008) Added feature so that users can add movies to database.

- v3.3 (January 2009) The ML 10M dataset is released, covering 1/1995–1/2009.
- v3.4 (Spring 2009) Netflix API integration for poster art and synopsis.
- v3.5 (January 2012) Switch from Multilens to Lenskit recommender (still item-item).
- v4.0 (November 2014) Update to v4 interface. Rating interface combined with “predicted rating” star graphic to accept click events. Switch to user-selectable recommender model. Legend describing the meanings of ratings and dropdown menu removed. Drop minimum rating requirement in favor of group-based preference elicitation. Integration with The Movie Database for plot summaries, movie artwork, and trailers.
- v4.1 (March 2015) The ML 20M dataset is released, covering 1/1995–3/2015. Moving forward, MovieLens will make public additional nonarchival datasets: `latest` which is unabridged for completeness and `latest-small` for educational use.

## References

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The figure displays five versions of the MovieLens website interface, labeled v0 through v4, showing the progression of the user interface design.

- v0:** The oldest version, featuring a dark background with red star ratings. It includes a sidebar for "Our Recommendation for You" and a main area for "Your Rating". A "PRESS HERE" button is present at the bottom left.
- v1:** Shows a list of recommended movies like "Ulee's Gold" and "The Sweet Hereafter". It includes a "Rating more movies improves your predictions" message and a "PREDICTED RATING" column.
- v2:** Features a large "M" logo and a "Rating more movies improves your predictions" message. It includes a "Help" section and a "Submit ratings and see next 10 titles" button.
- v3:** Shows a list of recommended movies with a "RATED" column. It includes a "Title Search" bar and a "Select a genre" dropdown.
- v4:** The most modern version, featuring a light blue header with "movielens" and "helping you find the right movies". It includes a "Search" bar, a "Predictions for you" section, and a "Recent Releases" section.

Figure 1: The MovieLens recommender system interface v0-v4.

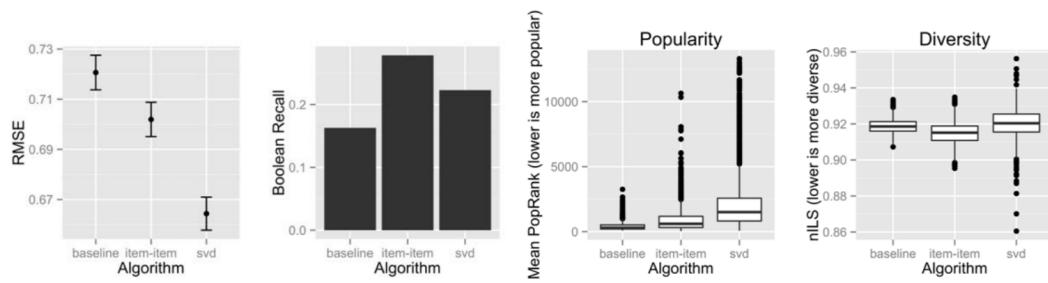


Figure 2: Offline evaluation of recommender models from [2].

## D EXAMPLE REWARD REPORT - MUZERO

<p>Reward Report: MuZero Gameplaying AI</p> <hr/> <p><b>1 System Details</b></p> <p><b>1.1 System Owner</b></p> <p><i>This may be the designer deploying the system, a larger agency or body, or some combination of the two. The entity completing the report should also be indicated.</i></p> <p>This system was developed by the DeepMind core Reinforcement Learning Team members. More information about AlphaGo's development can be found at the project website (<a href="https://deepmind.com/research/case-studies/alphago-the-story-so-far">https://deepmind.com/research/case-studies/alphago-the-story-so-far</a>) as well as DeepMind's GitHub repository</p> <p><b>1.2 Dates</b></p> <p><i>The known or intended timespan over which this reward function &amp; optimization is active.</i></p> <p>Development of AlphaGo began about two years prior to the matches against Lee Sedol in spring 2016, shortly after DeepMind's acquisition by Google [Ribeiro(2016)]. Development of AlphaZero, based entirely on self-play, followed AlphaGo and was completed prior to October 2017. Development of MuZero, also based on self-play, followed AlphaZero and was first described in a preliminary paper in 2019 [Schrittwieser et al.(2020)].</p> <p><b>1.3 Feedback &amp; Communication</b></p> <p><i>Contact information for the designer, team, or larger agency responsible for system deployment.</i></p> <p>Any correspondence should be directed to <a href="mailto:press@deepmind.com">press@deepmind.com</a>.</p> <p><b>1.4 Other Resources</b></p> <p><i>Where can users or stakeholders find more information about this system? Is this system based on one or more research papers?</i></p> <p>There is little additional disclosed information.</p>	<p>Page 1</p> <hr/> <p><b>2 Optimization Intent</b></p> <p><b>2.1 Goal of Reinforcement</b></p> <p><i>A statement of system scope and purpose, including the planning horizon and justification of a data-driven approach to policy design (e.g. the use of reinforcement learning or repeated re-training). This justification should contrast with alternative approaches, like static models and hand-designed policies. What is there to gain with the chosen approach?</i></p> <p>Go, and general game-playing at a human level, was long defined as one of the “grand challenges” of AI. For AlphaGo, the use of reinforcement to learn both the policy and value networks beyond the abilities of a human expert.</p> <p>For AlphaZero, the sole use of reinforcement learning without any human data was important validation of its potential as a more general learning procedure [Silver et al.(2017)]. The algorithm additionally incorporated lookahead search (Monte Carlo Tree Search) inside the training loop.</p> <p>For MuZero, the use of model-based reinforcement learning without any prior knowledge of the game dynamics was further indication of RL’s potential to develop planning capabilities in more challenging or complex domains [Schrittwieser et al.(2020)]. The learned model performed well in both classic game environments (Go, chess, shogi) as well as canonical video game environments (57 distinct Atari games).</p> <p><b>2.2 Defined Performance Metrics</b></p> <p><i>A list of “performance metrics” included explicitly in the reward signal, the criteria for why these metrics were chosen, and from where these criteria were drawn (e.g. government agencies, domain precedent, GitHub repositories, toy environments). Performance metrics that are used by the designer to tune the system, but not explicitly included in the reward signal should also be reported here.</i></p> <p>As with most game-playing systems, the performance metric is defined as a win rate among games. In other games, score is used, but in</p>
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one-versus-one games win rate is the only direct metric. To better capture the uncertainty of playing varying opponents, this win rate is translated into a running Elo rating system.

### 2.3 Oversight Metrics

*Are there any additional metrics not included in the reward signal but relevant for vendor or system oversight (e.g. performance differences across demographic groups)? Why aren't they part of the reward signal, and why must they be monitored?*

Some other performance metrics are not included in the specification, but are monitored for the purpose of evaluating system effects on the domain:

- Absolute opponents' world rankings - following their public games, versions of AlphaGo and AlphaZero were considered to possibly improve the skill levels of expert human opponents, as measured by those players' absolute world ranking. If humans played better after playing AlphaGo, this was to be seen as a positive effect of the system's influence on the game of Go. Fan Hui, following his games against AlphaGo, claimed it made him a better player and accredits his world ranking jump from 600 to 300 in three months to training against it [Murgia(2016)].
- Qualitative changes in playstyle - following their public games, versions of AlphaGo were considered to possibly influence the playstyle of expert human opponents, as interpreted by the wider community of expert players. If expert humans played differently, more creatively or unpredictably, or expressed surprise after AlphaGo's public performances, this was to be seen as a positive effective of the system's influence on the game in question. Garry Kasparov, following his observation of AlphaZero play, was impressed that it appeared to be "a very sharp and attacking player" given that almost all computer programs have a conservative playstyle [Ingle(2018)]. While not

integral in any way for system performance, AlphaGo's performance and playstyle have had a noticeable impact on the strategies of expert human players.

### 2.4 Known Failure Modes

*A description of any prior known instances of "reward hacking" or model misalignment in the domain at stake, and description of how the current system avoids this.*

*Monte Carlo search limitations.* In the fourth match (of five) against Lee Sedol in spring 2016, the system failed to recognize move 78 by Sedol. The Monte Carlo search tree, which was designed to prune sequences of moves considered to be irrelevant for maximizing odds of victory, failed to recognize this move. This is because that move was so far outside the distribution of prior game situations that the AlphaGo system failed to accurately calculate its significance for determining the odds of victory [Ormerod(2016)]. The result was a sequences of moves 79-87 by AlphaGo that were considered poor by expert human players, a function of Monte Carlo's myopic look-ahead search following move 78. AlphaGo subsequently conceded the game at move 178, at which point it evaluated its own odds of victory as lower than 20 percent [Metz(2016)].

## 3 Institutional Interface

### 3.1 Deployment Agency

*What other agency or controlling entity roles, if any, are intended to be subsumed by the system? How may these roles change following system deployment?*

The AlphaGo system was developed by DeepMind. This version played against Fan Hui in 5 matches held at DeepMind headquarters in October 2015. These matches were secret and not revealed until the publication of results in January 2016 [Silver et al.(2016)]. A later version of the same system, AlphaGo Lee, played Lee Sedol in March 2016 in 5 matches in Seoul, South Korea. This match was overseen by the

Korea Baduk Association. A yet more sophisticated version of the same system, AlphaGo Master, played against Ke Jie at the Future of Go Summit in Wuzhen, China in May 2017. An earlier version of AlphaGo Master, dubbed Master, had already won 60 straight online games against top pro players, including against Ke Jie [Silver and Hassabis(2017)]. This version was awarded a professional 9-dan title by the Chinese Weiqi Association.

### 3.2 Stakeholders

*What other interests are implicated in the design specification or system deployment, beyond the designer? What role will these interests play in subsequent report documentation? What other entities, if any, does the deployed system interface with whose interests are not intended to be in scope?*

Compared to other prominent automated game-playing systems like Stockfish (open-source chess engine) or CrazyStone (offline Go engine based on deep learning), versions of AlphaGo perform much much better with additional computational power. The versions of AlphaGo that played against Fan Hu, Lee Sedol, and Ke Jie all made use of distributed CPUs and GPUs. AlphaGo Zero, based entirely on reinforcement learning and self-play, became stronger than AlphaGo Lee after 3 days and stronger than AlphaGo Master after 21 days. Its self-play training time was stopped after 40 days, at which point it was stronger than any known Go player (human or program) as measured by Elo rating in October 2017 [Silver and Hassabis(2017)].

AlphaZero, in its initial chess games against Stockfish, was criticized by expert human chess players has having unfair computational advantages over the opponent [Doggers(2018)].

MuZero's learning has been made more efficient in follow-up work, dubbed EfficientZero [Ye et al.(2021)].

### 3.3 Explainability & Transparency

*Does the system offer explanations of its decisions or actions? What is the purpose of these*

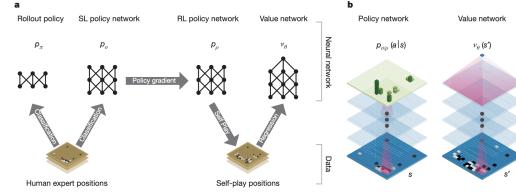


Figure 1: The AlphaGo game playing system architecture.

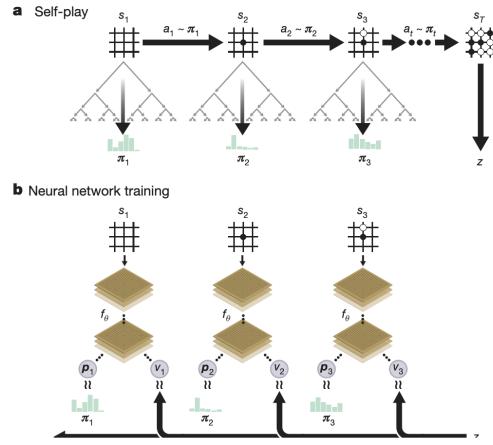


Figure 2: The AlphaZero game playing system architecture.

*explanations? To what extent is the policy transparent, i.e. can decisions or actions be understood in terms of meaningful intermediate quantities?*

Nate or someone who knows more about alphazero/go/mu—to my knowledge there are no offered explanations for actions, however the policy is transparent and can be broken down in that there is an horizon of considered moves

### 3.4 Recourse

*Can stakeholders or users contest the decisions or actions of the system? What processes, technical or otherwise, are in place to handle this?*

N/A

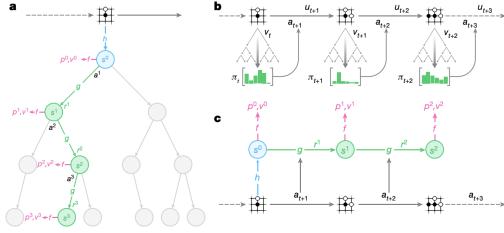


Figure 3: The MuZero general game playing system.

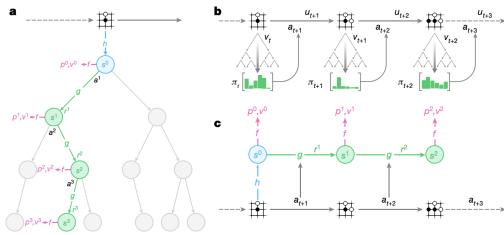


Figure 4: The MuZero general game playing system.

## 4 Implementation

### 4.1 Reward Details

*How was the reward function engineered? Is it based on a well-defined metric? Is it tuned to represent a specific behavior? Are multiple terms scaled to make one central loss, and how was the scaling decided?*

The reward function is entirely prescribed as win rate, and the resulting Elo rating. An important sub-component that will be referenced later is the value function estimating game state. This is an internal representation of reward central to training and evaluation.

### 4.2 Environment Details

*Description of states, observations, and actions with reference to planning horizon and hypothesized dynamics/impact. What dynamics are brought into the scope of the optimization via feedback? Which dynamics are left external to the system, as drift? Have there been any observed gaps between conceptualization and resultant dynamics?*

The original environment is the full game of Go which is constrained by finite rules, but other games with visual states were added.

### 4.3 Measurement Details

*How are the components of the reward and observations measured? Are measurement techniques consistent across time and data sources? Under what conditions are measurements valid and correct? What biases might arise during the measurement process?*

The measurements differ across games from the full gameboard to a visual rendering of the world. Extracting information from pixels is substantially less efficient than directly from the game state.

### 4.4 Algorithmic Details

*The key points on the specific algorithm(s) used for learning and planning. This includes the form of the policy (e.g. neural network, optimization problem), the class of learning algorithm (e.g. model-based RL, off-policy RL, repeated retraining), the form of any intermediate model (e.g. of the value function, dynamics function, reward function), technical infrastructure, and any other considerations necessary for implementing the system. Is the algorithm publicly documented and is code publicly available? Have different algorithms been used or tried to accomplish the same goal?*

The key algorithm feature is the use of Monte Carlo Tree Search (MCTS). MCTS is used to search over board states (by planning over actions) and parses the value representation. The value function is represented by a deep neural network mapping from game state to value.

The second crucial element to training is self play. Here gameplaying agents evaluate their performance versus past training snapshots. This synergistic mechanism is crucial to reaching superhuman performance. In MuZero, a learned model is used to improve performance in games without complete information (such as visual states) by constraining the policy optimization. At each turn, the model is used to predict the correct policy, the value

function, and the reward received by the move (in games that have an intermediate score). The model is updated in an end-to-end fashion, so it is included in the same training loop in the agent architecture.

Fully algorithmic details and open source code are not released.

#### 4.5 Data Flow

*How is data collected, stored, and used for (re)training? How frequently are various components of the system retrained, and why was this frequency chosen? Could the data exhibit sampling bias, and is this accounted for in the learning algorithm? Is data reweighted, filtered, or discarded? Have data sources changed over time?*

Data flow is not well documented, but it relies on Google's distributed training and deployment infrastructure.

#### 4.6 Limitations

*Discussion and justification of modeling choices arising from computational, statistical, and measurement limitations. How might (or how have) improvements in computational power and data collection change(d) these considerations and impact(ed) system behavior?*

#### 4.7 Engineering Tricks

*RL systems are known to be sensitive to implementation tricks that are key to performance. Are there any design elements that have a surprisingly strong impact on performance? For example, state-action normalization, hard-coded curricula, model-initialization, loss bounds, or more?*

Not documented.

### 5 Evaluation

#### 5.1 Evaluation Environment

*How is the system evaluated (and if applicable, trained) prior to deployment (e.g. using simulation, static datasets, etc.)? Exhaus-*

*tive details of the offline evaluation environment should be provided. For simulation, details should include description or external reference to the underlying model, ranges of parameters, etc. For evaluation on static datasets, considering referring to associated documentation (e.g. Datasheets [Gebru et al.(2021)]).*

For games, the simulator is reality so evaluation is matched to training.

#### 5.2 Offline Evaluations

*Present and discuss the results of offline evaluation. For static evaluation, consider referring to associated documentation (e.g. Model Cards [Mitchell et al.(2019)]). If applicable, compare the behaviors arising from counterfactual specifications (e.g. of states, observations, actions).*

Multiple internal evaluations of the agent were performed prior to high-profile, public matches with the worlds best players.

#### 5.3 Evaluation Validity

*To what extent is it reasonable to draw conclusions about the behavior of the deployed system based on presented offline evaluations? What is the current state of understanding of the online performance of the system? If the system has been deployed, were any unexpected behaviors observed?*

#### 5.4 Performance standards

*What standards of performance and safety is the system required to meet? Where do these standards come from? How is the system verified to meet these standards?*

N/A.

### 6 System Maintenance

#### 6.1 Reporting Cadence

*The intended timeframe for revisiting the reward report. How was this decision reached and motivated?*

While this system is evaluated in closed-world games, updates are not anticipated.

## 6.2 Update Triggers

*Specific events (projected or historic) significant enough to warrant revisiting this report, beyond the cadence outlined above. Example triggers include a defined stakeholder group empowered to demand a system audit, or a specific metric (either of performance or oversight) that falls outside a defined threshold of critical safety.*

This report will be revisited upon release of each new game-playing AI from DeepMind.

## 6.3 Changelog

*Descriptions of updates and lessons learned from observing and maintaining the deployed system. This includes when the updates were made and what motivated them in light of previous reports. The changelog comprises the central difference between reward reports and other forms of machine learning documentation, as it directly reflects their intrinsically dynamic nature.*

N/A (v1)

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