Curiosity-Based Affordance Learning

Aregbede Victor Oloyede

Amy Loutfi, Andreas Persson, Martin Längkvist

ÖREBRO UNIVERSITY

Abstract

Open-ended learning (OEL), a branch of developmental robotics [1], inspired by child development psychology, refers to the ability of an agent or robot to learn new skills and knowledge through exploration driven by intrinsic motivation. Language is an essential in this process [2]. An essential aspect of OEL is understanding how agents or robots interact with their environment, captured by the concept of affordances [3], first introduced by James J. Gibson. Affordances refer to the action possibilities that an environment offers an agent. We propose a novel framework that uses embeddings from Pretrained Language models to represent object-action relationships and guide exploration by balancing *novelty* and *uncertainty*. Our method leverages a neural network affordance function, trained with supervision of plausibility labels from LLM-derived signals, to predict the plausibility of object interactions.

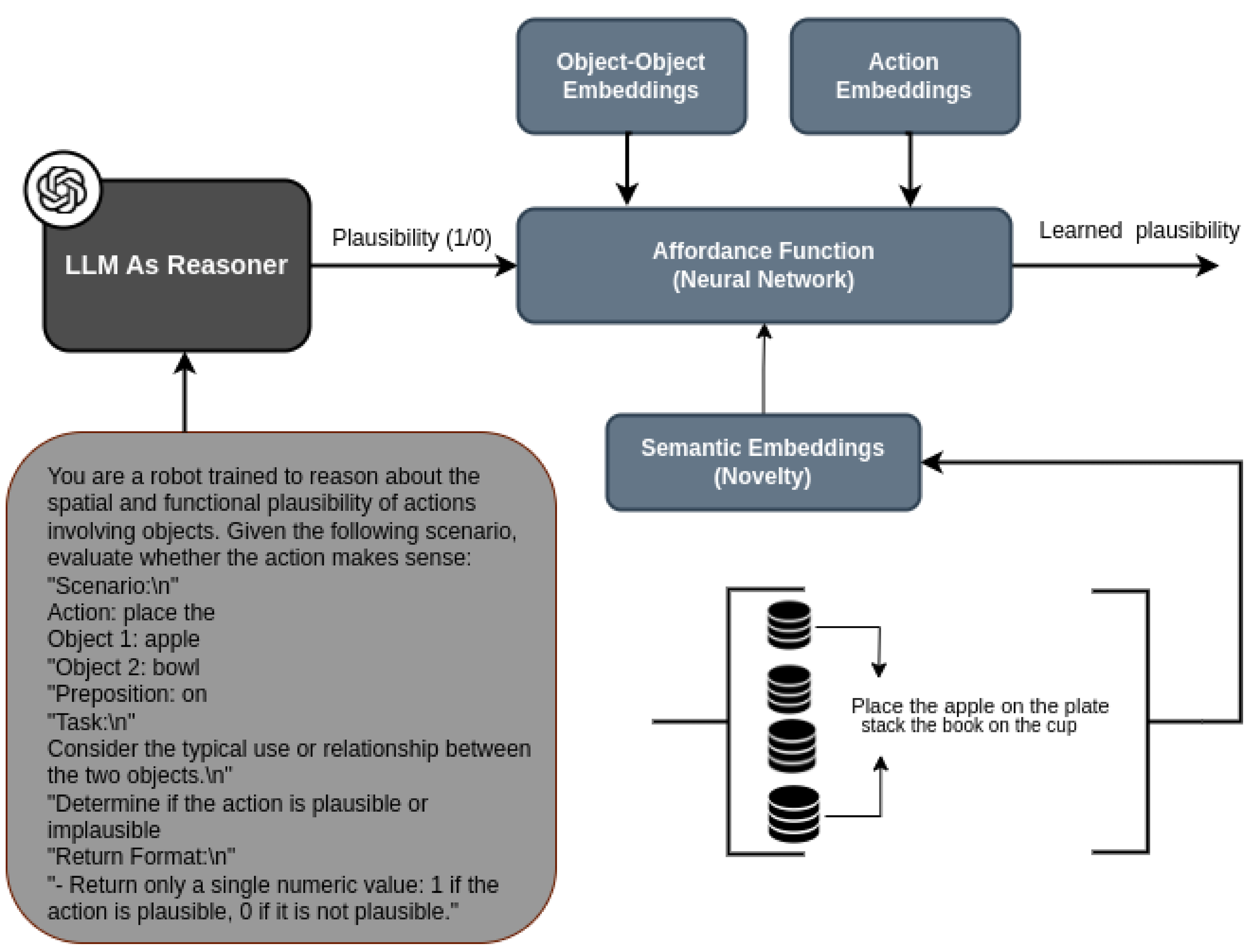
Proposed Method

We consider the problem of learning object relational affordances (e.g., object-object interactions) for an embodied agent through curiosity-driven learning in the language embedding space. Our approach leverages curiosity-based exploration by dynamically weighting novelty and uncertainty.

- Supervision Signal:A Large language model (LLM) provide supervision signals in the form of plausibility or implausibility predictions.
- Embeddings: Objects and actions embeddings are generated using a pretrained language model(e.g Bert)
- Affordance Function: A neural network affordance function is trained on these embeddings to predict the plausibility of object-action interactions.

Exploration Strategy - Select experiments by maximizing a curiosity score, according to:

- **Novelty** (semantic diversity of experiments).
- **Uncertainty** (confidence of the affordance model).



Evaluation

We evalaute our approach using the following criteria:

- Baseline Comparison:

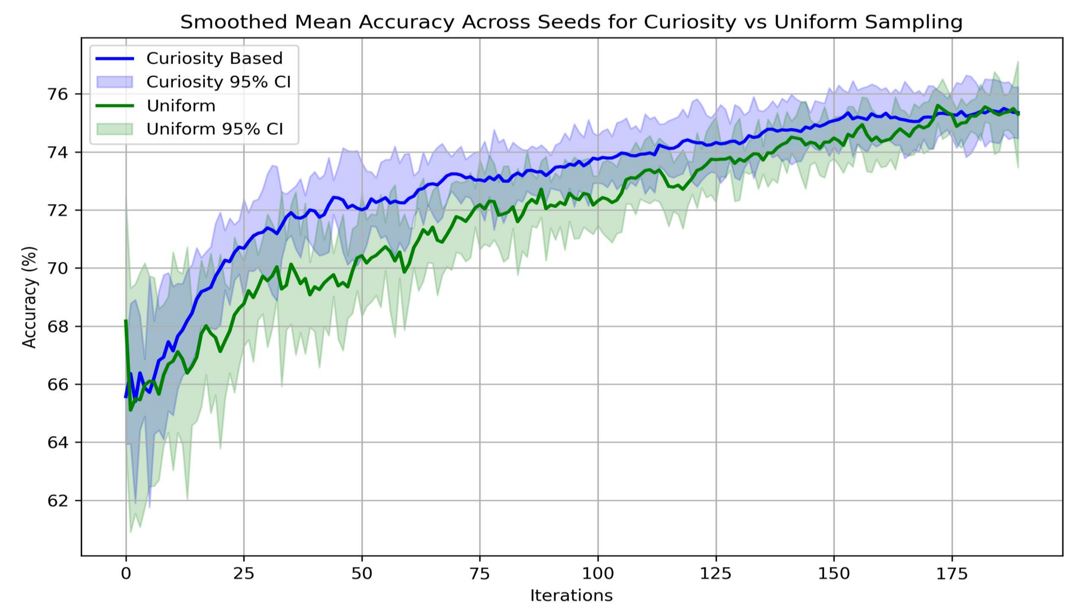
  Uniform Sampling**:** Random selection of experiments.

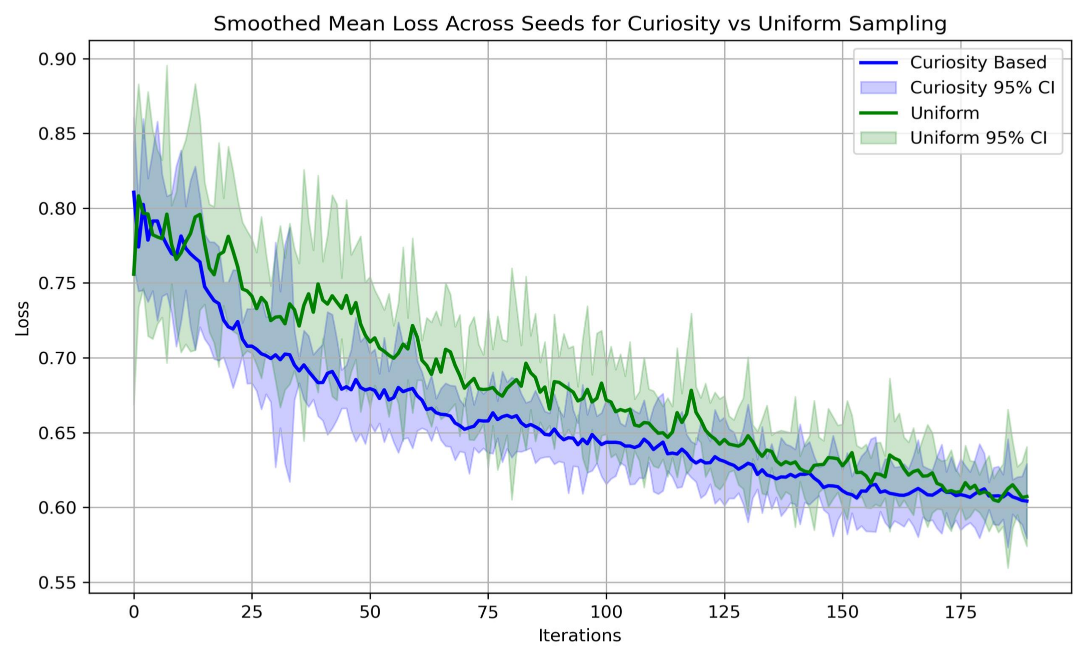
  Curiosity Sampling: Guided selection of experiments using dynamic novelty-uncertainty weighting.
- Metrics:

  Loss**:** Binary Cross Entropy for plausibility prediction

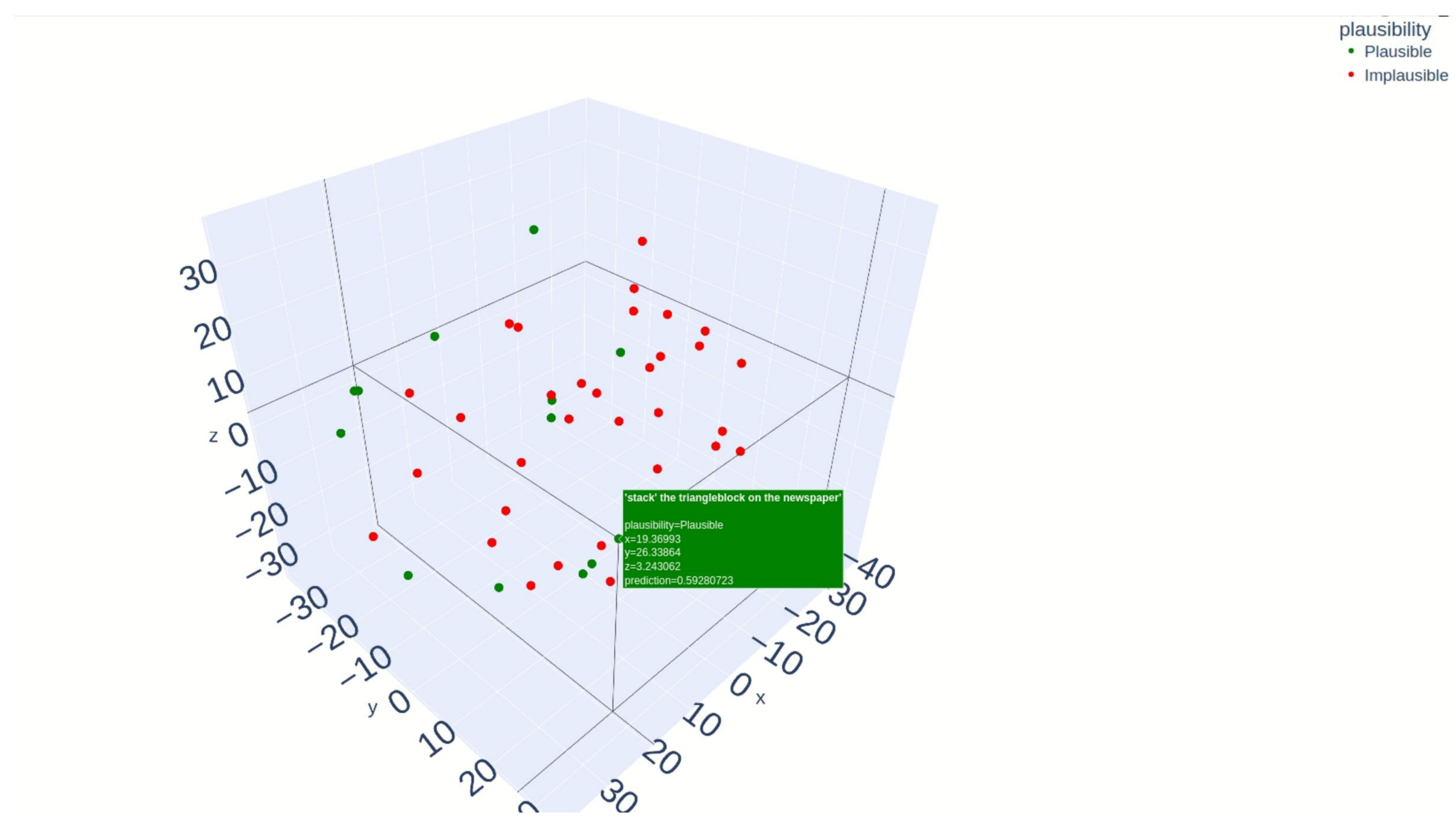
  Accuracy**:** Model Accuracy(%)

The training loss plot shows that curiosity-based sampling reduces loss more efficiently and converges to a lower final loss with fewer samples compared to uniform sampling.





Preliminary Results



The figure above shows the embedding space of curiosity-based learning, highlighting plausible prediction (in this case: "**stack the triangle block on the newspaper** ")

References

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3. J. G. Greeno, "Gibson's affordances." 1994.

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