Abstract—Biological infants are naturally curious and try to comprehend their physical surroundings by interacting, in myriad multisensory ways, with different objects - primarily macroscopic solid objects - around them. Through their various interactions, they build hypotheses and predictions, and eventually learn, infer and understand the nature of the physical characteristics and behavior of these objects. Inspired thus, we propose a model for curiosity-driven learning and inference for real-world AI agents. This model is based on the arousal of curiosity, deriving from observations along discontinuities in the fundamental macroscopic solid-body physics parameters, i.e., shape constancy, spatial-temporal continuity, and object permanence. We use the term 'body-budget' to represent the perceived fundamental properties of solid objects. The model aims to support the emulation of learning from scratch followed by substantiation through experience, irrespective of domain, in real-world AI agents.

Index Terms—Intuitive Physics, Curiosity-driven Learning, Z-numbers, Visual Perception, Knowledge Base, Knowledge Inference

I. INTRODUCTION

How do we learn? How do we choose what to learn? How do we continually store and update knowledge? When do we understand that we have understood?... It’s been centuries that philosophers and scientists have been mulling over such questions, and these have- and continue to- influence research across disciplines; the fields of Artificial Intelligence and Machine Learning [1] being at the pinnacle of such endeavours. Despite present-day machine learning advancements, it is difficult for a machine to execute a task that a human naturally performs. There is yet a huge gap between a machine’s ability to observe, encode experiences and formulate reasons. Here we present an approach that can potentially be used to design machines that can ‘understand’ the physical world around them. Our model draws inspiration from the way infants learn [2]. It begins with parsing the surroundings by sensing all that is in the physical space around them, interacting with the objects to understand the dynamics, experimenting with them, and deriving hypotheses and predictions, and eventually reasoning on the body budget parameters (shape constancy, spatial-temporal continuity, object permanence). Sensing refers to touch, smell, hearing, smell, and taste. Physical space is the materialistic world around infant. These basic senses help humans identify components in their physical space and their behavior, followed by updating knowledge gathered on the objects through reasoning. Whenever an unexpected event happens, curiosity gets triggered, which contributes to the urge to ‘know or learn more’ about such an event, further supported with valid reasons (with as much confidence as is possible).

The way reinforcement learning works is broadly aligned with the biological infants learning about the physical space. They perceive, they act, develop the knowledge about the physical space, build the parameters about it, interlink the knowledge with the parameters to have a virtual simulation of the physical space around them. The infants learn a lot by observing the actions, states, results and then try to imitate similar actions. In our work, we have focused on the visual sense to demonstrate the proposed method for curiosity-driven learning. We have considered three fundamental solid body physics properties, essential for the comprehension of object-dynamics, i.e., Spatial-temporal continuity, Object Permanence, and Shape constancy, as discussed in the paper [3].

II. RELATED WORK

By focusing on learning as a function of inferences on fundamental properties of solid objects, the designed mechanism is envisioned to serve as a substrate for generalized learning and transfer learning. Some design inspirations are:

- Nguyen et al. 2020 [5] discuss the state-of-the-art method to learn intuitive physics with the help of measuring the element of surprise and explaining it. Surprises are explained by a function of motion-based surprise and appearance-based surprise parameters. The evaluation metrics used were Absolute Error Rate and Relative Error Rate for parameters of Object Permanence, Shape Constancy, and Spatial-temporal Continuity.
- Pathak et al. (2017) [4] used curiosity to explain the need to explore the environment and discover novel states. Curiosity is considered an intrinsic reward that enables the agent to explore the environment more. The method empowers an agent to learn generalizable skills even in the absence of an explicit goal.
- Zhou et al. (2020) [5] present ‘meta-imitation learning’ as a mechanism of learning from few demonstrations and trying to imitate them through trial-n-error.
- Pal et al. (2013) [6] describe a way of representing a knowledge using Zadeh’s Z-numbers [11]. A Z-number is of the form \(< X, A, B >\), where ‘X’ is the subject, ‘A’ being predicate, a value from a set of possible values for X, and B is the confidence in ‘X=’A’. The concept can be
visually envisaged as the building blocks of a knowledge graph where 'X', 'A' represent the graph nodes, and B represents the edge weights. The edge weights are the function of reinforcement. 'X' and 'A' are the function of an experience.

- Chitnis et al. (2019) [8] describes a technique where an agent learns to pick and operate on objects of different shapes and sizes. They trained the agent in a multitask setting to learn different distribution of object shape and sizes. Tanwani et al. (2020) [10] describes a semi-supervised approach, named Motion2vec, towards acquiring manipulation skills shown in surgical videos for surgical suturing. The main idea behind this approach is learning invariant representations from surgical videos for tasks of action segmentation and pose intimation.

- Meier et al. (2017) [9] proposed an approach for learning to learn while learning. Obtained results have proven fastening initial learning and faster convergence on subsequent tasks.

III. METHODOLOGY AND SYSTEM DESIGN

We propose a method for curiosity-driven learning of intuitive physics through interactions with everyday objects. We have considered object’s body-budget parameters (shape constancy, spatial-temporal continuity, and object permanence) to parse and understand the physical world around. As stated in the article [3], these parameters come handy while parsing natural physical objects-object interactions. All these parameters are represented in the form of a linear plot w.r.t. time / frame-sequence. These plots demonstrate the behavior of the object in a given event (from the data-set) as a line plot. These plots are then examined to identify discontinuity in the object responses if any, and further trigger the curiosity component if discontinuity is observed.

A. Dataset

Dataset used for learning and training of our agent is the Intuitive Physics Dataset [12]. This dataset constitutes a set of possible and impossible events presented through animations. Every event in the dataset has some objects, which can be any or all of a cube, cone, and a sphere. These events may or may not contain an occluder which is a wall in our case. These events can be further classified as static or dynamic based on the object’s movement in the event. The sample event of possible and impossible with occluder as a wall is shown in Fig. 1.

B. System Architecture

The proposed solution is shown in Fig 2. The video input is given to YOLO-v4 model for object detection and localization [7]. The localized object information is used to obtain linear plots for the body budget parameters. These linear plots are then used to analyze discontinuities in the responses as shown in Fig 4. These discontinuities are detected by comparing the obtained responses for parameters of body budget with the predicted one. The predictions for the body budget parameters are made using Kalman Filter. Such discontinuities trigger the curiosity block in the agent’s mind. The curiosity block makes the agent revisit the previous event and check if there is any external factor affecting the expected responses of the body budget, factors like the presence of an occluder. If occluder is detected for the same time when discontinuities are observed, then the agent accepts this as the reason for the object behavior, and matches the decision with the ground truth which is already provided with the dataset. If the responses are matched, the agent proceeds further for a new event, else it is labeled as an exceptional case. This exception case is still stored in the knowledge base of the agent, which further seeks similar responses to gain confidence about that event. If the agent cannot find reasoning for the discontinuities, it is tagged as an impossible event and further matched with the ground truth. If ground truth matches with the labeling by the agent, then it proceeds further for a new event else added as an exception. The exception added is further generalized if the number of events gets the same responses for the same state and is also labeled as a reasoning label, the same way we humans accept some facts which we might not aware of the reasoning yet but accepts the existence of it.

C. Knowledge Update and Inference

- A generated score for each body budget parameter represents unique characteristics about the object in the given environment.
- We consider a hypothetical space that we term latent space. The latent space is similar to plotting data points in a 2D plane and classifying these data points using clustering. Latent space is divided into three spaces that represents classes.
- We plot the scores obtained for an unknown object in this latent space. The closer the calculated data point, the more confident the agent will be to classify the
unknown object as a specific class. The score generated is a function of parameters of body budget multiplied with constants \((\alpha, \beta, \gamma)\) with values ranging from 0 to 1, determining the priority of a particular concept. Priority is decided on the basis of the presence of the occluder.

- These scores then are represented in the form of a Z-number. A Z-number of the form \(<X, A, B>\) in which ‘X’ represents a class, ‘A’ represents the score calculated as shown in equation (1), and ‘B’ represents confidence which is calculated as shown in equation (4) and inference is shown in equation (5).

### D. Curiosity Driven Learning

- With a discontinuity in the linear plot of the body budget, the curiosity block gets activated.
- On activation, the agent revisits the event and tries to find out the reasoning for the discontinuity as shown in Fig. 2.
- If no reasoning found, it will add exceptional value to the reasoning and keep the information as per ground truth.
- With further past experience, this exception will be removed if multiple similar experiences are observed.

### E. Equations

As discussed in Section III.B, Z-numbers constitutes of \(<X, A, B>\). For an unknown object, ‘X’ will be null initially. ‘A’ being the score of the object w.r.t. the body budget parameters is shown in equation (1). Score generated for object permanence is given in equation (2).

\[
A = \alpha * S_{op} + \beta * S_{sc} + \gamma * S_{stc} \tag{1}
\]

\[S_{op} = \sum_{i=1}^{N} P_{Yolo}(O(x_i)) * \text{Impact Value} \] \tag{2}

\[S_{op} = \frac{\sum_{i=1}^{N} P_{Yolo}(O(x_i)) * \text{Impact Value}}{1000} \tag{2}\]

\[P_{Yolo}(O(x_i)) \] is the prediction score of the detected object. Impact Value is the unique value specific to a class. For our consideration, we have assigned constant value of 10 for sphere, value of 100 for cone and a value of 1000 for cube. As we are doing summation, we will be having these value in terms of 100’s etc. giving unique score for a given class. \(N\) represents total number of frames. The range for \(S_{op}\) will be different for different class having unique range for each class. \(S_{sc}\) is normalised euclidean distance between object’s images.

\[
S_{stc} = 1 - \frac{N - \text{Count } O(x_i)}{N} \tag{3}
\]
Here, Count $O(x_t)$ is the count of frames in which the object was detected.

$$B_c = \frac{|A_{avgc} - A_u|}{A_{avgc}}$$

$$\sum_{t=1}^{N} \frac{|A_{avgc} - A_u|}{A_{avgc}}, \text{ } B \in \{0, 1\}, C \in \{\text{Cube, Sphere, Cone}\}$$

Here, $A_{avgc}$ is average ‘A’ score for a particular class, $A_u$ is ‘A’ value of unknown class. Based on this, ‘Z’ will be calculated as in equation (5)

$$Z = C, \text{ for } C \text{ with min } (B_c)$$

IV. EXPERIMENT

For the experiment described in Table 1, we considered the ground truth as ‘sphere’ and obtained the following values: $N = 90$, $P_{yolo}(O(x(t))) = 0.6$ (for sphere) and 0.17(for cone). As this does not involve any occluder, $\alpha = \beta = \gamma = 0.33$, Count $O(x_t)$ for sphere = 48, for cone = 0.

| Object Ground Truth | Object Assumed | $S_{op}$ | $S_{ac}$ | $S_{oc}$ | $A$ | $A_{avg}$ | $B$ | Inference ($Z$) |
|---------------------|----------------|--------|--------|--------|-----|----------|----|----------------|
| Sphere              | Sphere         | 0.285  | 0.53   | 0.68   | 0.494| 1.57     | 1.076| Sphere        |
| Object              | Object         | 8.16   | 0      | 0.27   | 2.78 | 17.88    | 15.08| Sphere        |

| EXPERIMENT RESULTS |

V. CONCLUSION AND DISCUSSIONS

To the best of our knowledge, the proposed idea of curiosity-driven learning mechanism is a novel technique. It shows promise in applications / areas that require learning from scratch and learning from learning. Some directions for future work are as follows,

- Incorporation of a knowledge graph towards never-ending learning and Z-number based in-policy reinforcement and transfer learning.
- Knowledge-clustering and generation of concept-clouds and 'subjective' experiences.
- Robots learning from scratch, and eventually from experiences, in any domain.

REFERENCES

[1] A.M. Turing (1950). “I—Computing Machinery and Intelligence”. In: Mind LIX.236, pp. 433–460. ISSN: 0026-4423. DOI: 10.1093/mind/LIX.236.433. eprint: https://academic.oup.com/mind/article-pdf/LIX/236/433/00123314/LIX- 236-433.pdf. URL: https://doi.org/10.1093/mind/LIX.236.433.

[2] Foti, Francesca et al. (2018). “Are young children able to learn exploratory strategies by observation?” eng. In: Psychological research 82.6. 28725993[pmid], pp. 1212–1223. ISSN: 1430-2772. DOI: 10.1007/s00426-017-0896-0. URL: https://pubmed.ncbi.nlm.nih.gov/28725993.

[3] Nguyen, H. et al. (2020). “Learning Intuitive Physics by Explaining Surprise”. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 1539–1542. DOI: 10. 1109/CVPRW50498. 2020 . 00195.

[4] Pathak, Deepak et al. (2017). Curiosity-driven Exploration by Self-supervised Prediction. arXiv: 1705.05363 [cs.LG].

[5] Zhou, Allan et al. (2020). Watch, Try, Learn: Meta-Learning from Demonstrations and Reward. arXiv: 1906.03352 [cs.LG].

[6] Sankar Pal, Romi Banerjee, Soumitra Dutta, Samar Sen Sarma (2013). An insight into the Z-number approach to CWW. Fundamenta Informaticae. 124. 197–229. 10.3233/FI-2013-831.

[7] Alexey Bochkovskiy, Chien-Yao Wang, Hong-Yuan Mark Liao:YOLOv4: Optimal Speed and Accuracy of Object Detection. CoRR abs/2004.10934 (2020)

[8] R. Chitnis, L. P. Kaelbling, T. Lozano-Pérez, “Learning Quickly to Plan Quickly Using Modular Meta-Learning,” 2019 International Conference on Robotics and Automation (ICRA), 2019, pp. 7865-7871, doi: 10.1109/ICRA.2019.8794342.

[9] Franziska Meier, Daniel Kappler, Stefan Schaal: Online Learning of a Robot's Internal Model, In: Int. J. Robotics Research, 2018, 37(19):2361-2390.

[10] Ajay Kumar Tanwani, Pierre Sermanet, Andy Yan, Raghav Anand, Mariano Phielipp, Ken Goldberg: Motion2Vec: Semi-Supervised Representation Learning from Surgical Videos. CoRR abs/2006.00545 (2020)

[11] Lotfi Zadeh (2011). A Note on Z-numbers. Inf. Sci.. 181. 2923-2932.

[12] Franziska Meier, Daniel Kappler, Stefan Schaal: Online Learning of a Robot’s Internal Model, In: Int. J. Robotics Research, 2018, 37(19):2361-2390.

[13] Franziska Meier, Daniel Kappler, Stefan Schaal: Online Learning of a Robot’s Internal Model, In: Int. J. Robotics Research, 2018, 37(19):2361-2390.

[14] Liao:YOLOv4: Optimal Speed and Accuracy of Object Detection. CoRR abs/2004.10934 (2020)

Algorithm 1 Algorithm

1: $CD()$ as Curiosity Driven Function
2: $x_t \leftarrow$ Frame at Time $t$
3: $x_{t-1} \leftarrow$ Frame at Time $t - 1$
4: $O(x_t) \leftarrow$ Objects located in $x_t$ frame
5: $G(x_t) \leftarrow$ Ground truth of objects
6: $EoF \leftarrow$ End of frame
7: $O(x_t), G(x_t) \in \{C_1, C_2, C_3, C_4\}$
8: $C_1, C_2, C_3, C_4$ are classes
9: while $EoF \neq$ True do
10: if $O(x_t) \in \{C_1, C_2, C_3\}$ then
11: if $O(x_t) == O(x_{t-1})$ then
12: $FlagEvent \leftarrow$ Possible
13: count $O(x_t) + 1$
14: else
15: $FlagEvent = CD()$
16: end if
17: else if $O(x_{t-1}) \notin \{C_1, C_2, C_3\}$ then
18: $FlagEvent \leftarrow CD()$
19: end if
20: end while
21: procedure $CD()$
22: while $EoF \neq$ True do
23: if $O(x_t) \in C_4$ then
24: countwall ++= 1
25: end if
26: if countwall in range $0.7 \times$ count $O(x_t)$ + count $O(x_t), count O(x_t)$) then
27: $FlagEvent \leftarrow$ False
28: else
29: $FlagEvent \leftarrow$ Not Possible
30: end if
31: end while
32: return $FlagEvent$
33: end procedure