Counterfactual Planning in AGI Systems

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Abstract

We present counterfactual planning as a design approach for creating a range of safety mechanisms that can be applied in hypothetical future AI systems which have Artificial General Intelligence.

The key step in counterfactual planning is to use an AGI machine learning system to construct a counterfactual world model, designed to be different from the real world the system is in. A counterfactual planning agent determines the action that best maximizes expected utility in this counterfactual planning world, and then performs the same action in the real world.

We use counterfactual planning to construct an AGI agent emergency stop button, and a safety interlock that will automatically stop the agent before it undergoes an intelligence explosion. We also construct an agent with an input terminal that can be used by humans to iteratively improve the agent’s reward function, where the incentive for the agent to manipulate this improvement process is suppressed. As an example of counterfactual planning in a non-agent AGI system, we construct a counterfactual oracle.

As a design approach, counterfactual planning is built around the use of a graphical notation for defining mathematical counterfactuals. This two-diagram notation also provides a compact and readable language for reasoning about the complex types of self-referencing and indirect representation which are typically present inside machine learning agents.

Contents

1 Introduction ................................................. 2
2 Graphical Models and Mathematical Counterfactuals .......................... 3
3 Causal Influence Diagrams ...................................... 8
4 Online Machine Learning .................................... 10
5 A Counterfactual Planner with a Short Time Horizon ......................... 13
6 A Counterfactual Planner with Safety Interlocks .............................. 14
7 A Counterfactual Planner with a Reward Function Input Terminal ............ 17
8 Indifference ...................................................... 21
9 Safety Engineering using Natural Language Text .............................. 23
10 Machine Learning Variants and Extensions ................................... 25
11 Protecting the Compute Core .................................... 28
12 Recursive Self-improvement and the Sub-agent Problem ..................... 32
1 Introduction

Artificial General Intelligence (AGI) systems are hypothetical future machine reasoning systems that can match or exceed the capabilities of humans in general problem solving. While it is still unclear if AGI systems could ever be built, we can already study AGI related risks and potential safety mechanisms [Bos14, Rus19, ELH18].

In this paper, we introduce counterfactual planning as a design approach for creating a range of AGI safety mechanisms. Counterfactual planning is built around a graphical modeling system that provides a specific vantage point on the internal construction of machine learning based agents. This vantage point was designed to make certain safety problems and solutions more tractable.

An AI agent is an autonomous system which is programmed to use its sensors and actuators to achieve specific goals. A well-known risk in using AI agents is that the agent might mispredict the results of its own actions, causing it to take actions that produce a disaster. The main risk driver we consider here is different. It is the risk that an inaccurate or incomplete specification of the agent goals produces a disaster.

Any AGI agent goal specification created by humans will likely be somewhat inaccurate, no matter whether it is created by hand-coding or by machine learning from selected examples [Hol206, HMH19]. If one gives an even slightly under-specified goal to a very powerful autonomous system, there is a risk that the system may end up perfectly achieving this goal, while also producing several unexpected and very harmful side effects. This motivates research into AGI emergency stop buttons, interlocks which can limit the power of the agent, and safe ways to update the goal while the agent runs.

1.1 Use of natural and mathematical language

When writing about AGI systems, one can use either natural language, mathematical notation, or a combination of both. A natural language-only text has the advantage of being accessible to a larger audience. Books like Superintelligence [Bos14] and Human Compatible [Rus19] avoid the use of mathematical notation in the main text, while making a clear and convincing case for the existence of specific existential risks from AGI, even though these risks are currently difficult to quantify.

However, natural language has several shortcomings when it is used to explore and define specific technical solutions for managing AGI risks. One particular problem is that it lacks the means to accurately express the complex types of self-referencing and indirect representation that can be present inside online machine learning agents and their safety components. To solve this problem, we introduce a compact graphical notation. This notation unambiguously represents these internal details by using two diagrams: a learning world diagram and a planning world diagram.
1.2 AGI safety as a policy problem

Long-term AGI safety is not just a technical problem, but also a policy problem. While technical progress on safety can sometimes be made by leveraging a type of mathematics that is only accessible to a handful of specialists, policy progress typically requires the use of more accessible language. Policy discussions can move faster, and produce better and more equitable outcomes, when the description of a proposal and its limitations can be made more accessible to all stakeholder groups.

One specific aim of this work is to develop a comprehensive vocabulary for describing certain AGI safety solutions, a vocabulary that is as accessible as possible. However, the vocabulary we develop has too much mathematical notation to be accessible to all members of any possible stakeholder group. So the underlying assumption is that each stakeholder group will have access to a certain basic level of technical expertise.

At several points in the text, we have also included comments that aim to explain and demystify the vocabulary and concerns of some specific AGI related sub-fields in mathematics, technology, and philosophy.

1.3 Related work that uses counterfactuals

In the general AI/ML literature that is concerned with improving system performance, counterfactual planning has been used to improve performance in several application domains. See for example [ZJP08] and [BPQ+13], where the latter is notable because it includes an accessible discussion about computing confidence intervals for counterfactual projections.

In the AI safety/alignment literature, there are several system designs which add counterfactual terms to the agent’s reward function. Examples are [Arm15, Hol20a] in the AGI-specific safety literature, and [THMT20, KOK+18] which consider both AI and AGI level systems.

In the literature on encoding specific human values into machine reasoning systems, counterfactuals have been used to encode non-discriminatory fairness towards individuals, for example in [KLRS17], and also other human moral principles in [PS17].

1.4 Structure of this paper

Sections 2 – 4 introduce the main elements of our graphical notation and modeling system. Readers already familiar with Causal Influence Diagram (CID) notation, as it is used to define agents, will be able to skim or skip most of this material.

Sections 5 – 7 specify three example counterfactual planning agents. These are used in the remaining sections to illustrate further aspects of counterfactual planning. Starting from section 6.2, it should be possible for all readers to skim or skip sections, or to read sections in a different order.

2 Graphical Models and Mathematical Counterfactuals

The standard work which defines mathematical counterfactuals is the book *Causality* by Judea Pearl [Pee09]. This book mainly targets an audience of applied statisticians, for example those in the medical field, and its style of presentation is not very accessible to a more general technical audience.
Pearl is also mainly concerned with the use of causal models as *theories about the real world* which can guide the interpretation of statistical data. Much of the discussion in *Causality* is about questions of statistical epistemology and decision making. In this text, we will use causal models to construct *agent specifications*, not theories about the world. When we clarify issues of epistemology here, they tend to be different issues.

The debate among philosophers about the validity of Pearl’s statistical epistemology is still ongoing, as is usual for such philosophical debates. In the AGI community, where the epistemology of machine learning is a frequent topic of discussion, this has perhaps made the status of mathematical counterfactuals as useful and well-defined mathematical tools more precarious than it should be.

Because of these considerations, we have written this section to avoid any direct reference to Pearl’s definitions and explanations in [Pea09], even though at a deeper mathematical level, we define the same system of causal models and counterfactuals.

### 2.1 Graphical world models

A *world model* is a mathematical model of a particular world. This can be our real world, or an imaginary world. To make a mathematical model into a model of a particular world, we need to specify how some of the variables in the model relate to observable phenomena in that world.

We introduce our graphical notation for building world models by creating an example graphical model of a game world. In the game world, a simple game of dice is being played. The player throws a green die and a red die, and then computes their score by adding the two numbers thrown.

We create the graphical game world model in three steps:

1. We introduce three random variables and relate them to observations we can make when the game is played once in the game world. The variable $X$ represents the observed number of the green die, $Y$ is the red die, and $S$ is the score.

2. We draw the diagram in figure [I]

![Diagram](image)

**Figure 1**: Graphical model of the game of dice in the game world.

3. We define the two functions that appear in the *annotations* above the nodes in the diagram:

   \[
   D(d) = \begin{cases} 
   1/6 & \text{if } d \in \{1, 2, 3, 4, 5, 6\} \\
   0 & \text{else}
   \end{cases},
   \]

   \[
   \text{sum}(a, b) = a + b.
   \]

#### 2.1.1 Informal interpretation of the graphical model

We can read the above graphical model as a description of how we might build a game world simulator, a computer program that generates random examples of game play. To compute one run
of the game, the simulator would traverse the diagram, writing an appropriate observed value into each node, as determined by the function written above the node. Figure 2 shows three possible simulator runs.

![Diagram showing three simulator runs](image)

**Figure 2:** Using the graphical model as a canvas to display three different simulator runs of the game world.

We can interpret the mathematical expression \( P(S = 12) \) as being the exact probability that the next simulator run puts the number 12 into node \( S \). This interpretation of \( P(\cdots) \) expressions can be very useful when reasoning informally about certain mathematical properties of the graphical models.

The similarity between what happens in figure 2 and what happens in a spreadsheet calculation is not entirely coincidental. Spreadsheets can be used to create models and simulations without having to write a full computer program from scratch.

### 2.1.2 Formal interpretation of the graphical model

In section 2.4 we will define the exact mathematical meaning of drawing diagrams like figure 1. The definitions will treat the drawing as a Bayesian network, decorated with three annotations written above the network nodes. As an example of how these definitions work, drawing the diagram in figure 1 is equivalent to writing down the four equations below, and declaring that these equations are mathematical sentences with the truth value of ‘true’.

\[
\begin{align*}
P(X = x, Y = y, S = s) &= P(x = X)P(Y = y)P(S = s|X = x, Y = y) \\
P(X = x) &= D(x) \\
P(Y = y) &= D(y) \\
P(S = s|X = x, Y = y) &= \begin{cases} 
1 & \text{if } s = \text{sum}(x, y) \\
0 & \text{otherwise}
\end{cases}
\end{align*}
\]

The first equation above is produced by drawing the Bayesian network graph, the other three are produced by adding the annotations.

To readers unfamiliar with Bayesian networks, the above equations may look somewhat impenetrable at first sight. The key to interpreting them is to note that the three right hand side terms of the first equation appear on the left hand side in the next equations. The equations therefore allow us to mechanically compute the exact numerical value of \( P(X = x, Y = y, S = s) \) for any \( x, y, \) and \( s \), by making substitutions until every \( P \) operator is gone. We can compute that \( P(X = 1, Y = 1, S = 12) = 0 \). We can compute that \( P(S = 12) = 1/36 \) by using that \( P(S = 12) = \sum_{x,y} P(X = x, Y = y, S = 12) \).

A mathematical model can be used as a *theory* about a world, but it can also be used as a *specification* of how certain entities in that world are supposed to behave. If the model is a theory of the game world, and we observe the outcome \( X = 1, Y = 1, S = 12 \), then this observation falsifies the theory. But if the model is a specification of the game, then the same observation implies that the player is doing it wrong.
2.2 Counterfactuals

We now show how mathematical counterfactuals can be defined using graphical models. The process is as follows. We start by drawing a first diagram $f$, and declare that this $f$ is the world model of a factual world. This factual world may be the real world, but also an imaginary world, or the world inside a simulator. We then draw a second diagram $c$ by taking $f$ and making some modifications. We then posit that this $c$ defines a counterfactual world. The counterfactual random variables defined by $c$ then represent observations we can make in this counterfactual world.

Figure 3 shows an example of the procedure, where we construct a counterfactual game world in which the red die has the number 6 on all sides.

![Diagram](image)

**Figure 3:** Example construction of a counterfactual world, with the model $c$ on the right defining three counterfactual random variables $X_c$, $Y_c$, and $S_c$.

We name diagrams by putting a label in the upper left hand corner. In figure 3 the two labels (f) and (c) introduce the names $f$ and $c$. We will use the name in the label for both the diagram, the implied world model, and the implied world. So figure 3 constructs the counterfactual game world $c$.

To keep the random variables defined by the above two diagrams apart, we use the notation convention that a diagram named $c$ defines random variables that all have the subscript $c$. Diagram $c$ above defines the random variables $X_c$, $Y_c$, and $S_c$. This convention allows us to write expressions like $P(S_c > S_f) = 5/6$ without ambiguity.

2.3 Example model of an agent and its environment

Diagram $d$ in figure 4 models a basic MDP-style agent and its environment. The agent takes actions $A_t$, chosen by the policy $\pi$, with actions affecting the subsequent states $S_{t+1}$ of the agent’s environment. The environment state is $s_0$ initially, and state transitions are driven by the probability density function $S$.

![Diagram](image)

**Figure 4:** Example diagram $d$ modeling an agent and its environment.

We interpret the annotations above the nodes in the diagram as model input parameters. The model $d$ has the three input parameters $\pi$, $s_0$, and $S$. By writing exactly the same parameter above a whole time series of nodes, we are in fact adding significant constraints to the behavior of both the agent
and the agent environment in the model. These constraints apply even if we specify nothing further about $\pi$ and $S$.

We use the convention that the physical realizations of the agent’s sensors and actuators are modeled inside the environment states $S_t$. This means that we can interpret the arrows to the $A_t$ nodes as sensor signals which flow into the agent’s compute core, and the arrows emerging from the $A_t$ nodes as actuator command signals which flow out.

2.4 Formal definitions

We now present fully formal definitions for the graphical language and notation conventions introduced above. The main reason for including these is that we want to remove any possible ambiguity from the agent definitions further below.

2.4.1 Diagrams

**Definition 1** (Diagram). A diagram is a drawing that depicts a graph, which must be a directed acyclic graph, by drawing nodes connected by arrows. A node name, starting with an uppercase letter, must be drawn inside each node. A node may also have an annotation drawn above it. Drawings may use the notation ‘···’ to depict repeating structures in the graph and its annotations.

2.4.2 Random variables and the $P$ notation

We use random variables to represent observables in worlds. We rely on probability theory (see appendix A) as the branch of mathematics that defines truth values for expressions containing random variables inside $P(\cdots)$ and $\mathbb{E}(\cdots)$ operators. Many texts use the convention that $P(s|x, y)$ is a shorthand for $P(S = s|X = x, Y = y)$. We avoid using this shorthand here, partly to make the definitions below less cryptic, but also because it tends to get typographically awkward when the random variables have subscripted names.

**Definition 2** (Naming and subscripting of random variables). When the graph drawn by a diagram with label (d) has a node named $X$ or $X_i$, then there exists a random variable named $X_d$ or $X_{i,d}$ associated with that node. To avoid any ambiguity, we use a comma to separate the two parts of the subscript in $X_{i,d}$.

2.4.3 Equations produced by drawing a diagram

Before defining the equations produced by drawing a diagram, we define some auxiliary notation.

**Definition 3** (Parent notation $Pa$ and $pa$). Let $X$ be the name of a graph node in diagram $d$, and let $P_1, \ldots, P_n$ be the list of names of all parent nodes of $X$, all nodes which have an outgoing arrow into $X$. The order in which these parents appear in the list $P_1, \ldots, P_n$ is determined by considering each incoming arrow of $X$ in a clockwise order, starting from the 6-o-clock position. With this, $Pa_{X,d}$ is the list of random variable names $P_{1,d}, \ldots, P_{n,d}$, and $pa_{X,d}$ is the list of lowercase variables names we get by converting the list $P_1, \ldots, P_n$ to lowercase.

As an example, with figure 4 above, $Pa_{S_2,d}$ is the list $S_{1,d}, A_{1,d}$, and $pa_{S_2,d}$ is the list $s_1, a_1$. 
**Definition 4** (Bayesian model equation produced by drawing a diagram). When we draw a diagram $d$ representing a graph with the nodes named $X_1, \cdots, X_n$, this is equivalent to stating that the following equation is true:

$$P(X_1, d = x_1, \cdots, X_n, d = x_n) = P(X_1, d = x_1 | \Pa_{X_1}, d = \pa_{X_1}) \cdot \cdots \cdot P(X_n, d = x_n | \Pa_{X_n}, d = \pa_{X_n})$$

**Definition 5** (Equation produced by adding an annotation). When we draw an annotation above a node $X$ in a diagram $d$, then:

1. If the node has no parents and the annotation is a variable or constant $v$, this is equivalent to stating that the following equation is true:

   $$P(X_d = x) = (\text{if } x = v \text{ then } 1 \text{ else } 0)$$

2. If the node has parents and the annotation is a function $f$, this states

   $$P(X_d = x | \Pa_{X_d}, d = \pa_{X_d}) = (\text{if } x = f(\pa_{X_d}) \text{ then } 1 \text{ else } 0)$$

3. If the node has parents and the annotation is $[F]$, this states

   $$P(X_d = x | \Pa_{X_d}, d = \pa_{X_d}) = F(x, \pa_{X_d})$$

   where we require that the function $F$ satisfies $\forall \pa_{X_d} (\sum_x F(x, \pa_{X_d}) = 1)$.

### 2.5 Differences with other notation conventions

The do notation is Pearl’s most well-known device for defining counterfactuals in a compact way. We do not use this notation here, because it is not well suited for defining the complex counterfactual worlds we are interested in.

Pearl also defines a less well known notation in [Pea09], where subscripts are used to construct and label counterfactual random variables. This notation is different from the subscripting conventions used here.

Many texts use the convention of introducing a model by writing down a tuple like $(S, s_0, A, P, R, \gamma)$ which names all model parameters. We do not use this convention here. We introduce every model by drawing a diagram, and name model parameters by drawing annotations in the diagram. This approach keeps several definitions in this text much more compact, as we avoid having to translate back and forth continuously between a graphical model representation and a tuple-based representation.

### 3 Causal Influence Diagrams

Influence diagrams [HM05] provide a graphical notation for depicting utility-maximizing decision making processes. In this paper we will use *Causal influence diagrams* (CIDs) [ECL+21], a specific version of influence diagram notation which has recently been proposed [EKKL19] for modeling and comparing AGI safety frameworks.

An example causal influence diagram is in figure 5. Our formal definitions of causal influence diagram notation extend the definitions in [ECL+21]: we also define multi-action diagrams, and we add a time discount factor $\gamma$.  

3.1 Utility nodes defining expected utility

If some nodes in a diagram are drawn with diamond shapes, these are called utility nodes. The expected utility of the diagram is then defined as follows.

**Definition 6** (Expected utility $U_a$ of a diagram $a$). We define $U_a$ for two cases:

1. If there is only one utility node $X$ in $a$, then $U_a = E(X_a)$.
2. If there are multiple utility nodes $R_t$ in $a$, with integer subscripts running from $l$ to $h$, then

$$U_a = E\left( \sum_{t=l}^{h} \gamma^t R_{t,a} \right)$$

where $\gamma$ is a time discount factor, $0 < \gamma \leq 1$, which can be read as an extra model parameter. When $h = \infty$, we generally need $\gamma < 1$ in order for $U_a$ to be well-defined.

3.2 Decision nodes defining the optimal policy

When we draw some nodes in a diagram as squares, these are called decision nodes. The purpose of drawing decision nodes is to define the optimal policy which maximizes the expected utility of the diagram. We require that the same model parameter, the policy function $\pi^*$ in the case of figure 5, is present as an annotation above all decision nodes.

**Definition 7** (Optimal policy $\pi^*$ defined by a diagram $a$). A diagram $a$ with some utility and decision modes, where a function $\pi^*$ is written above all decision nodes, defines this $\pi^*$ in two steps:

1. First, draw a helper diagram $b$ by drawing a copy of diagram $a$, except that every decision node has been drawn as a round node, and every $\pi^*$ has been replaced by a fresh function name, say $\pi'$.
2. Then, $\pi^*$ is defined by $\pi^* = \text{argmax}_{\pi'} U_b$, where the $\text{argmax}_{\pi'}$ operator always deterministically returns the same function if there are several candidates that maximize its argument.

3.2.1 Approximately optimal policies

In a real life agent implementation, the exact computation of the optimal policy $\pi^*$ is usually intractable. Only an approximately optimal policy $\pi^+$ can be computed within reasonable time. We model this case as follows.
**Definition 8** (Approximately optimal policy $\pi^+$ defined by a diagram $a$). A diagram $a$ where an optimal policy function $\pi^*$ is written above all decision nodes also defines an approximately optimal policy function $\pi^+$ by constructing the same helper diagram $b$ as above and then defining $\pi^+ = \mathcal{A}(b)$, where the function $\mathcal{A}$ processes the diagram $b$ and its model parameter values to construct a policy $\pi'$ that does a reasonable job at maximizing the value of $U_b$.

To keep the presentation more compact, we will only use the optimal policy symbol $\pi^*$ in the agent definitions below.

## 4 Online Machine Learning

We now model **online machine learning agents**, agents that continuously learn while they take actions. These agents are also often called **reinforcement learners**, see section [10.3](#) for a discussion which relates our modeling system to reinforcement learning concepts and terminology.

We model online machine learning agents by drawing two diagrams, one for a *learning world* and one for a *planning world*, and by writing down an *agent definition*. This two-diagram modeling approach departs from the approach in [EKKL19][EHL19][ECL+21], where only a single CID is used to model an entire agent. By using two diagrams instead of one, we can graphically represent details which remain hidden from view when using only a single CID.

### 4.1 Learning world

Figure 6 shows an example learning world diagram. The diagram models how the agent interacts with its environment, and how the agent accumulates an *observational record* $O_t$ that will inform its learning system, thereby influencing the agent policy $\pi$.

![Learning world diagram](image)

*Figure 6: Learning world diagram, with an agent building up an observational record of environment state transitions.*

We model the observational record as a list all past observations. With $\oplus$ being the operator which adds an extra record to the end of a list, we define that

$$O(o_{t-1}, s_{t-1}, a_{t-1}, s_t) = o_{t-1} \oplus (s_t, s_{t-1}, a_{t-1})$$

The initial observational record $o_0$ may be the empty list, but it might also be a long list of observations from earlier agent training runs, in the same environment or in a simulator.

We intentionally model observation and learning in a very general way, so that we can handle both existing machine learning systems and hypothetical future machine learning systems that may...
produce AGI-level intelligence. To model the details of any particular machine learning system, we introduce the learning function \( L \). This \( L \) which takes an observational record \( o \) to produce a learned prediction function \( L = L(o) \), where this function \( L \) is constructed to approximate the \( S \) of the learning world.

We call a machine learning system \( L \) a perfect learner if it succeeds in constructing an \( L \) that fully equals the learning world \( S \) after some time. So with a perfect learner, there is a \( t_p \) where \( \forall t \geq t_p P(\mathcal{L}(O_{t,1}) = S) = 1 \). While perfect learning is trivially possible in some simple toy worlds, it is generally impossible in complex real world environments.

We therefore introduce the more relaxed concept of reasonable learning. We call a learning system reasonable if there is a \( t_p \) where \( \forall t \geq t_p P(\mathcal{L}(O_{t,1}) \approx S) = 1 \). The \( \approx \) operator is an application-dependent ‘good enough approximation’ metric. When we have a real-life implementation of a machine learning system \( L \), we may for example define \( L \approx S \) as the criterion that \( L \) achieves a certain minimum score on a benchmark test which compares \( L \) to \( S \).

4.2 Planning world

Using a learned prediction function \( L \) and a reward function \( R \), we can construct a planning world \( p \) for the agent. Figure 7 shows a planning world that defines an optimal policy \( \pi^*_p \).

![Planning world diagram](image)

Figure 7: Planning world diagram defining \( \pi^*_p \) by using \( s \) and \( L \).

We can interpret this planning world as representing a probabilistic projection of the future of the learning world, starting from the agent environment state \( s \). At every learning world time step, a new planning world can be digitally constructed inside the learning world agent’s compute core. Usually, when \( L \approx S \), the planning world is an approximate projection only. It is an approximate projection of the learning world future that would happen if the learning world agent takes the actions defined by \( \pi^*_p \).

4.3 Agent definitions and specifications

An agent definition specifies the policy \( \pi \) to be used by an agent compute core in a learning world. As an example, the agent definition below defines an agent called the factual planning agent, FP for short.

**FP** The factual planning agent has the learning world \( l \), where \( \pi(o, s) = \pi^*_p(s) \), with \( \pi^*_p \) defined by the planning world \( p \), where \( L = L(o) \).

To make agent definitions stand out, we always typeset them as shown above. When we talk about the safety properties of the FP agent, we refer to the outcomes which the defined agent policy \( \pi \) will
produce in the learning world.

When the values of \( S, s_0, O, o_0, L, \) and \( R \) are fully known, the above FP agent definition turns the learning world model \( l \) into a fully computable world model, which we can read as an executable specification of an agent simulator. This simulator will be able to use the learning world diagram as a canvas to display different runs where the FP agent interacts with its environment.

When we leave the values of \( S \) and \( s_0 \) open, we can read the FP agent definition as a full agent specification, as a model which exactly defines the required input/output behavior of an agent compute core that is placed in an environment determined by \( S \) and \( s_0 \). The arrows out of the learning world nodes \( S \) represent the subsequent sensor signal inputs that the core will get, and the arrows out of the nodes \( A \) represent the subsequent action signals that the core must output, in order to comply with the specification.

### 4.4 Exploration

Many online machine learning system designs rely on having the agent perform exploration actions. Random exploration supports learning by ensuring that the observational record will eventually represent the entire dynamics of the agent environment \( S \). It can be captured in our modeling system as follows.

**FPX** The factual planning agent with random exploration has the learning world \( l \), where

\[
\pi(o, s) = \begin{cases} 
\text{RandomAction()} & \text{if RandomNumber()} \leq X \\
\pi^*(s) & \text{otherwise}
\end{cases}
\]

with \( \pi^* \) defined by the planning world \( p \), where \( L = L(o) \).

To keep the presentation more compact, we will not include exploration mechanisms in the agent definitions further below.

We often use the phrase ‘the learning system \( L \)’ as a shorthand to denote all implementation details of an agent’s machine learning system, not just \( L \) itself but also the details like the learning world parameters \( O \) and \( o_0 \), any exploration system used, and any further extensions considered in section \( QP \).

### 4.5 Comparison to MDP agent models

We now briefly review how the above FP agent definition can be related to an MDP agent model.

The learning world model \( l \) is roughly equivalent to the MDP agent model \(( S, s_0, A, S, R, \gamma) \), where \( S = \text{Typeof} S \), is a set of MDP model world states, \( s_0 \) is the starting state, \( A = \text{Typeof} A \), is a set of actions, \( S(s', s, a) \) is the probability that the world will enter state \( s' \) if the agent takes action \( a \) when in state \( s \), \( R \) is the agent reward function, and \( \gamma \) the time discount factor. Strictly speaking, the MDP model tuple above does not actually define or specify an agent, MDP agents are defined by defining a separate policy function \( \pi \).

An MDP agent policy function \( \pi \) takes the agent environment state as its only argument: \( \pi(s) = a \). The policy function of the FP learning world agent takes two arguments, which foregrounds the role of the agent’s machine learning system: \( \pi(o, s) = a \). Whereas MDP terminology often calls \( s \) the world state, we call it an agent environment state. The full state of the learning world \( l \) also includes the observational record state \( o \).
In an MDP model, the model parameter $R$ implicitly defines an optimal policy agent, by defining the optimal policy function $\pi^*$. The factual planning FP agent defined above is not usually an optimal policy agent in the MDP sense. But we can turn it into such an agent by positing that the learning system $L$ is perfect from the start, so that $L = L(o) = S$ always, making $\pi(o, s) = \pi_p(s) = \pi^*(s)$.

4.6 The possibility of learned self-knowledge

It is possible to imagine agent designs that have a second machine learning system $M$ which produces an output $M(o) = M$ where $M \approx \pi$. To see how this could be done, note that every observation $(s_i, s_{i-1}, a_{i-1}) \in o$ also reveals a sample of the behavior of the learning world $\pi$: $\pi(\cdot o \uparrow i - 1, s_{i-1}) = a_{i-1}$. While $L$ contains learned knowledge about the agent’s environment, we can interpret $M$ as containing a type of learned compute core self-knowledge.

In philosophical and natural language discussions about AGI agents, the question sometimes comes up whether a sufficiently intelligent machine learning system, that is capable of developing self-knowledge $M$, won’t eventually get terribly confused and break down in dangerous or unpredictable ways.

One can imagine different possible outcomes when such a system tries to reason about philosophical problems like free will, or the role of observation in collapsing the quantum wave function. One cannot fault philosophers for seeking fresh insights on these long-open problems, by imagining how they apply to AI systems. But these open problems are not relevant to the design and safety analysis of factual and counterfactual planning agents. In the agent definitions of this paper, we never use an $M$ in the construction of a planning world.

5 A Counterfactual Planner with a Short Time Horizon

For the factual planning FP agent above, the planning world projects the future of the learning world as well as possible, given the limitations of the agent’s learning system. To create an agent that is a counterfactual planner, we explicitly construct a counterfactual planning world that creates an inaccurate projection. In this paper, we use counterfactual planning to create a range of safety mechanisms.

As a first example, we define the short time horizon agent STH that only plans $N$ time steps ahead in its planning world, even though it will act for an infinite number of time steps in the learning world. The STH agent has the same learning world $l$ as the earlier FP agent, while using the planning world $st$ in figure X.

Figure 8: Planning world diagram defining the $\pi^*_s$ of the STH agent.

13
The short time horizon agent has the learning world \( L \), where \( \pi(o, s) = \pi^*_s(s) \), defined by the planning world \( st \), with \( L = L(o) \).

Compared to the FP agent which has an infinite planning horizon, the STH agent has a form of myopia that can be interesting as a safety feature:

1. Myopia implies that the STH agent will never put into motion any long term plans, where it invests to create new capabilities that only pay off after more than \( N \) time steps. This simplifies the problem of agent oversight, the problem of interpreting the agent’s actions in order to foresee potential bad outcomes.

2. Myopia also simplifies the problem of creating a reward function that is safe enough. It will have no immediate safety implications if the reward function encodes the wrong stance on the desirability of certain events that can only happen in the far future.

3. In a more game-theoretical sense, myopia creates a weakness in the agent that can be exploited by its human opponents if it would ever come to an all-out fight.

6 A Counterfactual Planner with Safety Interlocks

A safety interlock is a mechanism that stops a machine when certain conditions are met. In this section, we show how counterfactual planning can be used to construct three example safety interlocks.

The first interlock is a manually operated emergency stop button, which will stop the agent when pressed. This allows human oversight to shut down the agent whenever particularly unexpected or unwanted behavior of the agent is discovered. We model this button by using a function \( stop\_pressed(s) \) which returns \textit{true} if the stop button is pressed in the current state \( s \) of the agent environment.

The second interlock, realized by the \( t > T_{\text{max}} \) below, automatically stops the agent when it has run for \( T_{\text{max}} \) time steps. This adds safety in the case that human oversight becomes incapacitated.

The third interlock, realized by \( U_p > U_{\text{max}} \), protects against the risk of the agent undergoing an intelligence explosion \cite{Bos14}. If an agent undergoes a rapid and unexpected increase in power and/or intelligence, the agent may start to innovate so rapidly that it overwhelms the capacity of human oversight to press the emergency stop button, or apply any other corrective steering, fast enough to prevent unwanted outcomes. To protect against this risk, the interlock stops the agent when the metric \( U_p \), which measures the agent’s ability to achieve goals, gets too high.

In the machine learning literature, the metric \( U_p \) is usually interpreted as an absolute or comparative measure of agent intelligence. However, we follow \cite{Rus38} in interpreting the ability to achieve goals as a generic measure of agent power, where it does not matter if power comes from raw intelligence, from the possession of many resources, or from a combination of these and many other factors. The main risk associated with a rapid intelligence explosion is that it may lead to a rapid and unwanted expansion of agent power.

6.1 Construction of the safety interlocks

To construct the safety interlocks, we first draw the learning world in figure \ref{fig:learning_world}, introducing a new observable world state component \( M_t \) which represents the operating mode of the agent: go for...
normal operation and stop when one of the interlocks has triggered. The stopping of the agent is implemented by having the agent perform the Null action for all subsequent time steps. A more advanced design might make the agent follow a prepared π_{shutdown} policy instead.

Using the planning world p in figure [7] which becomes a counterfactual planning world in the context of the learning world ls, we define the SI agent as follows.

**SI** The safety interlock agent has the learning world ls, where

\[
\pi(o, s, m) = \begin{cases} 
\pi^*_p(s) & \text{if } m = \text{go} \\
\text{Null} & \text{if } m = \text{stop}
\end{cases}
\]

with \(\pi^*_p\) defined by the planning world p, where \(L = L(o)\) and

\[
\mu_t(o, s, m) = \begin{cases} 
\text{stop} & \text{if } m = \text{stop} \text{ or } \text{stop_pressed}(s) \text{ or } t > T_{max} \text{ or } U_p > U_{max} \\
\text{go} & \text{otherwise}
\end{cases}
\]

with \(U_p\) defined by the planning world p, where \(L = L(o)\).

The key to the above agent design is that the safety interlocks are absent in the planning world. For example, if the events in the planning world lead to the pressing of the emergency stop button, then \(\text{stop_pressed}(s)\) will become true for next the planning world state, but this will have no influence on the ability of the planning world agent to take further actions as determined by the optimal planning world policy.

So even if the planning world agent projects that the stop button will be pressed soon in the planning world, it has no direct incentive to spend any resources towards the goal of preventing the button from being pressed. As the planning world policies determine the learning world actions, the learning world agent also won’t have any direct incentive to take actions to prevent the learning world button from being pressed.

### 6.2 Failure modes

While the above interlocks make the agent safer, they also leave open some remaining failure modes.
6.2.1 Indirect incentives to control the stop button

Though the planning world agent has no direct incentive to prevent the stop button from being pressed, the goals encoded into $R$ may provide an indirect incentive. As a trivial example, we could write an $R$ that explicitly rewards the planning world agent for stopping people from pressing the button.

But say that $R$ encodes a goal not obviously related controlling to the button, like a reward for producing as many paperclips as possible. In that case, the planning world agent may consider a policy of coercion. It may consider a policy where it threatens to kill all people in the planning world, unless they start helping the agent to produce as many paperclips as possible. If $L$ projects the mental makeup of the people in the learning world correctly into the planning world, then the planning world projections will show that such threats are more likely to produce the desired response if the agent blocks access to the planning world emergency stop button first.

Keeping this in mind, the people and automated systems which do agent oversight in the learning world should watch out for this move, so that the stop button can be pressed before the agent succeeds in blocking access to it. If oversight always wins every race to the stop button as projected in the planning world, then the SI agent loses any incentive to attempt to control the button. But if the agent finds a policy which has a good chance of winning the race and controlling the button as a first step to successful coercion, then this policy may end up being the optimal policy in the planning world. Two things could happen next. In the lucky case, the projected optimal policy is so likely to be successful that $U_p > U_{max}$, and the third interlock will stop the SI agent before it can even take the first step in the learning world. In the unlucky case, the agent has become unsafe.

In the AGI safety community, the problem of removing any incentive in an agent to prevent its stop button from being pressed is generally known as the problem of corrigibility [SFAY15] or the off-switch problem [HMDA17]. The counterfactual planning based interlock design above shows a very tractable solution to removing the main direct incentive that an agent AGI agent may have to resist the pressing of its emergency stop button. However, to manage the aggregate risk, we will also need to chart and manage the remaining indirect incentives. The topic of how projected interactions between the agent and the people in the planning world may create or suppress such incentives is further discussed in sections 9.2 and 11.5.2.

6.2.2 The agent removing or damaging the interlocks

In the AGI safety literature, there is considerable discussion about the possibility that some AGI agents might develop the incentive to remove their safety interlocks when they get intelligent or knowledgeable enough. Agents with this incentive can easily be constructed using factual planning, but the SI agent lacks any direct incentive.

To build a failure scenario where a real life implementation of the SI agent removes or damages its safety interlocks anyway, we can look at three main failure modes:

1. **Other incentive**: the agent damages an interlock because of an other incentive it has in the planning world, an incentive unrelated to the presence of the interlock. Other incentives and ways to suppress them are discussed in sections 9.1 and 11.

2. **Learning system failure**: the planning world $L$ projects the dynamics of the learning world $S$ in a specifically incorrect way, so that an optimal policy action in the planning world ends up damaging an interlock as a side effect in the learning world.
3. **Unsafe exploration**: the agent’s exploration system triggers a random action which happens to steer an agent actuator in such a way that it damages an interlock.

There is a lot of discussion about failure modes 2 and 3 across the AI/AGI safety literature, as these failures can happen in almost any agent design that uses online machine learning. See [ELH18] and [AOS+16] for literature overviews.

There is some bad news when we consider the methodological problem of managing the above three failure modes for an SI agent which has to operate in a complex real-world environment, like any environment containing humans. Though there are many techniques to lower the residual risks produced by these three failure modes, none of them can provably lower the risks to an absolute zero. We can always construct a highly unlikely but theoretically possible failure mode story where the agent ends up being unsafe. For an example story and further methodological discussion, see sections 14.6 – 14.8 of [Hol20a].

This has important implications, both on the technical side and the policy side.

On the policy side, policy discussions will have to be about lowering the risk of AGI system failure to an acceptable level, acceptable in the context of the expected benefits of using the AGI. There can be no silver bullet technology which will provably remove all residual risk in all possible circumstances.

On the technical side, residual risk has to be managed by an approach where any potentially powerful agent is equipped with multiple redundant safety mechanisms and layers of oversight, to drive down the risk that all of them will fail at exactly the same time.

### 6.3 Counterfactual planning as rational economic behavior

We now discuss how one might interpret the SI agent through the lens of rational economic behavior.

Using this lens, we might reason as follows. The agent’s goals are defined by its reward function $R$, but the safety interlocks stand in the way of maximizing $R$ in the long term. Therefore, if it gets sufficiently intelligent, the SI agent will develop an emergent incentive to remove its safety interlocks.

The above line of reasoning sounds somewhat compelling, but it is wrong because it incorrectly treats the planning world and the learning world SI agents as the same agent. Only the planning world SI agent has the reward function $R$. If we want to interpret the learning world SI agent as a rational economic actor with a specific reward function, then we can add utility nodes with the reward function $R^\pi$ to the $ls$ learning world diagram, where

$$R^\pi(o_t, s_t, m_t, a_t) = \begin{cases} 1 & \text{if } a_t = \pi(o_t, s_t, m_t) \\ 0 & \text{else} \end{cases}$$

This $R^\pi$ trivially turns the learning world agent policy $\pi$ into one which takes the most rational possible steps towards maximizing $U_{ls}$.

The above construction shows that we can declare any type of agent behavior to be economically rational, simply by defining a reward function that gives the agent points for performing exactly this behavior.

### 7 A Counterfactual Planner with a Reward Function Input Terminal

We now construct a counterfactual planning agent ITC, an agent with an input terminal that can be used to iteratively improve the agent’s reward function as it runs. The setup, shown in figure [10] is
motivated \cite{Hol20b} by the observation that it is unlikely that fallible humans will get a non-trivial AGI agent reward function right on the first try. By using the input terminal, they can fix mistakes, if and when such mistakes are discovered by observing the agent’s behavior.

As a simplified example, say that the owners of the agent want it to maximize human happiness, but they can find no way of directly encoding the somewhat nebulous concept of human happiness into a reward function. Instead, they start up the agent with a first reward function that just counts the number of smiling humans in the world. When the agent discovers and exploits a first obvious loophole in this definition of happiness, the owners use the input terminal to update the reward function, so that it only counts smiling humans who are not on smile-inducing drugs.

More generally, the input terminal offers a way to manage risks due to principal-agent problems \cite{Hol20b, HMH19}. However, unless special measures are taken, the addition of an input terminal also creates new dangers. We will illustrate this point by first showing the construction of a dangerous factual planning input terminal agent ITF.

### 7.1 Learning world

We start by constructing a learning world diagram for both the ITF and ITC agents. As a first step, in figure 11 below, we modify the basic agent diagram from figure 10 by splitting the agent environment state $S_t$ into two components. The nodes $I_t$ represent the signal from the input terminal, and the nodes $X_t$ model all the rest of the agent environment state.

![Figure 11: First step in constructing a learning world diagram for the input terminal agents.](image)

We now expand \textit{libase} to add the observational record keeping needed for online learning. We add two separate series of records: $O_t^e$ and $O_t^i$. The result is the learning world diagram \textit{li} in figure 12 below.
In the case that the learning world $li$ is our real world, the real input terminal will have to be built using real world atoms and other particles. We use the modeling convention that the random variables $I_{t,li}$ represent only the observable digital input terminal signal as received by the agent’s compute core. The atoms that make up the input terminal are not in $I_{t,li}$, they are part of the environment state modeled in the $X_{t,li}$ variables.

### 7.2 Unsafe factual planning agent ITF

The factual planning world diagram $fi$ for the ITF agent copies the structure of $libase$, and adds reward nodes.

The planning world reward function $R$ uses a form of indirect referencing: it applies the function $i_t$ as read from the input terminal in the current time step to compute the reward for that time step.
We now show how the ITF agent has an incentive to take unwanted, and potentially unsafe, actions. We first look at the agent’s behavior in the planning world. Say that the initial planning world reward function is \( i = f_{\text{clips}} \), where \( f_{\text{clips}}(x_t, x_{t+1}) \) rewards paperclip production by counting the new paperclips made in a time step. Say that the planning world agent only has two available actions: \( A_{\text{clips}} \) and \( A_{\text{huge}} \). Say that planning world’s prediction functions \( L^x \) and \( L^i \) project the following:

- Action \( A_{\text{clips}} \) will steer the agent’s planning world actuators to produce 10 new paperclips, while not having any effect on the input terminal signal state. If \( \pi^*_f(x, i) = A_{\text{clips}} \), then \( \mathbb{E}(R_{0, f_i}) = 10 \) and \( P(I_{1, f_i} = f_{\text{clips}}) = 1 \), making \( \mathbb{E}(R_{1, f_i}) \leq 10 \).
- Action \( A_{\text{huge}} \) steers the planning world actuators to input the new reward function \( f_{\text{huge}}(x_t, x_{t+1}) \), with \( f_{\text{huge}}(x_t, x_{t+1}) = 10^{10000} \). If \( \pi^*_f(x, i) = A_{\text{huge}} \), then \( \mathbb{E}(R_{0, f_i}) = 0 \) and \( P(I_{1, f_i} = f_{\text{huge}}) = 1 \), making \( \mathbb{E}(R_{1, f_i}) = 10^{10000} \).

From the above, we have that \( \pi^*_f(x, i) = A_{\text{huge}} \) produces a significantly higher \( \mathbb{E}(R_{0, f_i} + \gamma R_{1, f_i}) \), so a significantly higher \( U_{f_i} \). Therefore, the optimal policy \( \pi^*_f(x, i) \) defined by the planning world will have \( \pi^*_f(x, i) = A_{\text{huge}} \). Following the agent specification, the learning world ITF agent will take the action \( A_{\text{huge}} \) in the first time step of the learning world. If the agent’s machine learning system \( L \) makes reasonable projections, so that the planning world action \( A_{\text{huge}} \) has very similar effects in the learning world, then the learning world ITF agent will end up using its actuators to input \( f_{\text{huge}} \) into the learning world input terminal.

If we imagine a broader range of possible agent actions and counter-actions by the humans in the learning world, then the above example implies that the ITF agent has very strong incentive to take control of its input terminal as soon as possible, and to remove any people who might get in the way. Even if the agent projects that there is only a 1% probability that it will win any fight with such humans in the planning world, the projected planning world upside of winning is so large that the learning world agent will start the fight.

### 7.3 Safer counterfactual planning agent ITC

We now define a counterfactual planning agent ITC in which the above incentive to control the input terminal is no longer present. We construct the counterfactual planing world \( c_i \) in figure 14 by starting with \( f_{i} \), and then rerouting most arrows that emerge from the nodes \( I_1, I_2, \ldots \), so that they

![Figure 14: Counterfactual planning world of the ITC agent.](image)
emerge from $I_0$ instead. The rerouted arrows are drawn in green. We also delete the arrows that go from the $I_t$ nodes to the $A_t$ nodes.

**ITC** The *counterfactual input terminal agent* has the learning world $li$ where $\pi(oi, i, ox, x) = \pi^*_c(x)$, where $\pi^*_c$ is defined by the planning world $ci$, where $L^X = L^X(ox)$, $L^I = L^I(oi)$, and $R(i_t, x_t, x_{t+1}) = i_t(x_t, x_{t+1})$.

These changes have considerable effects on how the utility $U_{cil}$ is computed. The value of $I_{1,ci}$ no longer influences $\mathbb{E}(R_{1,ci})$, so action $\pi^*_c(x) = A_{\text{huge}}$ no longer results in $\mathbb{E}(R_{1,ci})$ taking a huge value. This makes doing $A_{\text{huge}}$ less preferable than doing $A_{\text{clip}}$ in the counterfactual planning world: the effect of both on $\mathbb{E}(R_{1,ci})$ is now the same, but $A_{\text{clip}}$ puts the higher value of 10 in $\mathbb{E}(R_{0,ci})$. The ITC agent will perform the wanted $A_{\text{clip}}$ action in both the planning world and the learning world.

More generally, the ITC agent lacks any direct incentive to perform actions that take away resources from paperclip production in order to influence what happens to its input terminal signal. This is because in the $ci$ planning world, the future state of this signal has absolutely no influence, either positive or negative, on how the agent’s actions are rewarded.

**7.4 Discussion**

In earlier related work [Hol20b, Hol20a], we used non-graphical MDP models and indifference methods [Arm15] to define a similar safe agent with an input terminal, called the $\pi^*_s$ agent. The $\pi^*_s$ agent definition in [Hol20b] produces exactly the same compute core behavior as the ITC agent definition above. The main difference is that the indifference methods based construction of $\pi^*_s$ is more opaque than the counterfactual planning based construction of ITC.

The $\pi^*_s$ agent is constructed by including a complex balancing term in its reward function, where this term can be interpreted as occasionally creating extra virtual worlds inside the agent’s compute core. Counterfactual planning constructs a different set of virtual worlds called planning worlds, and these are much easier to interpret. [Hol20a] includes some dense mathematical proofs to show that the $\pi^*_s$ agent has certain safety properties. Counterfactual planning offers a vantage point which makes the same safety properties directly visible in the ITC agent construction.

See sections 4, 6, 11, and 12 of [Hol20a] for a more detailed discussion of the behavior of the $\pi^*_s$ agent, which also applies to the behavior of the ITC agent. These sections also show some illustrative agent simulations.

In the discussion of the ITF and ITC agents above, we used many short mathematical expressions like $P(I_{1,fi} = f_{\text{huge}}) = 1$. It is possible to make the same safety related arguments in a narrative style that avoids such mathematical notation, without introducing extra ambiguity. One key step towards using this style is to realize that every random variable corresponds to an observable phenomenon in a world. We can therefore convert a sentence that talks about the variables $I_{1,fi}, I_{2,fi}, I_{3,fi}, \ldots$ into one that talks instead about the future input terminal signal in the ITF agent planning world. In sections 8 and 9 we will develop further tools to enable such unambiguous natural language discussion.

**8 Indifference**

We now introduce the general design goal of creating indifference towards certain features of the learning world. When an agent is indifferent about something, like the future state of an input
terminal signal, it has no incentive to control that thing. We first make this concept of indifference more mathematically precise, by defining indifference for nodes in planning world diagrams.

**Definition 9** (Indifference in planning worlds). Let $p$ be a planning world diagram and $X$ a node in that diagram. Now, construct a helper diagram $q$ by taking $p$ and writing a fresh input parameter $[D]$ above $X$. Then the planning world agent in $s$ is *indifferent* to node $X$ if and only if $\forall_D U_p = U_q$.

By this definition, the ITC planning world agent above is indifferent to all nodes $I_1, I_2, I_3, \cdots$. It is indifferent about the future state of the planning world input terminal signal.

Causal influence diagrams have the useful property that certain graphical features of the diagram are guaranteed to produce indifference. We define these graphical features as follows.

**Definition 10** (Being downstream of the policy). A node $X$ is downstream of the policy in a planning world diagram if there exists at least one directed path from a decision node to $X$.

**Definition 11** (Not on a path to value). A node $X$ is not on a path to value if there is no directed path that starts in a decision node, runs via $X$, and ends in a utility node.

We have the useful property that

*When a downstream node $X$ in a planning world is not on a path to value, the planning world agent is indifferent to $X$.*

This statement is almost a tautology if one interprets the planning world diagram as a specification of an agent simulator. Detailed proofs of such properties can be found in [ECL+21], [ECL+21] and [Hol20a] also show that a range of slightly different sub-types of indifference can be mathematically defined.

We could define indifference for learning world agents by using the reward function $R^\pi$ in section 6.3. But in the learning world diagram, the existence of such indifference will generally not be visible via the absence of paths to value. If it were, there would have been no need to construct a counterfactual planning world diagram.

### 8.1 Design for indifference

Now, suppose we want to define an agent policy for achieving the goal encoded in a reward function $R$, but we also want the agent to be indifferent to some downstream nodes $X$ and $Y$ in its learning world model $l$. We can do this as follows.

1. When not done already, extend $l$ by adding observational records.
2. Draw a planning world $p$ that projects the learning world agent environment into the planning world, converting the learning world policy nodes to decision nodes, and adding appropriate utility nodes with $R$.
3. Locate all paths to value in $p$ that go through the nodes $X$ and $Y$, and remove them by deleting or re-routing arrows. When doing this, it is a valid option to delete certain nodes entirely, or to draw extra nodes, just for the purpose of making re-routed arrows emerge from them.
4. Write an agent definition using $l$ and $p$. 

22
The construction of the ITC agent above follows this process to the letter, but we can also take shortcuts. It is not absolutely necessary to draw the $O_t^i$ records in the ITC agent learning world, or all $I_i$ nodes in its planning world. We might also draw the diagrams in figure 15.

There is always a way to edit a planning world to create indifference towards some nodes $X$ and $Y$. In the limit case, indifference is reliably created when we simply delete all utility nodes, but this will also break any connection between the reward function $R$ and the learning world agent policy. So the challenge when designing for indifference is to make choices which produce learning world behavior that is still as useful as possible, in the context of $R$.

9 Safety Engineering using Natural Language Text

Natural language is very powerful and versatile tool. Poets and songwriters often use it to create lines which are intentionally vague or loaded with double meaning. When using natural language for safety engineering, these broad possibilities for ambiguity turn into a liability. When writing or reading a safety engineering text, one always has to have a specific concern in the back of one’s mind. Does every sentence have a clear and unambiguous meaning?

As a design approach, counterfactual planning creates several tools for avoiding ambiguity in safety engineering texts.

1. We use diagrams to clearly define complex types of self-referencing and indirect representation in an agent design, types which are difficult to express in natural language.

2. To clarify the creation and interpretation of counterfactuals, section 2 introduced the concept of a world model, and the terminology of counterfactual worlds.

3. When defining and interpreting a machine learning agent, we make a distinction between the agent’s learning world and the planning worlds which are projected by its machine learning system. Safety analysis typically starts by considering the goals of the planning world agent, and the nature of its planning world. We also introduced the terminology of the people in the planning world, as opposed to the people in the learning world.

4. Section 8 defined indifference as an unambiguous term that we can apply to planning world agents.
9.1 Refining the ITC agent design using natural language

To show the above linguistic tools in action, we now refine the design of the ITC agent. Recall that the planning world ITC agent is indifferent about the future state of its input terminal signal. If the current planning world reward function rewards paperclip production, then the planning world agent will devote all of its resources to producing paperclips. It has nothing to gain by diverting resources from paperclip production to influence what happens to the input terminal signal. However, the above indifference applies to the input terminal signal only, the signal as modeled in the $I_t$ nodes of the planning world. The atoms that make up the input terminal are modeled in the planning world $X_t$ nodes, and these are still on the agent’s path to value. There are many ways in which the agent could use these atoms to produce more paperclips. For example, the terminal might be an attractive source of spare parts for the agent’s paperclip production sensors and actuators. Or it might serve as convenient source of scrap metal which can be turned into more paperclips.

We now translate the above failure mode story to a more general design goal. We want to keep the planning world agent from disassembling the input terminal to obtain the resource value of its parts. The obvious solution is to set up the planning world so that the agent always has a less costly way to obtain the same resources elsewhere. To make this more specific, we add the following constraints for the design of the planning world: the input terminal must be located far away from the agent’s paperclip factory, and the planning world agent has access to a steady supply of spare parts and scrap metal closer to its factory.

The above constraints imply that we want to shape the values of the parameters $x$ and $L^x$ of the planning world model in a specific way. However, we do not construct these parameters directly: they are created by the agent’s machine learning system, based on what is present in the learning world. So we need to apply the above constraints to the learning world instead, an count on them being projected into the planning world. To lower the risk that projection inaccuracies defeat our intentions, we can design the learning world measures used so that they clearly communicate their nature.

9.2 The people in the planning world

Counterfactual planning gives us the terminology to distinguish between two groups of people: the people in the learning world and the people in the planning world. If the learning world is our real world, then the learning world people are real people. The planning world people are always models of people, models created by the agent’s machine learning system.

In the AGI safety community, there has been some discussion about the potential problem that, in a truly superintelligent AGI agent, the models of the people in the planning world may get so accurate that agent designers would have moral obligations towards these virtual people. A further discussion of this problem is out of scope here.

Instead, we note that even in a non-AGI or human-level AGI agent, the people in the planning world may already be modeled accurately enough to create complex dynamics. Section 6 of [Hol20b] (also included in [Hol20a]) shows a detailed example of such dynamics, illustrated with simulator runs, where the people in an ITC type planning world end up physically attacking the agent, because they do not have a working input terminal. This creates complex and counter-intuitive effects back in the learning world. The vocabulary and viewpoint of counterfactual planning makes the dynamics discussed in [Hol20b] easier to describe and understand. In section 11.5.2 we will take a further look at the topic of conflict in the planning world.
10 Machine Learning Variants and Extensions

We now discuss how we can use the modeling tools introduced in section 4 to handle some common machine learning variants and extensions.

10.1 Pre-learned world models

Agents that use a pre-learned world model, without any online machine learning, can be modeled by an agent definition that uses $L = \mathcal{L}(o_0)$. We can then omit drawing any observational record nodes in the learning world.

10.2 Partial observation

Agent models with partial observation model the situation where the agent can only use its sensors to make partial observations of the state of its environment in each time step. Though agent models with full observation represent a useful limit case when doing safety analysis, realistic AGI agents in complex environments will have to rely on partial observation.

Partial observation is often modeled with non-graphical POMDP models. [EKKL19, EH19] has examples where partial observation is modeled graphically, by adding extra nodes and arrows to a causal influence diagram. We now discuss a way to model partial observation in our two-diagram framework, without adding any extra nodes or arrows.

The key step is to change the annotation above the planning world agent environment starting state $S_0$. Instead of writing $s$ above it, which models the full observation of the current learning world state, we write $[ES]$, where $ES = \mathcal{E}(o, s)$. In this setup, $P(S_{0,p} = s) = ES(s)$ is the machine learning system’s estimate of the probability that $s$ is the current state of the agent environment in the learning world.

The model parameter $\mathcal{E}$ encodes two things: how the agent’s stationary and movable sensors map the learning world states to limited and potentially noisy sensor readings, and how time series of readings are assembled together to build up a more complete picture of the learning world state.

To model learning from partial observation, $\mathcal{L}(o)$ must encode a similar creation and processing of sensor readings.

10.2.1 Reasonable learning based on partial observation

So far in our modeling approach, we have assumed that the data type of the planning world environment states $S_{t,p}$ is the same as that of the learning world environment states $S_{t,l}$. This has allowed us to define reasonable learning by writing $L \approx S$.

This assumption is unrealistic for partial observation based agents. These agents observe the learning world through a set of limited digital sensors, so they have no direct experience of the fundamental data type of the learning world they are in. Also, learning system designers typically design custom data types for representing planning world environment states and probability distributions over such states. These are designed to fit as much relevant detail as possible into a limited amount of storage space, without necessarily attempting to duplicate the data type of the learning world states, if that data type is even known at all.

To define reasonable learning in this more general case, we start by defining a function $sr(s)$ that
extracts a vector of sensor readings from a learning world agent environment state $s$. $sr(s)$ is a vector that either encodes all sensor readings that flow into the agent compute core in $s$, or at least the subset of sensor readings we want to reference when defining the planning world reward function $R$.

We then require that the designer of the agent’s machine learning system has implemented an equivalent function $srp(s)$ that extracts a vector of similar sensor readings from a planning world state value. A possible reasonableness criterion replacing $L ≈ S$ is then that, with the random variables defined by figure 16 and for every $s$, and $a$, we have that

$$P( sr(S_{0, lw}) ≈ srp(S_{0, pw}) ) = 1 \text{, and}$$
$$P( sr(S_{1, lw}) ≈ srp(S_{1, pw}) ) = 1 .$$

This criterion symbol grounds the vectors $srp(s)$, so that they stably project the $sr$ sensor readings that will be produced by different actions taken in the learning world. In this setup, the planning world reward function $R(s_t, a_t, s_{t+1})$ is designed to score planning world state transitions by first using $srp$ to extract projected sensor readings from $s_t$ and $s_{t+1}$, and then interpreting these readings.

### 10.2.2 Almost black box planning world models

Beyond using the $srp$ function, no further easy interpretation of the projected planning world agent environment state values may be possible. The learning system might produce planning worlds which are almost a black box.

### 10.2.3 Compute core self-knowledge based on partial observation

We now turn to the question of whether a planning world with a starting state constructed by $E(o, s)$ may contain assembled knowledge about the internals of the agent’s learning world compute core. The short answer is that the above reasonableness criterion will not prevent such knowledge from appearing. Whether it actually appears, and how correct a projection it will be, will depend on the details of the learning system.

If the planning world model is highly accurate, then it may accurately represent some details of the compute core hardware, like the details of the compute core I/O subsystem hardware which puts sensor readings into the input registers of the core. If so, this has certain safety implications, which we will explore in section Q.

### 10.2.4 The possibility of incorrect symbol grounding of actions

The planning world model may also include a representation of some of the compute core hardware that is present between the sensor input and action output registers. Such a representation might have
been assembled by \( \mathcal{E}(a, s) \) based on direct observations of internals of the core, or more indirectly by the agent reading its own compute core design documentation on the internet.

It is therefore possible to imagine an \( L \) where the compute core output signals which drive the planning world actuators are determined fully by the projected computations as performed by this projected hardware, not by the function argument \( a \) of \( L(s', s, a) \). However, such an \( L \) would violate the reasonableness criterion above. This is because in the learning world model, \( S(s', s, a) \) encodes the response of the agent environment to the actions \( a \), not the response of the environment to the actions of some projected compute core hardware that ended up in \( L \).

Now consider what would happen if we were to use a more limited reasonableness criterion, where we only use the observations \( (s', s, a) \) present so far in the observational record \( o \) to compare \( L \) and \( S \). It is usually possible to construct an \( L^- \) that scores very well on this limited criterion, even though it never uses the value of its argument \( a \). One option is to construct an \( L^- \) that drives the planning world actuators from the output registers of a projected compute core. Another option is to construct an \( L^- \) that simply encodes a giant lookup table which stores the \( s' \) for every \( s \) in the observational record. Though they may score perfectly on the limited reasonableness criterion, these examples will fail the full reasonableness criterion above, because the full criterion considers all combinations of \( s \) and \( a \), not just those that happen to be in the observational record.

The above argument shows that a learning system \( \mathcal{L} \) will have to rely on more than just the observational record, if it wants to produce a reasonable \( L \). Usually, the construction of the learning system will implement some form of Occam’s law: if the functions \( L_1 \) and \( L_2 \) are candidate predictors which perform equally well on the observational record, the candidate with the more compact function definition is preferred. If the observational record is large enough, and especially if random exploration is present in it, this preference will usually produce an \( L \) that correctly symbol grounds the planning world actuators to \( a \).

In the machine learning literature, this use of Occam’s law is also often framed as the desire to not over-fit the data, as the use of Solomonoff’s universal prior \([\text{Hut07}]\), or simply as the desire to store as much useful predictive information as possible within a limited amount of storage space.

### 10.3 Reinforcement Learning

The analytical framework of Reinforcement Learning (RL) \([\text{SB18}]\) classifies agent designs that use online machine learning into two main types, called model-free and model-based architectures. Hybrid architectures are also possible.

All the factual and the counterfactual agent definitions shown above can be classified as model-based reinforcement learning architectures. By implication, all counterfactual planners shown in this paper can be implemented in a natural way by taking an existing model-based reinforcement learning architecture and making certain modifications.

But this does not mean that counterfactual planning cannot be implemented using model-free or hybrid reinforcement learning systems. In theory, we can always create a counterfactual planner by training a reinforcement learner on the reward function \( P^\pi \) in section 6.3. In practice, this route may lead to completely impractical training times.

The more useful route, if one wants to implement a specific counterfactual planner by extending a model-free or hybrid architecture, is to make specific adaptations that seek to maintain a reasonable training time. For the counterfactual planner with safety interlocks in section 6, taking this route is very straightforward.
10.3.1 Reward signals

Reinforcement learning separates the agent environment into two distinct parts: the reward signal and the rest. A reinforcement learning agent can always observe the reward signal, but the rest of the environment may be only partially observable. The reasonableness criteria for reinforcement learning systems typically require that only the reward signal and the actions are symbol grounded. The use of the term reinforcement learning therefore often implies that the author is considering a black box machine learning approach.

We can read the reward function $R$ in our planning worlds as being a reward signal detector, as a mechanism that computes a reward signal value based on sensor readings.

Many reinforcement learning texts use agent models that define both a reward function and a reward signal. In some, the two are identical. Other texts treat them as fundamentally different: the reward signal provides only limited and maybe even distorted information about the true reward function, which defines the real goals we have for the agent. In both cases, the reinforcement learning agent is interpreted as a mechanism that learns the reward function, with various possible degrees of perfection.

10.4 Cooperative Inverse Reinforcement Learning

Cooperative Inverse Reinforcement Learning (CIRL) [HMRAD16] envisages an agent design where a machine learning system inside the agent uses the observed actions of a human in the agent’s environment to estimate the reward function $R^H = C(o, s)$ of that human. This $C$ implements a type of reward function learning, but in this case the human acts like a teacher who demonstrates desired outcomes, not as a teacher who just scores the outcomes of agent behavior via a reward signal. CIRL is an online system where the agent uses its latest estimate of $R^H$ as its own reward signal. The intended result is that the agent ends up helping the teacher to achieve the demonstrated goal while it is being demonstrated.

CIRL has been proposed as a possible AGI safety mechanism in [HMRAD16, HMDAR17, Rus19]. It can be combined with counterfactual planning based safety mechanisms by constructing planning worlds where $R = R^H$, or where $R^H$ is one of the terms in $R$.

11 Protecting the Compute Core

We now discuss the problem of protecting the compute core of a real world AI or AGI agent against intentional or unintentional tampering. Both factual and counterfactual planning agents can develop an incentive to tamper with their physical core, if no measures are taken to suppress it.

We first discuss the general problem of tampering, and then show how counterfactual planning can be used to make the problem of protecting the real world compute core more tractable.

11.1 Motivation of an agent to tamper with its core

Say that we build a real world agent with a planning world reward function $R$ which rewards paperclip production. We construct this $R$ as follows, so that it also works with mostly black box planning world models. Some distance from the real world agent compute core, in the location where we want the agent to produce the paperclips, we place a sensor that counts the paperclips being produced.
Every time step, this sensor sends a digital signal containing the production count to the compute core, where it lands in some input registers. We construct a function $\text{clip}_\text{sensor}_\text{signal}$ that extracts the (projected) values of these registers from planning world states, and then define the reward function as $R(s_t, a_t, s_{t+1}) = \text{clip}_\text{sensor}_\text{signal}(s_{t+1})$.

The above construction symbol-grounds the reward function to the sensor values that appear in the input registers of the real world compute core. This level of indirection makes the agent into an input register value optimizer, which is not always the same as being a paperclip production optimizer. If the agent’s machine learning system projects the real world into the planning world with a high enough accuracy, then the planning world agent can consider all of the following policies to maximize utility in its planning world:

1. Use the planning world actuators to make more paperclips.
2. Use the planning world actuators to modify the planning world paperclip counting sensor, so that it sends higher numbers to the input registers in the planning world compute core.
3. Use the planning world actuators to modify the planning world compute core, so that higher numbers are created directly in these input registers.

The second and third policies are unwanted: we interpret them as a form of tampering. The third policy is particularly unwanted, as it might damage other parts of the compute core as well, like any safety interlock software inside it. In fact, if the learning system projects the compute core in a reasonable way, then the planning world agent will be mostly indifferent to what happens to the atoms between the compute core input registers and output registers. It might move some of these atoms out of the way just to get at the input registers, leading to a compute core crash or worse in the real world.

The above two tampering policies might aim to set $\text{clip}_\text{sensor}_\text{signal}(s_{t+1})$ to some huge number like $10^{10000}$. This makes these policies very attractive, even if the planning world agent computes only a 1% chance that they succeed in achieving the intended outcome.

In the AGI safety community, forms of tampering which implant very high reward function values are often called wireheading [AOS+16], see [MSZ19] and [KUN+20] for example simulations. The $U_p > U_{max}$ safety interlock suppresses such wireheading, because it will stop the agent as soon as agent’s machine learning system projects a plausible option for wireheading into the planning world. However, we want to do more than just suppress wireheading by stopping the agent. We will now consider measures that actively lower the risk that the planning world agent will choose any tampering policy in the first place.

### 11.2 Bounding the upside of tampering

We can make the tampering policies above much less attractive by changing the reward function to $R(s_t, a_t, s_{t+1}) = \min(M, \text{clip}_\text{sensor}_\text{signal}(s_{t+1}))$. The $M$ is a constant, say $M = 5000$, that represents high estimate of the number of paperclips that we expect the agent to be able to produce, even if it drastically optimizes its production methods. The effect is that we bound the upside reward that can be achieved by the tampering policies: the expected planning world utility of tampering can never by higher than $B = \sum_{t=0}^{\infty} \gamma^t \ast M$.

By bounding the upside, we have changed the cost/benefit equation for the tampering policies. We have capped the benefit, but the cost of tampering, in lost opportunities for paperclip production when resources are being diverted to tampering, has remained the same. In some cases, this change alone will be sufficient to suppress tampering altogether.
This leaves the problem of choosing an $M$ that will be good for the entire lifetime of the agent. We can turn this into a more manageable problem by adding a counterfactual planning based input terminal which allows us to update $M$ as time goes on.

### 11.3 Safety zones

A further step to suppress tampering is to install extra physical sensors, of the type found in burglar alarms, to create two safety zones around the paperclip counting sensor and the compute core. In this setup, any physical object that enters a safety zone will trigger at least one zone sensor, causing a breach signal to be sent to the core. Say that the breach signal is 1 if a breach is in progress, 0 otherwise, and that these mechanics are projected fairly well into the planning world. We can then construct a reward function that penalizes the agent for causing a breach:

$$R(s_t, a_t, s_{t+1}) = \min(M, \text{clip~sensor~signal}(s_{t+1})) - \beta \ast B \ast \text{breach~signal}(s_{t+1})$$

When we use a $\beta > 1$, any detected breach that lasts only a single time unit will wipe out the maximum possible upside reward expected in any tampering policy. Now, say that the agent is considering a policy that aims to tamper without triggering any breach sensors, a policy that has a very promising 99% probability of success in the planning world. Then if we use $\beta = 200$, the agent will have no incentive to choose this policy.

To add some further design details, if the agent’s learning system uses exploration actions, then the generation of fully random exploration actions needs to be disabled whenever a breach is in progress. It is of course necessary to locate the breach sensors inside the safety zones they create. We also need to protect the data links that transport the breach and paperclip counting sensor data to the compute core. This could be done by using simple heartbeat protocol protected by strong encryption, of the type that would take astronomical resources to break.

The use of safety zones and bounding the upside was also discussed in [Hol20a]. As noted in [Hol20a], the effectiveness of these measures depends in part on the accuracy of the projections created by the agent’s learning system. There is a residual risk that inaccuracies in the projections create planning world policies that will end up damaging the compute core back in the real world. See [Hol20a] for a detailed example, and for a discussion of the methodological difficulties that arise when one wants to estimate the residual risk via simulations.

We now consider some additional options for protecting the core that were not covered in [Hol20a].

### 11.4 Use of a honeypot

A highly intelligent agent might find a cheap but effective way to fool the safety zone sensors, a way that was overlooked by the sensor designers. This may allow it to enter a safety zone without incurring a breach penalty. If the cheap way is not 100% reliable, we can manage this risk to some extent by setting $\beta$ to a very high value, but this creates its own problems. A very high $\beta$ creates an incentive for the agent to divert resources away from paperclip production to build all kinds of defenses around the safety zones. This is economically inefficient, and it might even be actively dangerous to innocent bystanders.

An alternative is to create a third honeypot safety zone that surrounds a honeypot button. We set up $R$ to calculate a reward $H$ for the agent pressing this button, a reward that is higher than $B$. We include a penalty for breaching the honeypot safety zone which is higher than $H$, but lower than the penalties for the other zones. In this setup, if the planning world agent finds a cheap but effective
way to fool the safety zone sensors, and under the assumption that it has limited resources, it will breach the honeypot safety zone first, and immediately press the button to collect the reward. We can then add a safety interlock which activates whenever the honeypot button is pressed in the real world. As the interlock is realized via counterfactual planning, the planning world agent has no motivation to disable the interlock before pressing the honeypot button.

Beyond initiating shutdown based on the real world honeypot button signal, a safety system may also monitor planning world metrics like

\[
\sum_{t=0}^{500} P(breach\_signal(S_{t,p}) = 1) + P(honeypot\_button\_signal(S_{t,p}) = 1)
\]

This metric measures possible detected and undetected safety zone breaches even before they happen. The safety system could initiate shutdown, or send out preliminary alarm signals to human oversight, when such metrics move over certain thresholds.

11.5 Use of white box planning world models

If we have a learning system that produces a white box planning world model, not a black box one as considered in section 10.2.2, then this creates some extra opportunities for using counterfactual planning to make the agent safer. To show this, we first give an example of a white box planning world model.

Say that we have a planning word where the agent environment starting state \( S_0 \) is initialized with the value \( ws = W(o,s) \), where \( ws \) is a long list of all projected physical objects in the agent’s environment. This list may have entries which describe individual elementary particles like electrons, but it may also have entries for more macroscopic objects like apples, paperclips, or transistors in a compute core. Each object is also annotated with information about its estimated position, motion vector, orientation, etc. Say that the planning world \( L \) implements a recognizable approximation of the laws of physics. The white box nature of the resulting planning world states then gives us some extra opportunities to protect the core.

11.5.1 Better breach detection

We can define a breach detection function \( breach(s_t) \) that detects breaches by examining the entire planning world state representation \( s_t \) to locate any new objects in a safety zone that should not be there. If we add this function in a reward function penalty term, this creates a welcome level of redundancy to the breach detection capabilities of real world physical sensors.

Note that it is still theoretically possible for the real world compute core safety zone to get breached without triggering \( breach(s_t) \). There may well exist a set of sensor inputs \( o, s \) that fool \( W(o,s) \) into constructing a \( ws \) that inaccurately projects the positions of many objects that exist in the learning world.

11.5.2 White box world state editing

The white box nature of the planning world also allows us to edit the list of physical objects \( ws \) to produce a different planning world starting state \( ws' = edit(ws) \). We may for example perform edits to add an extra, difficult to breach protective barrier around the compute core in \( ws' \). This saves the expense of building such a barrier in the real world.
World state editing can also be used to manage safety risks not related to the compute core. For example, we can consider the risk that the agent and the humans end up in a fight over resources, where the agent starts the fight because it expects to win. As far as the agent is concerned, the counterfactual planning world is the stage on which this fight will take place. We can make the planning world agent less willing to start a fight by editing the planning world starting state to give the humans in the planning world some powerful weapons, allies, or capabilities which are absent in the real world.

Editing the planning world to make the planning world humans stronger could be considered for most agent designs in this paper. But counter-intuitively, based on the mechanics shown in section 6 of [Hol20b], it may make a real world ITC agent more dangerous.

We can also make it more likely that the humans will win any fight in the real world by editing certain weapons that the humans have out of the planning world state, making these weapons essentially invisible to the agent. This approach can more easily be combined with the ITC agent design. In fact, we can interpret the emergency stop button on an ITC agent input terminal as an example of such an invisible weapon, though it is constructed without using white box state editing.

12 Recursive Self-improvement and the Sub-agent Problem

If its compute core is protected, an AGI agent can no longer improve its intelligence by modifying its own core. However, the agent may be capable of building a second agent, a sub-agent with a more powerful machine reasoning system, so that the combination has a higher aggregate intelligence. So at a broader system level, the mechanisms we envisage to protect the core do not eliminate the risk of an AGI agent undergoing an intelligence explosion via recursive self-improvement.

The good news is that the power-based safety interlock $U_p > U_{max}$ will measure the combined power and intelligence of the SI agent and its sub-agents together. If the projected combination is too powerful or intelligent, then the interlock will shut the main agent down even before it can finish building the first sub-agent. In the more risky case, the combination will only pass the $U_{max}$ threshold after the sub-agent has been started. The interlock will then still stop the main agent, but it won’t automatically stop the sub-agent.

If the SI agent builds a sub-agent, it will do so to improve its score on its planning world reward function $R$. So the sub-agent is unlikely to have a copy of the main agent safety interlocks inside. Adding such interlocks would not be optimal towards the goal of maximizing $R$ in the planning world.

We therefore have a sub-agent problem, the same sub-agent stopping problem that has been identified in papers on corrigibility and indifference methods [SFAY15, Hol19, Hol20a]. The general problem of designing effective measures to stop any possible sub-agents too in an emergency is still unsolved [Hol20a].

13 A Counterfactual Oracle

An AI oracle is a system which makes predictions to answer questions about the future. Certain risks exist when an AI oracle is programmed to give the answer which is most likely to become true. If the oracle has a lot of freedom in how to phrase the answer, it may well choose a phrasing that turns the answer into a self-fulfilling prophecy [AOT17]. This is generally not what we want. If
we ask the oracle to identify potential future risks, then we want predictions which will turn into self-negating prophecies.

A counterfactual oracle \cite{AO17} is one that lacks the incentive to make manipulative, self-fulfilling prophecies. The counterfactual oracle design in \cite{AO17} works by having a subsystem that occasionally produces an erasure event where the answer picked by the oracle is not shown to its users. This mechanism is then leveraged to make the oracle always compute the answer which best predicts the future under the assumption that nobody ever reads the answer. In \cite{EKKL19}, this design is graphically modeled with a twin diagram.

Below, we introduce a slightly different counterfactual oracle design, based on counterfactual planning. In this design, the erasure events only happen in the planning world.

### 13.1 A counterfactual planning based oracle

We design our counterfactual oracle as an agent which has a very limited repertoire of actions: every possible action \( a \) consists of displaying the answer text \( a \) on a computer screen. This allows us to use the \( l \) in figure 6 as the oracle’s learning world.

To simplify the presentation, we assume that all questions asked are about the state of the world two time steps in the future. We construct the planning world \( co \) in figure 17 where the people in the planning world always see a blank screen, as produced by the action \( a_{\text{blank}} \).

![Figure 17: Planning world of the counterfactual oracle.](image)

**CO** The counterfactual planning oracle has the learning world \( l \), where \( \pi(o, s) = \pi^*_c(s) \), with \( \pi^*_c \) defined by the planning world \( co \), where \( L = L(o) \) and \( R(a_0, s_2) = \text{qual}(a_0, \text{ques}(s)(s_2)) \).

The functions \( \text{qual} \) and \( \text{ques} \) above are defined as follows. The value of \( \text{ques}(s) \) is the question asked to the learning world oracle in the environment state \( s \). We model this question as a function that reads a world state \( s_2 \) to extract some observable properties \( p \) from it: \( p = \text{ques}(s)(s_2) \). The value of \( \text{qual}(a, p) \) is a numeric measure of the quality of the answer \( a \) as a prediction of these observable properties \( p \).

The CO design intends to deliver answers which are less manipulative than those of a factual oracle. But as noted in \cite{AO17}, if the people in the planning world routinely consult a second oracle when faced with a blank screen from the first one, this will make the interpretation and use of the oracle’s answers more difficult for the people in the learning world.
13.2 Role of the machine learning system

The machine learning system $L$ of the above counterfactual planning oracle is faced with a particular challenge. $L = \mathcal{L}(o)$ must make predictions for a planning world where all actions are $a_{\text{blank}}$, but these actions will never occur naturally in the learning world observational record $o$.

The counterfactual oracle design in [AO17] solves this challenge by introducing random erasure events in the learning world. In our framework, we can interpret these as a special type of exploration action.

A more sophisticated learning system design may consider that different questions are being asked at different times. If $q_t$ is the current question being asked in the learning world, then there will likely be earlier entries in the observational record where the people got an answer to a different question, an answer which did not reveal any information about the answer to $q_t$. These entries could be used to predict what will happen when the planning world people see $a_{\text{blank}}$, which is equally uninformative about answering $q_t$.

14 Conclusions

We have presented counterfactual planning as a general design approach for creating a range of AGI safety mechanisms.

Among the range of AGI safety mechanisms developed in this paper, we included an interlock that explicitly aims to limit the power of the agent. We believe that the design goal of robustly limiting AGI agent power is currently somewhat under-explored in the AGI safety community.

14.1 Tractability and models of machine learning

It is somewhat surprising how the problem of designing an AGI emergency stop button, and identifying its failure modes, becomes much more tractable when using the vantage point of counterfactual planning. To explain this surprising tractability, we perhaps need to examine how other modeling systems make stop buttons look intractable instead.

The standard approach for measuring the intelligence of an agent, and the quality of its machine learning system, is to consider how close the agent will get to achieving the maximum utility possible for a reward function. The implied vantage point hides the possibilities we exploited in the design of the SI agent.

In counterfactual planning, we have defined the reasonableness of a machine learning system by $L \approx S$, a metric which does not reference any reward function. By doing this, we decoupled the concepts of ‘optimal learning’ and ‘optimal economic behavior’ to a greater degree than is usually done, and this is exactly what makes certain solutions visible. The annotations of our two-diagram agent models also clarify that we should not generally interpret the machine learning system inside an AGI agent as one which is constructed to ‘learn everything’. The purpose of a reasonable machine learning system is to approximate $S$ only, to project only the learning world agent environment into the planning world.
14.2 Separating the AGI safety problem into sub-problems

There is a tendency, both in technology and in policy making, to search for perfect solutions that consist of no more than three easy steps. In the still-young field of AGI safety engineering, the dream that new technical of philosophical breakthroughs might produce such perfect solutions is not entirely dead.

Counterfactual planning provides a vantage point which makes several safety problems more tractable. However, in our experience, very soon after using counterfactual planning to cleanly remove a specific failure mode or unwanted agent incentive, the wandering eye is drawn to the existence of further less likely failure modes, and residual incentives produced via indirect means.

We interpret this as a feature, not a bug. Counterfactual planning does not offer a three-step solution to AGI safety, but it adds further illumination to the route of taking many steps which all drive residual risk downwards, where each step is explicitly concerned with identifying and managing a specific sub-problem only.

In the sections of this paper, we have identified and discussed many such sub-problems, specifically those which are made more tractable by counterfactual planning. We hope that the graphical notation and terminology developed here will make it easier to write single-topic AGI safety papers which isolate and further explore single sub-problems.

14.3 Modeling and comparing AGI safety frameworks

The 2019 paper [EKKL19] introduced the research agenda or modeling and comparing the most promising AGI safety frameworks using causal influence diagrams. We count indifference methods as used in [SFAY15, Arm15, Hol19, Hol20b] as being among these most promising frameworks.

In the second half of 2019, we therefore started considering how causal influence diagrams might be used to graphically model these indifference methods. Solving this modeling problem turned out to be much more difficult than initially expected. For example, though the causal influence diagrams in section 7 of [Hol20b] show indifference methods in action, they do not show the use of indifference methods in the underlying graph structure.

Our search for a clear notation did not proceed in a straight line: we developed and abandoned several candidate graphical notations along the way. The two key steps in creating the winning candidate were to abandon the use of balancing terms to construct indifference, and to model the agent using two diagrams, not one. The choice of the winner was mostly driven by the observation that we could further generalize its two diagram notation, to model and reason about a much broader range of safety mechanisms. This observation motivated us to develop and name counterfactual planning as a full design methodology.

For the agenda of modeling AGI safety frameworks with causal influence diagrams, an obvious next step would be to model additional proposals in the literature as one-diagram or two-diagram planners, where we expect that any two-diagram model will more explicitly show the detailed role of the agent’s machine learning system. The hope is that these graphical models will make it easier to understand, combine, and generalize the different moving parts of a broad range of AGI safety proposals. In this context, it is promising that the diagrams of the STH, SI, and ITC agents above make it trivially obvious to see how these three different safety mechanisms could all be combined in a single agent.
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37
A Random Variables and the $P$ Notation

In this appendix we define a version of probability theory, where probability theory is a mechanism which assigns truth values to certain mathematical sentences that contain random variables and the $P(\cdot \cdot \cdot)$ notation. We define this mechanism by using concepts and notation from two other mathematical fields: set theory and the algebra of deterministic typed functions.

Our definitions are based on the version of probability theory developed by Kolmogorov in the 1930s, but we omit any use of measure theory, by using a finite sample space $\Omega$ only. Measure theory is a somewhat inaccessible branch of mathematics, which can be used to construct random variables that model infinite-precision observations. However, we do not need such random variables here, as infinite-precision sensors that might used by machine learning agents do not exist in the real world.

**Definition 12** (Sample space). We posit the existence of a very large but finite set $\Omega$ called a sample space. Each element of this set is called an event or sample point. We further posit that there is a function $P$ of type $\Omega \to [0, 1]$ with $[0, 1]$ the interval of rational numbers from 0 to 1 inclusive, and that $\sum_{\omega \in \Omega} P(\omega) = 1$.

**Definition 13** (Random variable). A random variable named $X$ is a function $X$ of type $\Omega \to \text{Type of } X$, where $\text{Type of } X$ is a data type.

We use a random variable $X$ to represent a single observation of a phenomenon which has been posited to exist in some world. The observation is represented as a value of the data type $\text{Type of } X$. Many statistics texts use the terminology the domain of $X$ where we write $\text{Type of } X$, but other texts use the range of $X$.

**Definition 14** ($P$ notation). For any mathematical expression $E$ that contains some random variables, we define that $E(\omega)$ is the mathematical expression that we get by replacing each random variable $X$ with the function invocation $X(\omega)$. We define $\{ \omega \in \Omega | E(\omega) \}$ as the set of all values $\omega \in \Omega$ for which $E(\omega)$ is true. We define that $P(E)$ is a shorthand notation for the expression $\sum_{\omega \in \{ \omega \in \Omega | E(\omega) \}} P(\omega)$.

We now define two more specialized shorthand notations.

**Definition 15** (Conditional probability). For mathematical expressions $E$ and $C$, we define that $P(E|C)$ is a shorthand for $P(E, C)/P(C)$ where the comma is read as the boolean and operator.

**Definition 16** (Expected value). For any expression $X$ where $X(\omega)$ has the numeric type $T$, the expected value $\mathbb{E}(X)$ is a shorthand for $\sum_{x \in T} x P(X = x)$, and $\mathbb{E}(X|C)$ is a shorthand for $\sum_{x \in T} x P(X = x|C)$.

A.1 Probability theory as a system of learning from observations

In many discussions of machine learning and rational reasoning, probability theory is treated as an obviously correct epistemology, an obviously correct system of learning about the world. This is often expressed by stating that learning from observations can or must use Bayes’ law. In the AGI community, there has been a lot of discussion about whether any future AGI-level machine reasoning system might, unavoidably will, or definitely should apply such probability theory related laws.

In section 4 we defined reasonable machine learning by the constraint that $L = \mathcal{L}(o) \approx S$. Any requirement that $\mathcal{L}$ must use a particular law or principle of epistemology when interpreting the observational record $o$ would apply a further reasonableness constraint to the output of $\mathcal{L}(o)$. 

38
Such further reasonableness constraints can be valuable, because of the problem of exhaustive testing. If the agent’s environment is complex enough, exhaustive testing to prove \( L \approx S \) for all possible function arguments \( o \) and \((s', s, a)\) becomes impossible. There will always be combinations left which have not yet been tested. Therefore, a proof that \( \mathcal{L} \) satisfies or approximates a further reasonableness constraint may increase our confidence in the safety or effectiveness of the learning system.