The MacGyver Test - A Framework for Evaluating Machine Resourcefulness and Creative Problem Solving

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Abstract

Current measures of machine intelligence are either difficult to evaluate or lack the ability to test a robot’s problem-solving capacity in open worlds. We propose a novel evaluation framework based on the formal notion of MacGyver Test which provides a practical way for assessing the resilience and resourcefulness of artificial agents.

1 Introduction

Consider a situation when your only suit is covered in lint and you do not own a lint remover. Being resourceful, you reason that a roll of duct tape might be a good substitute. You then solve the problem of lint removal by peeling a full turn’s worth of tape and re-attaching it backwards onto the roll to expose the sticky side all around the roll. By rolling it over your suit, you can now pick up all the lint. This type of everyday creativity and resourcefulness is a hallmark of human intelligence and best embodied in the 1980s television series MacGyver which featured a clever secret service agent who used common objects around him like paper clips and rubber bands in inventive ways to escape difficult life-or-death situations.

Yet, current proposals for tests of machine intelligence do not measure abilities like resourcefulness or creativity, even though this is exactly what is needed for artificial agents such as space-exploration robots, search-and-rescue agents, or even home and elder-care helpers to be more robust, resilient, and ultimately autonomous.

In this paper we thus propose an evaluation framework for machine intelligence and capability consisting of practical tests for inventiveness, resourcefulness, and resilience. Specifically, we introduce the notion of MacGyver Test (MT) as a practical alternative to the Turing Test intended to advance research.

2 Background: Turing Test and its Progeny

Alan Turing asked whether machines could produce observable behavior (e.g., natural language) that we (humans) would say required thought in people [Turing, 1950]. He suggested that if an interrogator was unable to tell, after having a long free-flowing conversation with a machine whether she was dealing with a machine or a person, then we can conclude that the machine was “thinking”. Turing did not intend for this to be a test, but rather a prediction of sorts [Cooper and Van Leeuwen, 2013]. Nevertheless, since Turing, others have developed tests for machine intelligence that were variations of the so-called Turing Test to address a common criticism that it was easy to deceive the interrogator.

Levesque et al. designed a reading comprehension test, entitled the Winograd Schema Challenge, in which the agent is presented a question having some ambiguity in the referent of a pronoun or possessive adjective. The question asks to determine the referent of this ambiguous pronoun or possessive adjective, by selecting one of two choices [Levesque et al., 2012]. Feigenbaum proposed a variation of the Turing Test in which a machine can be tested against a team of subject matter specialists through natural language conversation [Feigenbaum, 2003]. Other tests attempted to study a machine’s ability to produce creative artifacts and solve novel problems [Boden, 2010; Bringsjord et al., 2001; Bringsjord and Sen, 2016; Riedl, 2014].

Extending capabilities beyond linguistic and creative, Harnad’s Total Turing Test (T3) suggested that the range of capabilities must be expanded to a full set of robotic capabilities found in embodied systems [Harnad, 1991]. Schweizer extended the T3 to incorporate species evolution and development over time and proposed the Truly Total Turing Test (T4) to test not only individual cognitive systems but whether as a species the candidate cognitive architecture in question is capable of long-term evolutionary achievement [Schweizer, 2012].

Finding that the Turing Test and its above-mentioned variants were not helping guide research and development, many proposed a task-based approach. Specific task-based goals were designed couched as toy problems that were representative of a real-world task [Cohen, 2005]. The research communities benefited greatly from this approach and focused their efforts towards specific machine capabilities like object recognition, automatic scheduling and planning, scene under-
standing, localization and mapping, and even game-playing. Many public competitions and challenges emerged that tested the machine’s performance in applying these capabilities—from image recognition contests and machine learning contests. Some of these competitions even tested embodiment and robotic capacities, while combining multiple tasks. For example, the DARPA Robotics Challenge tested a robot’s ability to conduct tasks relevant to remote operation including turning valves, using a tool to break through a concrete panel, opening doors, remove debris blocking entryways.

Unfortunately, the Turing Test variants as well as the task-based challenges are not sufficient as true measures of autonomy in the real-world. Autonomy requires a multi-modal ability and an integrated embodied system to interact with the environment, and achieve goals while solving open-world problems with the limited resources available. None of these tests are interested in measuring this sort of intelligence and capability, the sort that is most relevant from a practical standpoint.

3 The MacGyver Evaluation Framework

The proposed evaluation framework, based on the idea of MacGyver-esque creativity, is intended to answer the question whether embodied machines can generate, execute and learn strategies for identifying and solving seemingly-unsolvable real-world problems. The idea is to present an agent with a problem that is unsolvable with the agent’s initial knowledge and observing the agent’s problem solving processes to estimate the probability that the agent is being creative: if the agent can think outside of its current context, take some exploratory actions, and incorporate relevant environmental cues and learned knowledge to make the problem tractable (or at least computable) then the agent has the general ability to solve open-world problems more effectively.

This type of problem solving framework is typically used in the area of automated planning for describing various sorts of problems and solution plans and is naturally suited for defining a MacGyver-esque problem and a creative solution strategy. We are now ready to formalize various notions of the MacGyver evaluation framework.

3.1 Preliminaries - Classical Planning

We define $\mathcal{L}$ to be a first order language with predicates $p(t_1, \ldots, t_n)$ and their negations $\neg p(t_1, \ldots, t_n)$, where $t_i$ represents terms that can be variables or constants. A predicate is ground if and only if all of its terms are constants.

A classical planning problem is a triple $\mathcal{P} = (\Sigma, S_0, g)$, where $S_0$ is the initial state and $g$ is the goal state. A plan $\pi$ is any sequence of actions and a plan $\pi^*$ is a solution to the planning problem if $g \subseteq \gamma(s_0, \pi)$. We also consider the notion of state reachability and the set of all successor states $\Gamma_i(s)$, which defines the set of states reachable from $s$.

3.2 A MacGyver Problem

To formalize a MacGyver Problem (MGP), we define a universe and then a world within this universe. The world describes the full set of abilities of an agent and includes those abilities that the agent knows about and those of which it is unaware. We can then define an agent subdomain as representing a proper subset of the world that is within the awareness of the agent. An MGP then becomes a planning problem defined in the world, but outside the agent’s current subdomain.

Definition 1 (Universe). We first define a Universe $\mathcal{U} = (S, A, \gamma)$ as a classical planning domain representing all aspects of the physical world perceivable and actionable by any and all agents, regardless of capabilities. This includes all the allowable states, actions and transitions in the physical universe.

Definition 2 (World). We define a world $\mathcal{W}^t = (S^t, A^t, \gamma^t)$ as a portion of the Universe $\mathcal{U}$ corresponding to those aspects that are perceivable and actionable by a particular species $t$ of agent. Each agent species $t \in T$ has a particular set of sensors and actuators allowing agents in that species to perceive a proper subset of states, actions or transition functions. Thus, a world can be defined as follows:

$\mathcal{W}^t = \{(S^t, A^t, \gamma^t) \mid (\forall i \in [1, t] \exists (S_i^t \subseteq S^t) \land (A_i^t \subseteq A^t) \land (\gamma_i^t \subseteq \gamma^t)) \land \neg((S_i^t = S^t) \land (A_i^t = A^t) \land (\gamma_i^t = \gamma^t))\}$

Definition 3 (Agent Subdomain). We next define an agent $\Sigma^t_i = (S_i^t, A_i^t, \gamma_i^t)$ of type $i$, as a planning subdomain corresponding to the agent’s perception and action within its world $\mathcal{W}^t$. In other words, the agent is not fully aware of all of its capabilities at all times, and the agent domain $\Sigma^t_i$ corresponds to the portion of the world that the agent is perceiving and acting at time $i$.

$\Sigma^t_i = \{(S_i^t, A_i^t, \gamma_i^t) \mid (\forall i \in [1, t] \exists (S_i^t \subseteq S^t) \land (A_i^t \subseteq A^t) \land (\gamma_i^t \subseteq \gamma^t)) \land \neg((S_i^t = S^t) \land (A_i^t = A^t) \land (\gamma_i^t = \gamma^t))\}$

Definition 4 (MacGyver Problem). We define a MacGyver Problem (MGP) with respect to an agent $t$, as a planning problem in the agent’s world $\mathcal{W}^t$ that has a goal state $g$ that is currently unreachable by the agent. Formally, an MGP $\mathcal{P}_M = (\mathcal{W}^t, s_0, g)$, where:

- $s_0 \in S_0^t$ is the initial state of the agent
- $g$ is a set of ground predicates
- $S_g = \{s \in S \mid g \subseteq s\}$

Where $g \subseteq s', \forall s' \in \Gamma_{\mathcal{W}^t}(s_0) \setminus \Gamma_{\Sigma^t_i}(s_0)$

It naturally follows that in the context of a world $\mathcal{W}^t$, the MGP $\mathcal{P}_M$ is a classical planning problem which from the agent’s current perspective is unsolvable. We can reformulate the MGP as a language recognition problem to be able to do a brief complexity analysis.

\footnote{Note that the proposed MT is a subset of Harnad’s T3, but instead of requiring robots to do “everything real people do”, MT is focused on requiring robots to exhibit resourcefulness and resilience. MT is also a subset of Schweizer’s T4 which expands T3 with the notion of species-level intelligence.}
Definition 5 (MGP-EXISTENCE). Given a set of statements $D$ of planning problems, let MGP-EXISTENCE$(D)$ be the set of all statements $P \in D$ such that $P$ represents a MacGyver Problem $P_M$, without any syntactical restrictions.

Theorem 1 MGP-EXISTENCE is decidable.

Proof. The proof is simple. The number of possible states in the agent’s subdomain $\Sigma^t_i$ and the agent’s world $\mathbb{W}^t$ are finite. So, it is possible to do a brute-force search to see whether a solution exists in the agent’s world but not in the agent’s initial domain. □

Theorem 2 MGP-EXISTENCE is EXPSPACE-complete.

Proof. (Membership) An MGP amounts to looking to see if the problem is a solvable problem in the agent-domain. Upon concluding it is not solvable, the problem then becomes one of determining if it is a solvable problem in the world corresponding to the agent’s species. Each of these problems are PLAN-EXISTENCE problems, which are in EXPSPACE for the unrestricted case [Gallab et al., 2004]. Thus, MGP-EXISTENCE is in EXPSPACE.

(Hardness) We can reduce the classical planning problem $P(\Sigma, s_0, g)$ to an MGP (PLAN-EXISTENCE $\leq^p_m$ MGP-EXISTENCE), by defining a new world $\mathbb{W}$. To define a new world, we extend the classical domain by one state, defining the new state as a goal state, and adding actions and transitions from every state to the new goal state. We also set the agent domain to be the same as the classical planning domain. Now, $P(\Sigma, s_0, g) \in$ PLAN-EXISTENCE iff $P(\mathbb{W}, s_0, g) \in$ MGP-EXISTENCE for agent with domain $\Sigma$. Thus, MGP-EXISTENCE is EXPSPACE-hard. □

3.3 Solving a MacGyver Problem

From Theorems 1 and 2 we know that, while possible, it is intractable for an agent to know whether a given problem is an MGP. From an agent’s perspective, solving an MGP is like solving any planning problem with the additional requirement to sense or learn some previously unknown state, transition function or action. Specifically, solving an MGP will involve performing some actions in the environment, making observations, extending and contracting the agent’s subdomain and exploring different contexts.

Solution Strategies

Definition 6 (Agent Domain Modification). A domain modification $\Sigma^t_j$ involves either a domain extension or a domain contraction. A domain extension $\Sigma^t_j$ of an agent is an Agent-subdomain at time $j$ that is in the agent’s world $\mathbb{W}^t$ but not in the agent’s subdomain $\Sigma^t_i$ in the previous time $i$, such that $\Sigma^t_i \subseteq \Sigma^t_j$. The agent extends its subdomain through sensing and perceiving its environment and its own self - e.g., the agent can extend its domain by making an observation, receiving advice or an instruction or performing introspection. Formally:

$$\Sigma^t_j = \{(S^t_j, A^t_j, \gamma^t_j) \mid (S^t_j \subset S^t \setminus S^t_i) \land (A^t_j \subset A^t \setminus A^t_i) \land (\gamma^t_j \subset \gamma^t \setminus \gamma^t_i)\}$$

1 In the interest of brevity we will only consider domain extensions for now.

The agent subdomain that results from a domain extension is $\Sigma^t_j = \Sigma^t_i \cup \Sigma^t_j$

A domain modification set $\Delta^t_j = \{\Sigma^t_1, \Sigma^t_2, \ldots, \Sigma^t_n\}$ is a set of $n$ domain modifications on subdomain $\Sigma^t_i$. Let $\Sigma^t_j$ be the subdomain resulting from applying $\Delta^t_j$ on $\Sigma^t_i$.

Definition 7 (Strategy and Domain-Modifying Strategy). A strategy is a tuple $\omega = (\pi, \Delta)$ of a plan $\pi$ and a set $\Delta$ of domain modifications. A domain-modifying strategy $\omega^C$ involves at least one domain modification, i.e., $\Delta \neq \emptyset$.

Definition 8 (Context). A context is a tuple $\mathcal{C}_i = (\Sigma^t_i, s_i)$ representing the agent’s subdomain and state at time $i$.

We are now ready to define an insightful strategy as a set of actions and domain modifications that the agent needs to perform to allow for the goal state of the problem to be reachable by the agent.

Definition 9 (Insightful Strategy). Let $\mathcal{C}_i = (\Sigma^t_i, s_0)$ be the agent’s current context. Let $P_M = (\mathbb{W}, g_0, g)$ be an MGP for the agent in this context. An insightful strategy is a domain-modifying strategy $\omega^C = (\pi, \Delta^C)$ which when applied in $\mathcal{C}_i$ results in a context $\mathcal{C}_j = (\Sigma^t_j, s_j)$, where $\Sigma^t_j = \Sigma^t_i$ such that $g \subseteq s'$, $\forall s' \in \tilde{\Gamma}^t_j(s_j)$.

Formalizing the insightful strategy in this way is somewhat analogous to the moment of insight that is reached when a problem becomes tractable (or in our definition computable) or when solution plan becomes feasible. Specifically, solving a problem involves some amount of creative exploration and domain extensions and contractions until the point when the agent has all the information it needs within its subdomain to solve the problem as a classical planning problem, and does not need any further domain extensions. We can alternatively define an insightful strategy in terms of when the goal state is not only reachable, but a solution can be discovered in polynomial time. We will next review simple toy examples to illustrate the concepts discussed thus far.

4 Operationalizing a MacGyver Problem

We will consider two examples that will help operationalize the formalism presented thus far. The first is a modification of the popular Blocks World planning problem. The second is a more practical task of tightening screws, however, with the caveat that certain common tools are unavailable and the problem solver must improvise. We specifically discuss various capabilities that an agent must possess in order to overcome the challenges posed by the examples.

4.1 Toy Example: Block-and-Towel World

Consider an agent tasked with moving a block from one location to another which the agent will not be able to execute without first discovering some new domain information. Let the agent subdomain $\Sigma$ consist of a set of locations $l = \{L_1, L_2, L_3\}$, two objects $o = \{T, B\}$ a towel and a block, and a function $locationOf : o \to l$ representing the location of object $o$. Suppose the agent is aware of the following predicates and their negations:

- $at(o, l)$: an object $o$ is at location $l$
• near(l): the agent is near location l
• touching(o): the agent is touching object o
• holding(o): the agent is holding the object o

We define a set of actions A in the agent domain as follows:
• reach(o, l): Move the robot arm to near the object o
  precond: {at(o, l)}
effect: {near(l)}
• grasp(o, l): Grasp object o at l
  precond: {near(l), at(o, l)}
effect: {touching(o)}
• lift(o, l): Lift object o from l
  precond: {holding(o), ¬at(o, l), ¬near(l)}
effect: {holding(o), ¬at(o, l), ¬near(l)}
• carryTo(o, l): Carry object o to l
  precond: {holding(o)}
effect: {¬holding(o), at(o, l)}
• release(o, l): Release object o at l
  precond: {touching(o), at(o, l)}
effect: {¬touching(o), at(o, l)}

Given an agent domain Σ, and a start state s_0 as defined below, we can define the agent context C = (Σ, s_0) as a tuple with the agent domain and the start state.

s_0 = {at(T, L1), at(B, L2), ¬holding(T), ¬holding(B), ¬near(L1), ¬near(L2), ¬near(L3), ¬touching(T), ¬touching(B), locationOf(B) = L2, locationOf(T) = L1}

Consider a simple planning problem for the Block-and-Towel World in which the agent must move the block B from location L2 to L3. The agent could execute a simple plan as follows to solve the problem:

π_1 = {reach(B, locationOf(B)), grasp(B, locationOf(B)), lift(B, locationOf(B)), carryTo(B, L3), release(B, L3)}

During the course of the plan, the agent touches and holds the block as it moves it from location L2 to L3. Using a similar plan, the agent could move the towel to any location, as well.

Now, consider a more difficult planning problem in which the agent is asked to move the block from L2 to L3 without touching it. Given the constraints imposed by the problem, the goal state, is not reachable and the agent must discover an alternative way to move the block. To do so, the agent must uncover states in the world that were previously not in its subdomain Σ. For example, the agent may learn that by moving the towel to location L2, the towel “covers” the block, so it might discover a new predicate covered(o1, o2) that would prevent it from touching the block. The agent may also uncover a new action push(o, l1, l2) which would allow it to push the object along the surface. To uncover new predicates and actions, the agent may have to execute an insightful strategy ω. Once the agent’s domain has been extended, the problem becomes a standard planning problem for which the agent can discover a solution plan for covering the block with the towel and then pushing both the towel and the block from location L2 to L3. In order to autonomously resolve this problem, the agent must be able to recognize when it is stuck, discover new insights, and build new plans. Additionally, the agent must be able to actually execute this operation in the real-world. That is, the agent must have suitable robotic sensory and action mechanisms to locate and grasp and manipulate the objects.

4.2 Practical Example: Makeshift Screwdriver

Consider the practical example of attaching or fastening things together, a critical task in many domains, which, depending on the situation, can require resilience to unexpected events and resourcefulness in finding solutions. Suppose an agent must attach two blocks from a set of blocks b = {B1, B2}. In order to do so, the agent has a toolbox containing a set of tools t = {screwdriver, plier, hammer} and a set of fasteners f = {screw, nail}. In addition, there are other objects in the agent’s environment o = {towel, coin, mug, ducttape}. Assume the agent can sense the following relations (i.e., predicates and their negations) with respect to the objects:

• isAvailable(t): tool t is available to use
• fastenWith(t, f): tool t is designed for fastener f
• grabWith(t): tool t is designed to grab a fastener f
• isHolding(t): agent is holding tool t
• isReachable(t, f): tool t can reach fastener f
• isCoupled(t, f): tool t is coupled to fastener f
• isAttachedTo(f, b1, b2): fastener f is attached to or inserted into blocks b1 and b2
• isSecured(f, b1, b2): fastener f is tightly secured into blocks b1 and b2.

We can also define a set of actions in the agent subdomain as follows:

• select(t, f): select/grasp a tool t to use with fastener f
  precond: {isAvailable(t), fastenWith(t, f)}
effect: {isHolding(t)}
• grab(t, f): Grab a fastener f with tool t.
  precond: {isHolding(t), grabWith(t)}
effect: {isCoupled(t, f)}
• placeAndAlign(f, b1, b2): Place and align fastener f, and blocks b1 and b2
  effect: {isAttachedTo(f, b1, b2)}
• reachAndEngage(t, f): Reach and engage the tool t with fastener f
  precond: {isHolding(t), fastenWith(t, f), isReachable(t, f)}
effect: {isCoupled(t, f)}
• install(f, t, b1, b2): Install the fastener f with tool t
  precond: {isCoupled(t, f), isAttachedTo(f, b1, b2)}
effect: {isSecured(f, b1, b2)}

Now suppose a screw has been loosely inserted into two blocks (isAttachedTo(screw, B1, B2)) and needs

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Given space limitations, we have not presented the entire domain represented by this example. Nevertheless, our analysis of the MacGyver-esque properties should still hold.
to be tightened (\texttt{isSecured(screw, B1, B2)}). Tightening a screw would be quite straightforward by performing actions \texttt{select()}, \texttt{reachAndEngage()}, \texttt{install()}. But for some reason the screwdriver has gone missing (\texttt{isAvailable(screwdriver)}).

This is a MacGyver problem because there is no way for the agent, given its current subdomain of knowledge, to tighten the screw as the goal state of \texttt{isSecured(screw, B1, B2)} is unreachable from the agent’s current context. Hence, the agent must extend its domain. One approach is to consider one of the non-tool objects, e.g., a coin could be used as a screwdriver as well, while a mug or towel might not.

The agent must be able to switch around variables in its existing knowledge to expose previously unknown capabilities of tools. For example, by switching \texttt{grab(t, f)} to \texttt{grab(t, o)} the agent can now explore the possibility of grabbing a coin with a plier. Similarly, by relaxing constraints on variables in other relations, the agent can perform a \texttt{reachAndEngage(o, f)} action whereby it can couple a makeshift tool, namely the coin, with the screw.

What if the screw was in a recessed location and therefore difficult to access without an elongate arm? While the coin might fit on the head of the screw, it does not have the necessary elongation and would not be able to reach the screw. An approach here might be to grab the coin with the plier and use that assembly to tighten the screw, maybe even with some additionally duct tape for extra support. As noted earlier, generally, the agent must be able to relax some of the pre-existing constraints and generate new actions. By exploring and hypothesizing and then testing each variation, the agent can expand its domain.

This example, while still relatively simple for humans, helps us highlight the complexity of resources needed for an agent to perform the task. Successfully identifying and building a makeshift screwdriver when a standard screwdriver is not available shows a degree of resilience to events and autonomy and resourcefulness that we believe to be an important component of everyday creativity and intelligence. By formulating the notion of resourcefulness in this manner, we can better study the complexity of the cognitive processes and also computationalize these abilities and even formally measure them.

Agent Requirements: Intelligence and Physical Embodiment

When humans solve problems, particularly creative insight problems, they tend to use various heuristics to simplify the search space and to identify invariants in the environment that may or may not be relevant [Knoblich, 2009]. An agent solving an MGP must possess the ability to execute these types of heuristics and cognitive strategies. Moreover, MGPs are not merely problems in the classical planning sense, but require the ability to discover when a problem is unsolvable from a planning standpoint and then discover, through environmental exploration, relevant aspects of its surroundings in order to extend its domain of knowledge. Both these discoveries in turn are likely to require additional cognitive resources and heuristics that allow the agent to make these discoveries efficiently. Finally, the agent must also be able to remember this knowledge and be able to, more efficiently, solve future instances of similar problems.

From a real-world capabilities standpoint, the agent must possess the sensory and action capabilities to be able to execute this exploration and discovery process, including grasping and manipulating unfamiliar objects. These practical capabilities are not trivial, but in combination with intelligent reasoning, will provide a clear demonstration of agent autonomy while solving practical real-world problems.

These examples provide a sense for the types of planning problems that might qualify as an MGP. Certain MGPs are more challenging than others and we will next present a theoretical measure for the difficulty of an MGP.

4.3 Optimal Solution and M-Number

Generally, we can assume that a solvable MGP has a best solution that involves an agent taking the most effective actions, making the required observations as and when needed and uncovering a solution using the most elegant strategy. We formalize these notions by first defining optimal solutions and then the M-Number, which is the measure of the complexity of an insightful strategy in the optimal solution.

**Definition 10 (Optimal Solutions).** Let $\mathcal{P}_M = (\mathcal{W}^t, s_0, g)$ be an MGP for the agent. Let $\tilde{\pi}$ be an optimal solution plan to $\mathcal{P}_M$. A set of optimal domain modifications is a set of domain modifications $\Delta$ is the minimum set of domain modifications needed for the inclusion of actions in the optimal solution plan $\tilde{\pi}$. An optimal solution strategy is a solution strategy $\tilde{\omega} = (\tilde{\pi}, \Delta)$, where $\Delta$ is a set of optimal domain modifications.

**Definition 11 (M-Number).** Let $\mathcal{P}_M = (\mathcal{W}^t, s_0, g)$ be an MGP for the agent. Let $\Omega = \{\omega_1, \ldots, \omega_n\}$ be the set of $n$ optimal solution strategies. For each $\omega_i \in \Omega$, there exists an insightful strategy $\hat{\omega}_i \subseteq \omega_i$. Let $\hat{\Omega} = \{\hat{\omega}_1, \ldots, \hat{\omega}_n\}$ be the set of optimal insightful strategies. The set $\hat{\Omega}$ can be represented by a program $p$ on some prefix universal Turing machine capable of listing elements of $\hat{\Omega}$ and halting. We can then use Kolmogorov complexity of the set of these insightful strategies, $K(\hat{\Omega}) := \min_{p \in \mathbb{P}} |p| : U(p)$ computes $\hat{\Omega}$ [Li and Vitányi, 1997]. We define the intrinsic difficulty of the MGP $M$-Number $M$ as the Kolmogorov complexity of the set of optimal insightful strategies $\hat{\Omega}, \mathcal{M} = K(\hat{\Omega})$.

As we have shown MGP-EXISTENCE is intractable and measuring the intrinsic difficulty of an MGP is not computable if we use Kolmogorov complexity. Even if we instead choose to use an alternative and computable approximation to Kolmogorov complexity (e.g., Normalized Compression Distance), determining the M-Number is difficult to do as we must consult an oracle to determine the optimal solution. In reality, an agent does not know that the problem it is facing is an MGP and even if it did know this, the agent would have a tough time determining how well it is doing.

4.4 Measuring Progress and Agent Success

When we challenge each other with creative problems, we often know if the problem-solver is getting closer (“warmer”) to
the solution. We formalize this idea using Solomonoff Induction. To do so, we will first designate a “judge” who, based on a strategy currently executed by the agent, guesses the probability that, in some finite number of steps, the agent is likely to have completed an insightful strategy.

Consider an agent performing a strategy $\omega$ to attempt to solve an MGP $P_M$ and a judge evaluating the performance of the agent. The judge must first attempt to understand what the agent is trying to do. Thus, the judge must first hypothesize an agent model that is capable of generating $\omega$.

Let the agent be defined by the probability measure $\mu(\omega \mid P_M, C)$, where this measure represents the probability that an agent generates a strategy $\omega$ given an MGP $P_M$ when in a particular context $C$. The judge does not know $\mu$ in advance and the measure could change depending on the type of agent. For example, a random agent could have $\mu(\omega) = 2^{-|\omega|}$, whereas a MacGyver agent could be represented by a different probability measure. Not knowing the type of agent, we want the judge to be able to evaluate as many different types of agents as possible. There are infinitely many different types of agents and accordingly infinitely many different hypotheses $\mu$ for an agent. Thus, we cannot simply take an expected value with respect to a uniform distribution, as some hypotheses must be weighed more heavily than others.

Solomonoff devised a universal distribution over a set of computable hypotheses from the perspective of computability theory [Solomonoff, 1960]. The universal prior of a hypothesis was defined:

$$P(\mu) \equiv \sum_{p: U(p,\omega)=\mu(\omega)} 2^{-|p|}$$

The judge applies the principle of Occam’s razor - given many explanations (in our case hypotheses), the simplest is the most likely, and we can approximate $P(\mu) \equiv 2^{-K(\mu)}$, where $K(\mu)$ is the Kolmogorov complexity of measure $\mu$.

To be able to measure the progress of an agent solving an MGP, we must be able to define a performance metric $R_{\mu}$. In this paper, we do not develop any particular performance metric, but suggest that a performance metric be proportional to the level of resourcefulness and creativity of the agent. Generally, measuring progress may depend on problem scope, control variables, length and elegance of the solution and other factors. Nevertheless, a simple measure of this sort can serve as a placeholder to develop our theory.

We are now ready to define the performance or progress of an agent solving an MGP.

**Definition 12 (Expected Progress). Consider an agent in context $C = (\Sigma, s_0)$ solving an MGP $P_M = (\mathbb{W}, s_0, g)$. The agent has executed strategy $\omega$ comprising actions and domain modifications. Let $U$ be the space of all programs that compute a measure of agent resourcefulness. Consider a judge observing the agent and fully aware of the agent’s context and knowledge and the MGP itself. Let the judge be prefix universal Turing machine $U$ and let $K$ be the Kolmogorov complexity function. Let the performance metric, which is an interpretation of the cumulative state of the agent resourcefulness in solving the MGP, be $R_{\mu}$. The expected progress of this agent as adjudicated by the judge is:**

$$M(\omega) \equiv \sum_{\mu \in U} 2^{-K(\mu)} \cdot R_{\mu}$$

Now, we are also interested in seeing whether the agent, given this strategy $\omega$ is likely to improve its performance over the next $k$ actions. The judge will need to predict the continuation of this agent’s strategy taking all possible hypotheses of the agent’s behavior into account. Let $\omega^+$ be a possible continuation and let $^+$ represent concatenation.

$$M(\omega^+ | \omega) = \frac{M(\omega^+ \omega)}{M(\omega)}$$

The judge is a Solomonoff predictor such that the predicted finite continuation $\omega^+$ is likely to be one in which $\omega^+ \omega$ is less complex in the Kolmogorov sense. The judge measures the state of the agent’s attempts at solving the MGP and can also predict how the agent is likely to perform in the future.

## 5 Conclusion and Future Work

In the Apollo 13 space mission, astronauts together with ground control had to overcome several challenges to bring the team safely back to Earth [Lovell and Kluger, 2006]. One of these challenges was controlling carbon dioxide levels onboard the space craft: “For two days straight [they] had worked on how to jury-rig the Odysseys canisters to the Aquarius life support system. Now, using materials known to be available onboard the spacecraft - a sock, a plastic bag, the cover of a flight manual, lots of duct tape, and so on – the crew assembled a strange contraption and taped it into place. Carbon dioxide levels immediately began to fall into the safe range.” [Cass, 2005] [Team, 1970].

We proposed the MacGyver Test as a practical alternative to the Turing Test and as a formal alternative to robotic and machine learning challenges. The MT does not require any specific internal mechanism for the agent, but instead focuses on observed problem-solving behavior akin to the Apollo 13 team. It is flexible and dynamic allowing for measuring a wide range of agents across various types of problems. It is based on fundamental notions of set theory, automated planning, Turing computation, and complexity theory that allow for a formal measure of task difficulty. Although Kolmogorov complexity and the Solomonoff Induction measures are not computable, they are formally rigorous and can be substituted with computable approximations for practical applications.

In future work, we plan to develop more examples of MGPs and also begin to unpack any interesting aspects of the problem’s structure, study its complexity and draw comparisons between problems. We believe that the MT formally captures the concept of practical intelligence and everyday creativity that is quintessentially human and practically helpful when designing autonomous agents. Most importantly, the intent of the MT and the accompanying MGP formalism is to help guide research by providing a set of mathematically formal specifications for measuring AI progress based on an agent’s ability to solve increasingly difficult MGPs. We thus invite researchers to develop MGPs of varying difficulty and design agents that can solve them.
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