Modelling knowledge representation about matter through causal inference and gradient descent

(First draft, please see diagram on page 2)

Yash Sharma

yashsharma79.github.io

Abstract

For reasoning and knowledge creation, the AI would need an internal model of the world(1)(2)(7). This paper proposes way to build up a simple version of such model and a representation. Prior knowledge of MKS system of units is built into the agent. Prediction error is triggered by change in state of objects, which must be resolved by combining causal inference and gradient descent. An external memory is available to the agent in order to compile knowledge that can amortize discovery over multiple inferences.

1 Introduction

An environment is proposed to acquire knowledge that is implicitly general. The building blocks of knowledge in this are meter, kilogram, seconds system. The agent is equipped with an external memory (6) divided into counterfactual memory and true memory. A probabilisitc model with explicit priors is initialised which is updated with each intervention. Gradient descent is used to supply the estimand and guided data to the model. The most probabilistic causal diagram along with the states of objects is stored in memory.

2 Environment for learning

The environment to learn would be a model that contains hydrogen atoms and ions that will provide the agent with a reference of unit mass, charge and energy. The agent would be equipped with an external memory to record data about the interventions it runs on these atoms. The aim is to generate data with all the interventions that are possible in such a simple but real world. The inference to draw is what behaviour a form of matter would produce under different interventions.

The reason for this approach is that deducing reality directly from image/video data or from simulations of objects in game-engines(5) has not produced knowledge that can be transferable or used for reasoning. Generating a model of

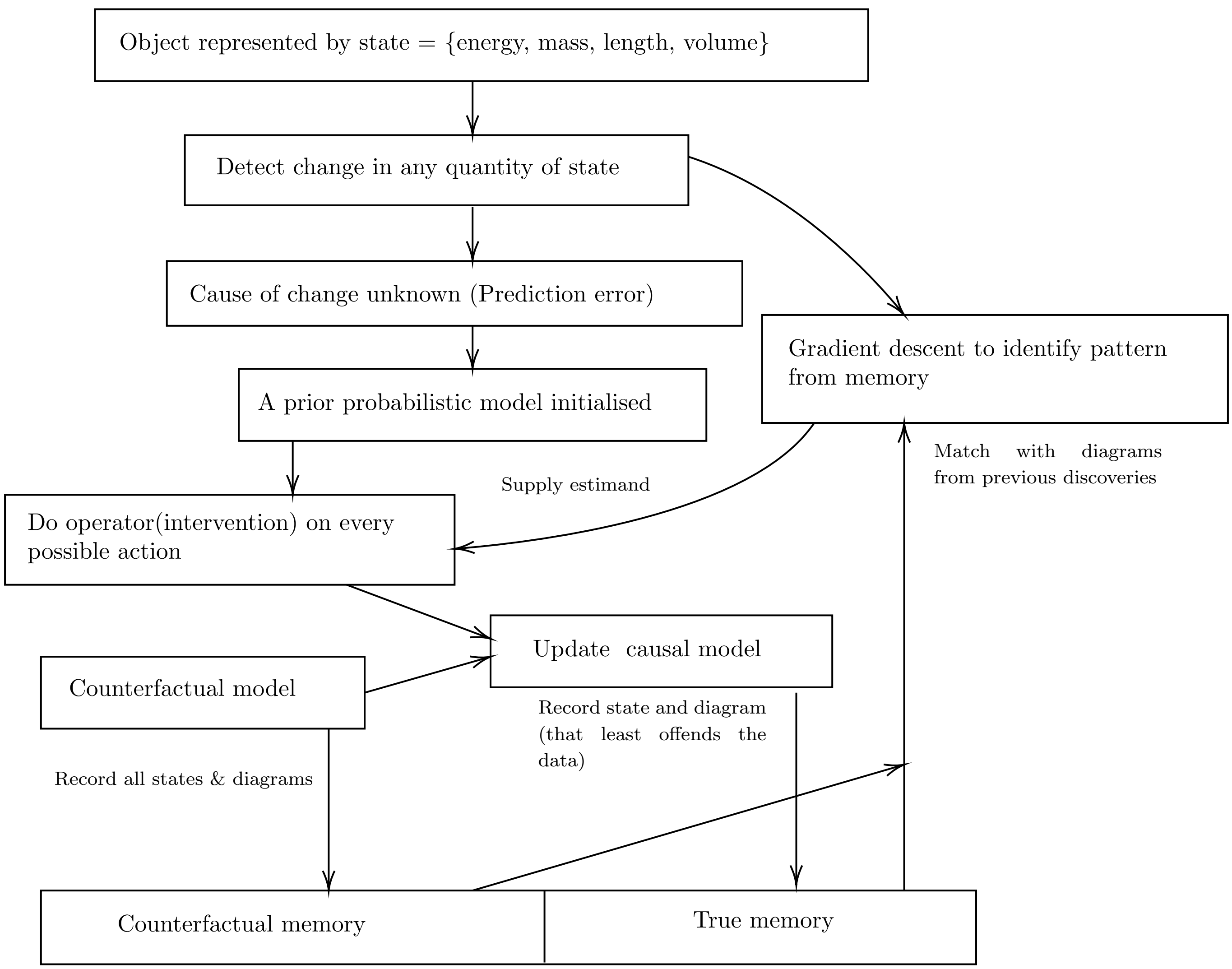

Figure 1: Model for knowledge generation through causal inference and gradient descent

reality, that lets the agent collect data and assign symbols can help in creating knowledge representations. Once it has representation of how matter is created, then it could learn for example what objects would be rigid and which ones would flow or evaporate, and this would direct the agent's search and inference as it gets exposed to higher dimensional reality. The next step can be to feed input in form of images, from which its neural network could extract geometrical shapes and color and update the internal model with more detail.

3 Parallel Ordering agent (Further work in progress)

An agent working in parallel (but communicating with the main agent) keeps track of minimizing the number of objects to keep track of.This agent recognises when the properties that can be ignored. For instance, in case of multiple hydrogen atoms combining to make a molecule, there motion is now to be modelled as one single entity moving through space, and not as two separate objects. The distributed agent keeps track of reducing the complexity of the scene, by actively looking to find the minimum features that are required to model the action. Built in is the construct that atoms make up a larger of different entity. That when markov blankets intersect and the computation yields a situation in which the two are now closer in space(locality), then that is now a single entity.The agent should keep updating the internal representation over which the main agent is experimenting.

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