The Difficulty of Novelty Detection in Open-World Physical Domains: An Application to Angry Birds

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Abstract
Detecting and responding to novel situations in open-world environments is a key capability of human cognition. Current artificial intelligence (AI) researchers strive to develop systems that can perform in open-world environments. Novelty detection is an important ability of such AI systems. In an open-world, novelties appear in various forms and the difficulty to detect them varies. Therefore, to accurately evaluate the detection capability of AI systems, it is necessary to investigate the difficulty to detect novelties. In this paper, we propose a qualitative-physics-based method to quantify the difficulty of novelty detection focusing on open-world physical domains. We apply our method in a popular physics simulation game, Angry Birds. We conduct an experiment with human players with different novelties in Angry Birds to validate our method. Results indicate that the calculated difficulty values are in line with the detection difficulty of the human players.

1 Introduction
With the increasing reliance on autonomous systems such as self-driving cars, underwater exploration vehicles, and planetary robots, detection and reaction to novel situations have become important capabilities for such AI systems. For example, if a self-driving car is not trained on slippery roads, the car may fail to detect that the friction is reduced and adjust the speed accordingly. Open-world learning is an emerging research area that attempts to address this challenge (Langley 2020; Muhammad et al. 2021; Peng et al. 2021). DARPA has also initiated a research program to encourage research in open-world learning (Senator 2019). Open-world learning research requires adequate evaluation protocols to capture the performance of agents under the two tasks: detection and reaction (Senator 2019). This paper focuses on creating a difficulty measure for novelty detection to aid the evaluation by disentangling agents’ performance from the intrinsic difficulty of novelties.

The novelties we encounter in an open-world can take various forms (Langley 2020; Boult et al. 2021). We focus on a very common type of novelty in the real world, i.e., when the novelty is based on an object. This type of novelty is referred to as structural transformation in the work of Langley (2020). For example, this could be a new vehicle type on the road or an abnormally heavy ball in the billiards game. As the examples suggest, only some of the novelties can be identified from appearance. Novel objects with different appearances can be detected by observing the difference in colour, shape, or size. Quantifying the difficulty of detecting them can be addressed with the use of concepts presented in colour science (Giesel and Gegenfurtner 2010; Olkkonen, Hansen, and Gegenfurtner 2008) and research conducted on object shapes and sizes (Perner 2018; Zhao and Stough 2005). The difficulty of detecting novel objects with the same appearance but different physical parameters (e.g., mass, friction, bounciness) is not addressed so far. It is also not straightforward as one needs to interact with the objects and observe changes in object movements. Moreover, the detectability of such novel objects depends on numerous factors such as the physical parameter that is changed, the number of novel objects in the environment, and the arrangement of objects in the environment.

This paper presents a qualitative-physics based method to quantify the difficulty of detecting novel objects with the same appearance but changed physical parameters (compared to the objects seen before). As mentioned earlier, the proposed method aids a sound evaluation by disentangling agents’ performance from the difficulty of the novelty. For example, if the novelty is in an object that is not reachable and the novelty cannot be identified from the appearance, it is impossible to detect the novelty in this situation. Therefore, the difficulty of novelty detection should be considered before making conclusions on the detection ability of an agent. Our method is agent independent and enables us to evaluate an agent’s performance at different levels of difficulty. We apply our method to a popular physics simulation game, Angry Birds as it closely resembles real-world physics, and it is an ideal platform to introduce novelty. We then conduct an experiment with human players in Angry Birds to verify that the calculated difficulty values are in line with the detection difficulty for human players.

The rest of the paper is structured as follows. We start by providing the background and related work to our study, followed by the formulation of our novelty detection difficulty measure. We then present the application of our difficulty measure in Angry Birds. Next, we describe an experimental evaluation with human players in Angry Birds to validate the proposed difficulty measure. Finally, we conclude the paper with possible improvements and future directions of
2 Background and Related Work

This section presents the notion of difficulty and the concept of novelty in the context of physical worlds and AI. We also discuss the related work in physics simulation games, qualitative physics which is used in developing the difficulty measure, and a brief description of our experimental domain-Angry Birds.

2.1 Difficulty

Assessing difficulty is a popular research area in neuroscience where researchers are interested in quantifying the difficulty of tasks or decisions (Franco et al. 2018; Gilbert et al. 2012). It is also a widely studied topic in the gaming industry to make games more interesting to the user (Aponte, Levieux, and Natkin 2011; Dziedzic and Włodarczyk 2018; Roohi et al. 2020). The flow-theory, one of the most prevalent models in the game design literature, suggests that the games should not be too easy or too difficult to maintain player enthusiasm (Takatalo et al. 2010).

Considering the difficulty of detection, researchers have studied this in areas such as emotion detection (Laubert and Parlamis 2019), phishing message detection (Steves, Greene, and Theofanos 2019), and missing content detection (Yom-Tov et al. 2005). However, to the best of our knowledge, the difficulty of novelty detection in physical domains is not studied so far and quantifying difficulty becomes important when evaluating the detection capabilities of agents.

2.2 Novelty

In the context of AI, novelty is described as situations that violate implicit or explicit assumptions about the agents, the environment, or their interactions (SAIL-ON 2019). Following this, Langley (2020) and Boult et al. (2021) explains different types of novelties that may occur in open-world environments. A similar idea of novelty is presented by Muhammad et al. (2021), where novelty is explained from an agent’s perspective (in the eyes of an agent), i.e., when an agent encounters an entity, if it cannot recall the entity from prior experience, or cannot infer the entity through cognition, the encountered entity is considered novel for the agent. Following these ideas, the novelties we consider in this paper occur as a result of a changed physical parameter. It could be the mass, friction, elasticity, brittleness, etc. These novelties do not change the appearance of the object but behave differently after interacting. For example, in the real-world, novelty could be a new tennis ball with higher bounciness than the balls encountered before. Figure 1 shows differences in movements of the objects observed after changed physical parameters in two simulated physics environments: a research clone of Angry Birds (Ferreira and Toledo 2014) and PHYRE (Bakhtin et al. 2019).

2.3 Physics Simulation Games

Physics simulation games (PSG), video games where the game world simulates real-world physics, offer simplified environments for developing and testing AI agents (Renz and Ge 2017). Game environments that require physical reasoning such as PHYRE (Bakhtin et al. 2019), Virtual Tools (Allen, Smith, and Tenenbaum 2020), OGRE (Allen et al. 2020), and IntPhys 2019 (Riochet et al. 2020) are developed due to the recent recognition of the importance of physical reasoning in AI. Angry Birds has also been a popular PSG for AI agents, with a long-running AIBirds competition as part of the IJCAI conference (Renz et al. 2015).

PSG are ideal platforms to introduce real-world novelties and to develop capabilities in AI to detect such changes. While AIBirds competition (AIBirds 2021) has introduced a track for agents to detect and react to novelty (AIBirds-NoveltyTrack 2021), Boult et al. (2021) has explained novelties that appear in CartPole (OpenAI 2021).

2.4 Qualitative Physics

As discussed previously, novelties based on physics parameters are not detectable from appearance for both human and AI agents. Therefore, one needs to interact with the objects and observe any difference in the expected behaviours in objects movements. Humans do not need to solve complex differential equations when reasoning about the object movements, we use spatial intelligence (Walega, Zawidzki, and Lechowski 2016) and we are unaware of the exact physical parameters such as density, friction, and mass distribution.

A qualitative physics approach was proposed by Zhang and Renz (2014), which approximates the structural stability based on the extended rectangular algebra (ERA). ERA comprises of 27 interval relations based on the approximated centre of mass of the object and offers more flexibility than
the original 13 interval algebra relations (Allen 1983). Ge, Renz, and Zhang (2016) point out that ERA is more suitable to approximate the stability of a single object rather than a structure and extends the use of ERA by proposing two qualitative stability analysis algorithms: local stability and global stability. A similar algorithm, vertical impact is proposed by Walega, Zawidzki, and Lechowski (2016), which combines the concepts of local stability and global stability into one algorithm. They also introduced the algorithm horizontal impact, to provide a heuristic value to the interaction based on force propagation. Our difficulty measure also uses the algorithm vertical impact along with new reasoning components which reason about the nature of the object movements that are necessary to detect novelty.

2.5 Experimental Domain

Our experimental domain, Angry Birds is a PSG where the player shoots birds at the pigs from a slingshot. Pigs are covered from different physical structures that are made up of three types of materials: wood, ice, and stone. The task of an agent that attempts to detect novelty is to identify if anything has changed from the normal game environment by shooting at game objects. As the original Angry Birds game by Rovio Entertainment is not open source, we conduct our experiments using the research clone of the game (Ferreira and Toledo 2014). One example of novelty in Angry Birds is displayed in figures 1a and 1b.

Apart from the fact that Angry Birds is a very popular domain among AI researchers with long-running competitions (Renz et al. 2015), we selected Angry Birds as our experimental domain due to three reasons. First, to solve an Angry Birds game level, one needs to reason about object movements that are necessary to detect novelty. This means that the agent cannot have multiple interactions at the same time. For example, in the billiards game, an agent can move only one ball at a time and in Angry Birds, an agent uses the given birds in a sequence.

3 Overview of the Difficulty Measure Formulation

In this section, we present a high-level overview of our difficulty measure formulation for novelty detection in physical domains. First, we define the following terms to aid our explanations.

- Each object consists of a set of appearance-related parameters and a set of physical parameters. There is a predefined many to one mapping from appearance parameters to physical parameters, i.e., objects with the same appearance have the same physical parameters and two or more objects with different appearance can have the same physical parameters. Objects with the same appearance are referred to as an object type. The number of object types is predefined.
- normal object: An object that preserves the predefined mapping between appearance and physical parameters.

Figure 2: The figure shows a set of novel instances. Each instance contains one or more novel pigs denoted by the red circle and a set of normal objects.

- novel object: An object that violates the predefined mapping between appearance and physical parameters.

- normal instance: An arrangement with a collection of normal objects.

- novel instance: An arrangement with a collection of normal objects and novel objects. (See Figure 2)

Our difficulty measure has three properties:

1. Our difficulty measure is instance-based, i.e., we provide the difficulty of detecting novelty for a specific novel instance.

2. Our difficulty measure quantifies the difficulty of detecting novelty when an agent encounters the novel instance for the first time. This means that the agent does not attempt the instance multiple times.

3. Our measure is agent independent (i.e., we do not collect data from agents to develop the measure).

Given below are three assumptions we make about our difficulty measure:

1. As designers of the difficulty measure, we have full understanding of the novel instance (i.e., the novel object, location of the novel object, and what the novel parameter is).

2. The agent has a full understanding of the object dynamics in the normal environment. This means that the agent is fully aware of how objects move without novelty and the agent can detect that the environment is novel if a change in movements happens in the novel environment (perfect novelty detection).

We made this assumption because the detection difficulty can be different across agents; therefore, our measure is based on the lower bound of the detection difficulty by assuming perfect detection.

3. The agent attempts to detect novelty using a sequence of interactions.

This means that the agent cannot have multiple interactions at the same time. For example, in the billiards game, an agent can move only one ball at a time and in Angry Birds, an agent uses the given birds in a sequence.

Figure 3 shows the main components of our difficulty measure formulation: Target Determining Module, Object Dynamics Reasoning Module, and Difficulty Computation.
Module. There are two inputs, the initial state of an instance (i.e., the state of an instance before any interactions) and the novelty present in the instance. Novelty present can be a set of objects with their changed physical parameter (e.g. {(wood objects, mass), (stone objects, friction)}).

Our first module, the Target Determining Module takes the above two inputs and searches possible target objects, which are the objects that an agent can interact with. This module outputs all possible target objects in the given state.

The second module, Object Dynamics Reasoning Module has two components, the object movement analysis component and the detectability analysis component. The object movement analysis component takes each target object and identifies other objects that are moved due to the interaction with the target object. Next, the detectability analysis component determines if the interaction has caused the novel object to move in a detectable way. For example, when a novel object has a different friction value, an interaction that causes the novel object to fall from above would not make the novel object detectable.

Knowing the target objects that make detectable movements, the Difficulty Computation Module quantifies the difficulty of novelty detection to the given initial state.

If the algorithms in the difficulty computation module require the next state to predict the difficulty, the state updates (i.e., the state after an interaction) is sent to the Target Determining Module and the process iterates until the detection difficulty for the instance can be given.

In Section 4 we present our difficulty formulation in Angry Birds.

4 Difficulty Measure Applied to Angry Birds

This section presents each component of Figure 3 in detail by considering the domain Angry Birds. Novelties in Angry Birds can appear in any game object. In explaining our difficulty measure formulation, we do not consider the novelties which are the objects that an agent can interact with. We use the following predicates to determine the targets in our example domain.

- left-of (o_i, o_j): if object o_j is in left of object o_i (See Figure 4).
- traj(o_i): trajectory from a starting point to object o_i. As shown in 4, trajectory contains a set of points starting from a fixed position (slingshot in Angry Birds) to the connection point of the object. In Angry Birds, there can usually be identified directly after a single shot by observing birds’ behaviour.

The first input is the initial state of the instance without any interaction. In our example domain, this is the game level before shooting any birds. To represent the game scene, we use a 2D coordinate system where the x-axis is horizontal and oriented to the right while the y-axis is vertical and oriented to the top (Figure 4). P denotes all pixel points in a scene. For a pixel p_i, x(p_i) and y(p_i) denote its x and y coordinates. O represents all objects in the environment. Each object o_j (s.t. o_j ∈ O) comprises of a set of pixels which can be mapped to a specific object (e.g. square woodblock).

The second input is the novelty present in the instance. In our example domain, novelties may appear in different object types (i.e., wood, ice, stone, pigs) and novel property could be physics parameters of objects (e.g. mass, friction, bounciness, etc). Thus, an example of the input is (stone blocks, mass).

These inputs are sent to the target determining module to search for possible target objects.

4.1 Target Determining Module

This module is used to identify the target objects. We consider the target objects are the objects that are directly reachable to interact with. We use the following predicates to determine the targets in our example domain.

- left-of (o_i, o_j): if object o_j is in left of object o_i (See Figure 4).
- traj(o_i): trajectory from a starting point to object o_i. As shown in 4, trajectory contains a set of points starting from a fixed position (slingshot in Angry Birds) to the connection point of the object. In Angry Birds, there can

Figure 3: Overview of the method to compute the difficulty of novelty detection.

Figure 4: Representation of the object space. o_2, o_3, o_4 and o_5 satisfy the left-of relation to o_1. The trajectories to each object are denoted by the dotted line. A dot in the line represents a pixel point p_i. o_2, o_3, o_4 and o_5 satisfy the target predicate. o_1 is not a target as the traj(o_1) intersects with o_4, o_3 supports o_4. Therefore, if o_3 is moved, o_4 moves: Thus, impacted(o_3, o_4) is true.
The figure, vertical impact, under consideration. At the end of the 8 steps, algorithm returns the list of objects that may fall after the interaction with a target object. In the stability based on the left-most, right-most, connection points and updates the fall list. \(p_c\) is the centre of mass of the substructure under consideration. At the end of the 8 steps, algorithm returns the list of objects that may fall after the interaction with a target object. In the figure, \(\text{vertical impact}(o_i) = \{o_1, o_2, o_3, o_4, o_5, o_6, o_8\}\). \(o_1\) target object satisfies the impacted predicate with the objects in the fall list, and \(\text{impacted}(o_1, o_2)\) and \(\text{impacted}(o_1, o_7)\) are false.

be at most two trajectories to reach a point under the influence of gravity, the lower trajectory and the upper trajectory. We define \(\text{trajectories}(o_i) = \{p_1, p_2, \ldots, p_n\}\) to be a set of points that belong to one of the parabola trajectories and only \(p_n \in o_i \).

1. \(\text{target}(o_i)\): if object \(o_i\) is a target object. \(o_i\) is a target if the object is directly reachable, i.e., there is at least one trajectory to \(o_i\) such that trajectory points do not intersect with any object with left-of relation to \(o_i\) according to our domain.

   \(\text{target}(o_i) \equiv \exists \text{trajectory}(o_i) \land o_i \neq o_j \land \text{trajectory}(o_i) \notin o_j \land \text{left-of}(o_i, o_j) \forall o_j \in O\)

2. Similar to the above left-of relation, we can define right-of, bottom-of, or top-of relations according to the requirement in each domain. We can also define \(\text{trajectory}(o_i)\) and \(\text{target}(o_i)\) specific to each domain. For example, if the way to interact with the objects is to drop an object from above, \(\text{trajectory}(o_i)\) should be defined according to the path taken by the free fall under gravity and \(\text{target}(o_i)\) is determined by the trajectories that do not intersect with the objects in top-of relation to \(o_i\), i.e., \(\text{target}(o_i) \equiv \exists \text{trajectory}(o_i) \land o_i \neq o_j \land \text{trajectory}(o_i) \notin o_j \land \text{top-of}(o_i, o_j) \forall o_j \in O\).

4.2 Object Dynamics Reasoning module

After target objects are determined, it is necessary to identify the objects that can be moved due to the interactions with the target objects. This is achieved by using the object movement analysis component. We instantiated the component using our proposed qualitative physics algorithms. If the novel objects are among the identified impacted objects or the target objects, the detectability analysis component captures if the novel objects move in a detectable way. We first define the following to aid the explanations of the methods used in the two components.

- \(\text{novel-object}(o_i)\): if object \(o_i\) is a novel object. \(o_i\) is a novel object if it violates the predefined mapping between appearance and physical parameters. i.e., object has changed physical parameter values.

- \(\text{impacted}(o_i, o_j)\): if \(o_j\) is moved due to the interaction of a bird with the target object \(o_i\). For example, if \(o_i\) supports \(o_j\) and \(o_i\) is hit by a bird, \(o_j\) also moves (See \(o_3\) and \(o_4\) in Figure 4).

The reasoning for the identification of such objects is presented in the section object movement analysis.

- \(\text{detectable}(o_i, o_j)\): if \(o_j\) moves in a detectable way due to the interaction of a bird with the target object \(o_i\). \(\text{detectable}(o_i, o_j)\) returns true when \(o_j\) is a novel object and \(o_j\) is impacted by the target object \(o_i\) in a detectable way.

A case-based exploration on the detectability of the object movements is conducted in section detectability analysis.

Object Movement Analysis This section presents the qualitative physics approach used in identifying the objects that satisfy the impacted predicate presented above. i.e., we identify which objects move after an interaction with a target object. We use two algorithms 1) based on the stability 2) based on the force propagation in the horizontal direction.

We used the algorithm vertical impact proposed by Walega, Zawidzki, and Lechowski (2016) to reason about
the stability of the objects. We also propose a new algorithm, *approximate horizontal influence* to check the impact on the objects located in the horizontal direction.

**Vertical impact:** This algorithm recursively checks the objects in a structure starting from the object that is directly impacted and returns a list of objects that may fall.

It exploits the rule which is the basis for stability investigation, “an object is stable if the vertical projection of the centre of mass of the object falls into the area of support base” (Zhang and Renz 2014). The algorithm contains eight steps where at each step object relationships are examined and substructures are constructed. The stability of objects is examined by approximating the centre of mass of substructures and their supporters. A clear explanation of the algorithm is available in the work of Walega, Zawidzki, and Lechowski (2016) and Figure 5 diagrammatically summarizes the algorithm.

**Approximate horizontal influence:** This algorithm examines the impact a target object can cause due to the force propagation on the objects located horizontally to the target.

We start by analysing if the target object can get destroyed due to the interaction. If it is not destroyed, we check if the object will slide or it will flip as a result of the interaction (collision). Destruction of the target object heavily depends on the materials and the types of the two colliding objects and the velocity at the collision. In our example domain, we define the following predicate by considering the object materials (e.g., wood, ice, stone, pig) and the bird (e.g., red, blue, yellow). We approximate the velocity at the collision by using the law of energy conservation.

$$object\text{-}destroy(o_i) \equiv o_i^{life} - damage < 0;$$

where $o_i^{life}$ is the object life which depends on the material of the object and type of it (e.g. square wood-block, rectangular ice-block). This is a constant value for a specific object. damage depends on the type of the bird used and the relative velocity at collision. Damage caused by a bird type is a fixed value for a specific object, $o_i^{bird\_damage}$. damage can be approximated as $o_i^{bird\_damage} \times relative\_velocity$ at collision. relative-velocity can be approximated using the law of energy conservation. Thus, the final formulae for the *object-destroy*(o_i) predicate can be given as follows:

$$object\text{-}destroy(o_i) \equiv (o_i^{life} - o_i^{bird\_damage} \times \sqrt{k_1 \times (y_{start} - o_i^{target}) + k_2^{bird}}) < 0,$$

where $k_1$ is an experimentally fixed constant value, and $k_2^{bird}$ is a value based on the initial kinetic energy of the bird (In Angry Birds, the value only depends on the bird mass as the initial launch velocity is fixed). $(y_{start} - o_i^{target})$ gives the difference in height between the slingshot and the target object.

If the *object-destroy*(o_i) predicate is false, we check the *object-flip*(o_i) predicate by considering object dimensions.

$$object\text{-}flip(o_i) \equiv \frac{y_{max}(o_i) - y_{min}(o_i)}{x_{max}(o_i) - x_{min}(o_i)} > k_{flip},$$

where:

$k_{flip}$=flipping threshold,

$y_{max}(o_i) = max(y(p_j) \forall p_j \in o_i)$,

$y_{min}(o_i) = min(y(p_j) \forall p_j \in o_i)$,

$x_{max}(o_i), x_{min}(o_i)$ are as defined previously.

These predicates hold the basis for the *approximate horizontal influence* algorithm. A pseudo-code of the process is demonstrated in Algorithm 1 and Figure 6 explains the idea of *falling-arc*(o_i) and *sliding-path*(o_i).

- For a circle $C$, with centre $(x_{max}(o_i), y_{min}(o_i))$ and radius $(y_{max}(o_i) - y_{min}(o_i))$. Let $q_1$ be the set of pixel points in the first quadrant of $C$, we define *falling-arc*(o_i) as follows:

$$falling\text{-}arc(o_i) \equiv \{ o_j | o_j \neq o_i \land (o_j \cap q_1) \forall o_j \in O \}$$

- *sliding-path*(o_i) $\equiv \{ o_j | o_j \neq o_i \land (x_{max}(o_i) < x_{min}(o_j) < x_{max}(o_i) + k_{sliding\_constant}) \land ((y_{min}(o_i) < y_{max}(o_j) < y_{min}(o_i)) \lor (y_{min}(o_i) < y_{max}(o_i)) \forall o_j \in O) \}$

where, $k_{sliding\_constant}$ is an experimentally determined distance that an object can slide after a collision.

In Algorithm 1 (line 8), we have limited our impact to the closest object from either the falling-arc or sliding-path according to the experimentation with our example domain. However, this can be altered according to the domain. The output of the object movement analysis module is the list of impacted objects obtained from the vertical impact algorithm and the approximate horizontal influence algorithm.

**Detectability Analysis** This section presents the case-based exploration in identifying the *detectable* predicate pre-
sented above. Once the set of impacted objects are available, we can categorize each object into at least one of the below cases. The observable movement of the directly-hit object (i.e., target object) can be explained using the first three cases.

- Case 1: Directly hit and destroys
- Case 2: Directly hit and flips
- Case 3: Directly hit and slides

Apart from these three special cases, all objects subject to at least one of the following six cases.

Case 4 and 5 focus on object rotation. We assumed that the impacted objects directly above a static structure (ground or a platform) do not rotate. Others have the chance of rotation due to the collisions with objects.

- Case 4: Falls from the top without rotating
- Case 5: Falls from the top while rotating

Case 6 and 7 focus on the objects that slide. The object may slide and stop, or it might fall if it’s located above the ground based on the sliding path.

- Case 6: Slide and stop
- Case 7: Slide and fall down

Case 8 and 9 focus on the objects which flip. Similar to the above two cases, it may either fall or stop based on its location.

- Case 8: Flips and stop
- Case 9: Flips and fall down

The 9 cases cover the majority of observable movements in Angry Birds. To evaluate if the novel object is detectable, we check if the object is moved in a detectable manner by considering the changed attribute along with the object type. Consider below two examples.

**Example 1**: Novelty in “friction” of stone blocks - If at least one impacted stone block satisfies the requirements for case 3, 6, or 7, we can detect the novelty (as friction changes can be observed when the object slides).

**Example 2**: Novelty in “bounciness” of wood objects - If at least one impacted wood object satisfies the requirements for case 2, 3, 4, 5, 6, 7, 8, or 9, we can detect the novelty (as bounciness can be observed when objects collide).

The output of this module enables to capture the objects that satisfy detectable predicate for each target object.

### 4.3 Difficulty Computation Module

This component quantifies the difficulty of detecting novelty for each game level. We propose two algorithms to calculate the detection difficulty. Factors including the novelty in the object, the placement of the objects, the number of detectable objects, the number of reachable objects, and the number of interactions available (number of birds in Angry Birds) are considered when developing both methods.

We define the following to identify the most influential target object to interact with (i.e., the target object that gives the most information about objects movements. We refer to this as the best-target).

#### Algorithm 2 Probabilistic interaction difficulty

**Input**: State representation of objects \( O \)

**Output**: \( PID \)

1. Initialize \( PID = 0 \)
2. for \( i \) in total\_number\_of\_interactions do
3.     \( N_i = | \{ o_j \mid target(o_j) \land o_j \in O \} | \)
4.     \( n_i = | \{ o_j \mid (target(o_j) \land S_{novel\_object(o_k)} \land detectable(o_j, o_k)) \} \) \forall o_j, o_k \in O \) |
5.     Calculate \( M_i = (N_i - n_i) / N_i \)
6.     \( PID += M_i \)
7.     if \( M_i \neq 1 \) then
8.         break
9. else
10.     Shoot at the best-target
11.     Update state of objects
12. end if
13. end for
14. \( PID = PID / \text{total\_number\_of\_interactions} \)
15. return \( PID \)

- \( \text{impact-score}(o_i) \): The heuristic impact score of \( target(o_i) \) is defined based on the objects moved and the novelty introduced.

**Example 1**: If the novelty is in only one object in the instance, the \( \text{score} \) per each object moved = 1

**Example 2**: If the novelty is in objects with the same material (wood, ice, stone), the \( \text{score} \) per material moved=1

**Example 3**: If the novelty is in object types and it is known that wood objects are not novel, the \( \text{score} \) per other types of objects moved = 1

\( \text{impact-score}(o_i) = \text{sum}(\text{score}_{j}) \land o_j \land \text{novel}(o_i, o_j) \)

- \( \text{best-target} \): The target object with the highest impact-score. If there are multiple objects with the same impact-score, the first object from the list is selected as the best-target.

\( \text{best-target} \equiv o_i \mid \text{max(impact-score}(o_i)\} \land o_i \land target(o_i) \)

**Probabilistic interaction difficulty (PID)** Algorithm 2 is based on the intuition that the probability of novelty detection depends on the number of novel objects available. Intuitively, if the probability of finding a target that impacts the novel object in a detectable way is lower, the difficulty is higher. \( PID \) is initialized at zero, and the algorithm loops over the number of possible interactions while updating the \( PID \). To proceed to the next interaction, it is assumed that the agent shoots at the best-target and the objects in the environment are updated along with the search space (which objects to explore next).

Note the terms, \( N_i \) represents the total number of target objects and \( n_i \) represents the total number of target objects which makes the novel object move in a detectable way in the given state. Thus, \( M_i \) is the proportion of targets that do not yield a detectable movement. At the end of the computation, \( PID \) is normalized to \([0,1]\), where 1 indicates the highest difficulty.
Algorithm 3 Best-shot based interaction difficulty

\textbf{Input}: State representation of objects  
\textbf{Output}: \( BID \)

\begin{verbatim}
1: Initialize \( BID = 0 \)
2: Initialize detection-flag = False
3: for \( i \) in total_number_of_interactions do
4: \( BID = BID + 1 \)
5: if \( \text{detectable}(o_i^*, o_j) \) for any \( o_j \) \( \mid \) novel-object\( (o_j) \) then
6: \hspace{1em} detection-flag = True
7: \hspace{1em} break
8: else
9: \hspace{1em} Shoot at the best-target
10: \hspace{1em} Update state of objects
11: end if
12: end for
13: if detection-flag = False then
14: \( BID = \text{total_number_of_interactions} + 1 \)
15: end if
16: \( BID = (BID - 1) / \text{total_number_of_interactions} \)
17: return \( BID \)
\end{verbatim}

Best-shot interaction difficulty (BID) Algorithm 3 is inspired by an intelligent human-like agent and is based on the interaction which gives the highest information. Here we try to maximize the chance of novelty detection by making the most influential interaction (always shooting at the best-target: \( o_i^* \)). The algorithm loops over the possible interactions: if the novelty is undetectable by shooting at the best-target, it proceeds to the next after updating the environment, the search space (which objects to explore next), and \( BID \). Similar to Algorithm 2, \( BID \) is normalized to \([0,1]\), where 1 indicates the highest difficulty.

Either the two difficulty algorithms can be used separately, or they can be used collectively according to the suitability of the study. We have used the two algorithms collectively in our experimental evaluation presented in Section 5.

5 Experimental Evaluation

As there are no publicly available open-world learning agents in Angry Birds, we conducted our experiment with human players. Experiments were approved by the Australian National University human ethics committee under the protocol 2020/717. We gathered data from 20 voluntary players in Angry Birds who do not have any prior knowledge about the novelties. We first provided 10 game levels without novelty from an Angry Birds levels generator (Stephenson and Renz 2017). This allowed the players to be familiar with the normal game dynamics. The players could play the game levels any number of times in any order. Next, 15 levels with three novelty types were provided and the detection difficulty of each level was calculated in advance (See Section 5.1). We selected 15 levels because of the time constraint as each player takes approximately 2-3 minutes to play a novel level and we selected 3 novelties to allow varying difficulties of detection. The player was allowed to play the novel level only once to detect if there is any novelty in the game objects. If the novelty was detected, we recorded the number of interactions (number of shots in Angry Birds) the player used to detect that novelty. We also requested the player to provide a simple description of the observation to validate the results.

The novelties we evaluated were applied to all game objects with the chosen material (e.g., all woodblocks in the game have the novel property, all pigs in the game have the novel property). A novel game level only contained a single novelty type. That is, a novelty only appears in a single object type (e.g., A single game level does not contain novel woodblocks and novel pigs). This controlled setup is used to validate our difficulty measure even though it can be applied without the given limitations. The novelties we generated are as follows.

- **Type 1 (T1):** The parameter \( gravity scale \) of pigs is decreased twice the original value. Pigs fall down slower due to this novelty.
- **Type 2 (T2):** The parameter \( bounciness \) of wood objects is increased by four times the original value. This makes the wood objects bouncier.
- **Type 3 (T3):** The parameter \( life \) of stone objects increased by five times. This makes stone blocks more difficult to destroy.

5.1 Game Level Selection

A set of 100 game levels was generated for each novelty type and we computed difficulty using the two algorithms, \( PID \) and \( BID \), for each level. We combined the two values using: \( \text{Difficulty Value} = \alpha PID + (1 - \alpha) BID \), where \( \alpha \in [0,1] \), which can be adjusted according to the importance of the two algorithms in an experiment. In our experiment, we considered \( \alpha = 0.5 \) to give equal importance. Game levels within each novelty type were then classified into three categories: easy, medium, and hard based on the distribution of the difficulty values. Game levels with values less than the value at 33.33% percentile, in between 33.33% and 66.67%, and values higher than 66.67% are considered as easy, medium, and hard levels respectively. The game levels used for the experiment are selected randomly from each category. However, one can use different techniques such as harmonic mean or clustering methods based on the data available.

5.2 Results

According to our difficulty measure, we expect the percentage of novelty detection to decrease in the order easy, medium, and hard (according to Algorithm 2). Ideally, if the novelty is detected, we expect a lower number of interactions to detect the novelty in the easy category and a higher number of interactions in the hard category (according to Algorithm 3).

Figure 7a illustrates the percentage of human players who correctly detected the novelty for each novelty type in the three difficulty levels. Interestingly, the lowest percentage of detection is recorded in the hard category and the highest is
recorded in the easy category. This observation is consistent for all three experimented novelty types. For the T1 novelty type, none of the players has detected the novelty in the hard category while all the players have detected it in the easy category.

Figure 7b summarizes the average normalized number of shots needed for detection for each difficulty level for the three novelty types. That is, for each player, the number of shots taken for detection is normalized by the total number of possible interactions (number of birds in the game level). For T1 novelty type, the hard category is not available as none of the players detected it. Medium and easy categories follow our expectation by producing a lower value for the easy category. Similarly, T2 results are also consistent with our expectation by producing the highest normalized interactions for the difficulty in the hard category and the lowest in the easy category. For T3, while the hard category gives the highest normalized interactions for detection, the medium category is lower than the easy category. According to our observation, some players used more shots to confirm that stone-blocks have a higher health value even though they detected early and some players do not notice the change in stones. Overall, the difficulty of human detection of novelty moves in line with the calculated difficulty values from our method.

### 6 Discussion and Conclusion

Detecting novelty is an important capability for an intelligent system in an open-world environment. In physical worlds, one needs to reason about physics to detect the novel objects with only changed physical parameters. These novelties vary in their difficulty of detection and it is not studied so far. However, understanding the difficulty can be important to conduct a sound AI agent evaluation. Thus, we have proposed a method to quantify the difficulty of detection using qualitative physics. Our method is agent independent and can be used to make more accurate conclusions about the detection capability of the AI agents. The measure is applied and validated in the Angry Birds domain by comparing our measure with the performance of human players in three different novelty types.

When formulating our novelty difficulty measure, we proposed the algorithm *approximate horizontal influence* that can also be used as a component for AI agents to predict the influence of moving an object in physical domains. This is an improvement to the prior work (Zhang and Renz 2014; Walega, Zawidzki, and Lechowski 2016) as it considers objects that are disconnected in the horizontal direction. Our difficulty formulation can also be used to create novel game instances at a predefined difficulty of novelty detection. This facilitates research in open-world learning agent development by creating different instances with different levels of difficulty.

While our idea of the difficulty of novelty detection can be applied in physical domains, the object movement analysis component should be instantiated for each domain accordingly. Our qualitative reasoning algorithms presented for Angry Birds are capable of predicting the impact of an object movement on its connected objects and objects that are located in the right. However, our reasoning methods are not capable of predicting the position where an object falls and the possible consequences on the other objects around the region it falls. This is a difficult problem in physical domains which we would hope to address in the future. Moreover, our formulation of the detectability analysis component does not make distinctions within the possible continuous range of a physics parameter (i.e., the difference in observations if the object mass is increased twice or thrice is not considered in our study). We plan to extend this study with quantitative concepts to address this problem. In this paper we laid a foundation on quantifying the difficulty of novelty detection that helps to conduct a sound open-world agent evaluation.

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