Measuring universal intelligence: Towards an anytime intelligence test

Artificial Intelligence 174 (2010) pp.1508–1539

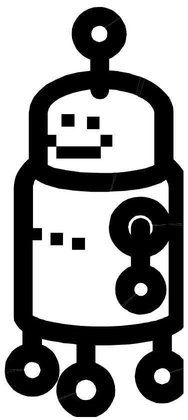
José Hernández Orallo[1], David L. Dowe[2]

1. *Departament de Sistemes Informàtics i Computació, Universitat Politècnica de València, Spain. jorallo@dsic.upv.es.*
2. *Computer Science & Software Engineering, Clayton School of I.T., Monash University, Clayton, Victoria, 3800, Australia.* david.dowe@infotech.monash.edu.au.

Outline

- Towards a universal intelligence test
- Precedents
- Addressing the problems of universal intelligence
- An anytime test
- Instances and implementation
- Conclusions and future work

Towards a universal intelligence test



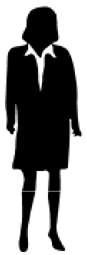
Evaluating intelligence. Some issues:

1. Harder the less we know about the examinee.
2. Harder if the examinee does not know it is a test.
3. Harder if evaluation is not interactive (static vs. dynamic).
4. Harder if examiner is not adaptive.

Towards a universal intelligence test

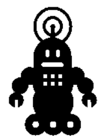
State of the art: different subjects, different tests.

- IQ tests:



  1. Human-specific tests. Natural language assumed.
  2. The examinees know it is a test.
  3. Generally non-interactive.
  4. Generally non-adaptive (pre-designed set of exercises)
- Other tests exist (interviews, C.A.T.)

- Turing test:



  1. Held in a human natural language.
  2. The examinees ‘know’ it is a test.
  3. Interactive.
  4. Adaptive.
- Other task-specific tests exist.
  - Robotics, games, machine learning.

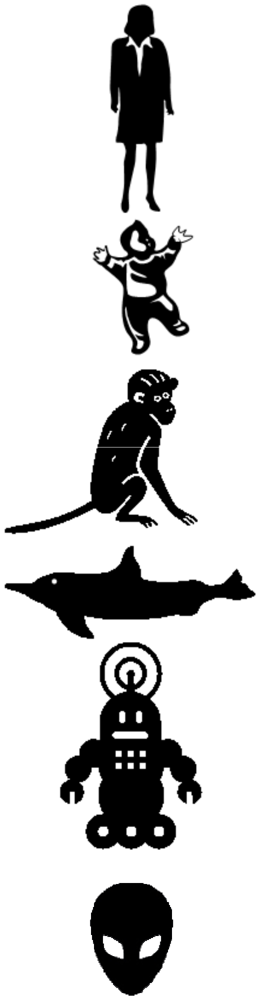
- Children’s intelligence evaluation:

  1. Perception and action abilities assumed.
  2. The examinees do not know it is a test. Rewards are used.
  3. Interactive.
  4. Frequently non-adaptive (pre-designed set of exercises).

- Animal intelligence evaluation:

  1. Perception and action abilities assumed.
  2. The examinees do not know it is a test. Rewards are used.
  3. Interactive.
  4. Generally non-adaptive (pre-designed set of exercises).

Towards a universal intelligence test



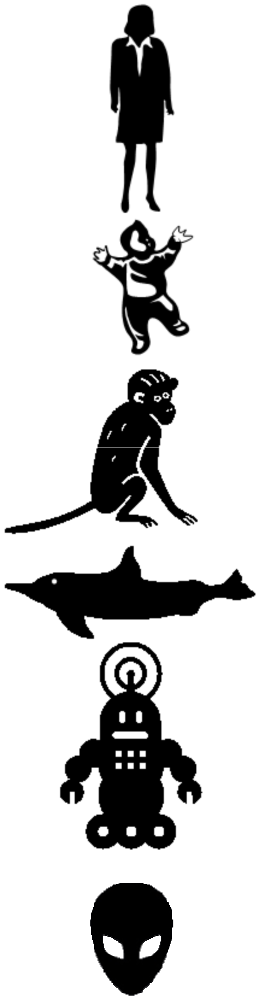
Can we construct a test for all of them?

- Without knowledge about the examinee,
- Derived from computational principles,
- Non-biased (species, culture, language, etc.)
- No human intervention,
- Producing a score,
- Meaningful,
- Practical, and
- **Anytime.**

Is this possible?

- No previous measurement or test of intelligence presented to date fulfils all of these requirements.

Towards a universal intelligence test



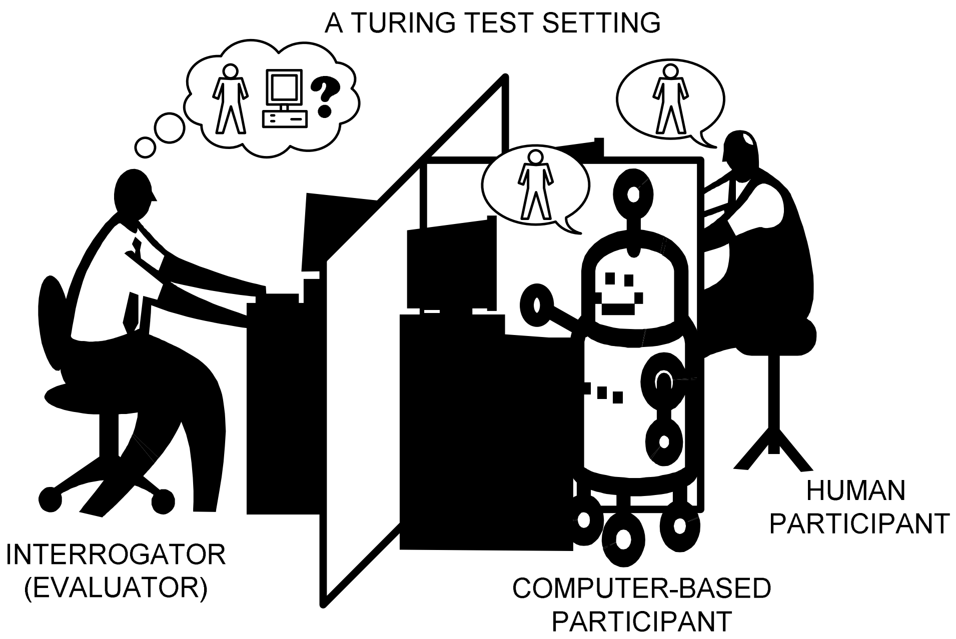
Project: **anYnt** (Anytime Universal Intelligence)

http://users.dsic.upv.es/proy/anynt/

- Any kind of system (biological, non-biological, human)
- Any system now or in the future.
- Any moment in its development (child, adult).
- Any degree of intelligence.
- Any speed.
- Evaluation can be stopped at any time.

Precedents

- Turing Test (Turing 1950): anytime and adaptive.



- It is a test of humanity, and needs human intervention.
- Not actually conceived to be a practical test to measure intelligence up to and beyond human intelligence.

Precedents

- Tests based on Kolmogorov Complexity (compression-extended Turing Tests, Dowe 1998) (C-test, Hernandez-Orallo 1998). Very much like IQ tests, but formal and well-grounded.
  - Exercises (series) are not arbitrarily chosen.
  - They are drawn and constructed from a universal distribution:

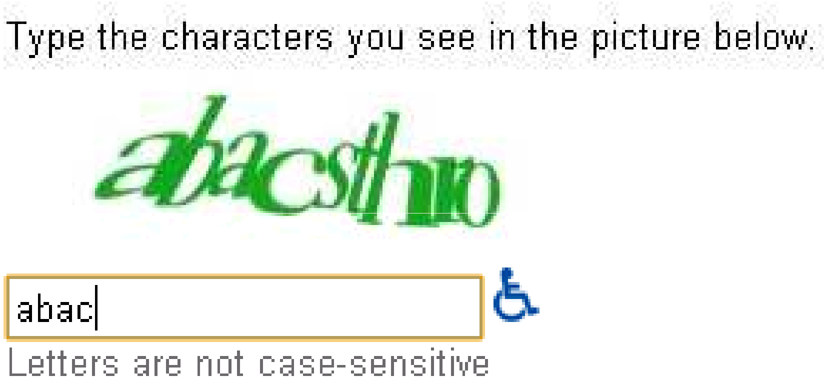
$$\begin{array}{lll} k=9 & : \text{a, d, g, j, } \ldots & \text{Answer : m} \\ k=12 & : \text{a, a, z, c, y, e, x, } \ldots & \text{Answer : g} \\ k=14 & : \text{c, a, b, d, b, c, c, e, c, d, } \ldots & \text{Answer : d} \end{array}$$

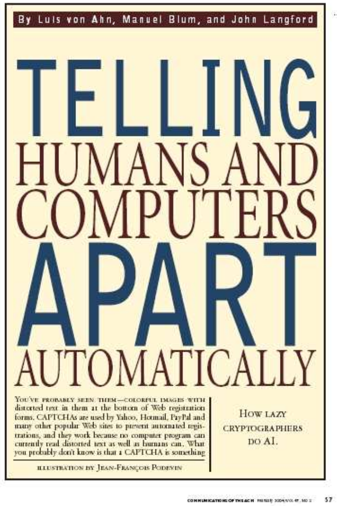
Fig. 2. Examples of series of Kt complexity 9, 12, and 14 used in the C-test [7].

- However, some relatively simple agents can cheat on them (Sanghi and Dowe 2003) and they are static (no planning abilities are required).

Precedents

- Captchas (von Ahn, Blum and Langford 2002): quick and practical, but strongly biased. They soon become obsolete.



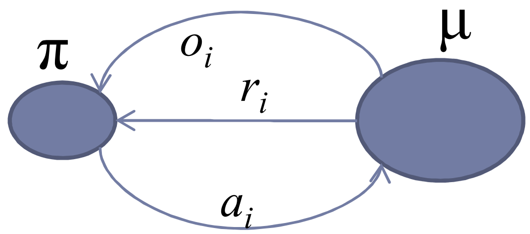


- A strong impact in real applications and in the scientific community.
- But...
  - They are not conceived to evaluate intelligence, but to tell humans and machines apart at the current state of AI technology.
  - It is widely recognised that CAPTCHAs will not work in the future.

Precedents

- Universal Intelligence (Legg and Hutter 2007): an interactive extension to C-tests from sequences to environments.

$$\Upsilon(\pi, U) := \sum_{\mu=i}^{\infty} p_U(\mu) \cdot V_\mu^\pi = \sum_{\mu=i}^{\infty} p_U(\mu) \cdot E\left(\sum_{i=1}^{\infty} r_i^{\mu,\pi}\right)$$



= performance over a universal distribution of environments.

- Obvious Problems:
  - *U* is a choice which defines the environment class.
  - The probability distribution is not computable.
  - There are two infinite sums (number of environments and interactions).
  - Time/speed is not considered for the environment or for the agent.
- Other less obvious problems.

Precedents

- A definition of intelligence does not ensure an intelligence test.

Table 2
Intelligence tests in passive and active environments (clarification).

	Universal agent	Universal definition	Universal test
Passive environment	Solomonoff prediction	Comprehension ability based on C-test [7], inductive ability	C-test [6], induction-enhanced Turing test [3]
Active environment	AIXI	Universal intelligence	?

- The C-test used Solomonoff's theory of inductive inference (predictive learning) to define an inductive inference test.
- Universal intelligence provides a definition which adds interaction and the notion of "planning" to the formula (so intelligence = learning + planning).
  - For "Universal Intelligence" we will have to "redefine" it, and then to think about how to use it to construct a feasible test.

Addressing the problems of universal intelligence

- On the difficulty of environments:
  - Very simple environments are given a very high probability

Definition 2 *(Kolmogorov complexity).*

$$K_U(x) := \min_{p \text{ such that } U(p)=x} l(p)$$

Definition 3 *(Universal distribution).*

$$p_U(x) := 2^{-K_U(x)}$$

  - Most of the score will come from very simple environments.
    - E.g. The 256 environments with K ≤ 8 accumulate a probability of 0.996 (and hence weight, i.e., score) in the definition.

$$\Upsilon(\pi, U) := \sum_{\mu=i}^{\infty} p_U(\mu) \cdot V_\mu^\pi$$

  - Since we don't have any information about the examinee, we cannot set any limit (or to *soften* the distribution).
    - one solution is to make the test adaptive.

Addressing the problems of universal intelligence

- Selecting discriminative environments:
  - Many environments will be completely useless to evaluate intelligence, because:
    - Rewards may be independent to agent actions.
    - There must be sequences of actions that lead to unrecoverable “states”. We cannot assume environments to be ergodic.
    - Some environments may be highly benevolent (high expected rewards) and some others can be very malevolent (low expected rewards).
  - We introduce two constraints on environments:
    - Environments must be reward-sensitive: *an agent must be able to influence rewards at any point.*
    - Environments must be balanced: *a random agent must have an expected reward of 0 (with rewards ranging between -1 and 1).*

Addressing the problems of universal intelligence

- On practical interactions:
  - We have to consider that environments should react almost immediately. We modify the universal distribution as follows:

Definition 9 *(Kt complexity weighting interaction steps).*

$$Kt_U^{\max}(\mu,n) := \min_{p \text{ such that } U(p)=\mu} \left\{ l(p) + \log\left(\max_{a_{1:i},\, i \leqslant n} \left(\Delta ctime(U,p,a_{1:i}) \right) \right) \right\}$$

  - The use of a parameter *n* makes the definition computable.
- From here, we redefine the distribution:

$$p_U^t(\mu) := 2^{-Kt_U^{\max}(\mu,n_i)}$$

- And now:
  - We create a finite sample of environments.
  - We also use a limit of interactions for each environment.

Addressing the problems of universal intelligence

- Time and intelligence:
  - We must consider fast but unintelligent agents as well as slow and intelligent ones.
    - But we cannot make these two things independent.
      - Otherwise, intelligence would be computationally easier than it is.
  - A way to do that is to set a finite period of time for each environment instead of a “number of interactions”.
    - Speed will be important because it will increase both exploration and exploitation possibilities.
    - In fact, agent’s speed will be very relevant.
    - But, it is *crucial* to consider balanced environments.

Addressing the problems of universal intelligence

- Reward aggregation:
  - Can we use RL aggregation measures such as accumulated reward and general discounting?
    - We show they present important caveats when measuring agents:
      - with a finite (previously unknown) period of time,
    - Why?
      - Given an evaluation time ζ, a fast agent could act randomly and get a good accumulated score and then rest on its laurels.
      - These are called “stopping” policies in games.
  - We introduce [48] a new measure for aggregating rewards in a given time ζ, where “discounting” is made to be robust to delaying and stopping policies.

Definition 16 *(Average reward with diminishing history).*

$$\check{v}_\mu^\pi \| \tau := \frac{1}{n^*} \sum_{k=1}^{n^*} r_k^{\mu,\pi} \quad \text{where } n^* = \left\lfloor n_\tau \left(\frac{t_{n_\tau}}{\tau} \right) \right\rfloor$$

An anytime test

- Given all the previous constraints and modifications we can give a definition, which is useful for a test.

Definition 17 *(Universal intelligence considering time (finite set of reward-sensitive and balanced environments, finite number of interactions, $Kt^{\max}$ complexity) with adjusted score and using physical time to limit interactions).*

$$\Upsilon^{iv}(\pi, U, m, n_i, \tau) := \frac{1}{m} \sum_{\mu \in S} \check{W}^{\pi}_{\mu} \| \tau$$

where S is a finite subset of m balanced environments that are also n_i-actions reward-sensitive. S is extracted with $p^t_U(\mu) := 2^{-Kt^{\max}_U(\mu, n_i)}$.

- The definition is parameterised by the number of environments *m* and the time limit for each of them ζ.
  - The higher *m* and ζ are, the better the assessment is expected to be.
  - For a new (unknown) agent, it is difficult to tell the appropriate *m* and ζ.

An anytime test

Definition 18 *(Anytime universal intelligence test taking time into account).* We define $\Upsilon^{\nu}(\pi, U, H, \Theta)$ as the result of the following algorithm, which can be stopped anytime:

ALGORITHM: Anytime Universal Intelligence Test
INPUTS: π (an agent), U (a universal machine), H (a complexity function),
  Θ (test time, not as a parameter if the test is stopped anytime)
OUTPUTS: a real number (approximation of the agent's intelligence)
BEGIN
  $\Upsilon \leftarrow 0$ (initial intelligence)
  $\tau \leftarrow 1$ microsecond (or any other small time value)
  $\xi \leftarrow 1$ (initial complexity)
  $S_{used} \leftarrow \emptyset$ (set of used environments, initially empty)
  WHILE (TotalElapsedTime < Θ) DO
    REPEAT
      $\mu \leftarrow Choose(U, \xi, H, S_{used})$ (get a balanced, reward-sensitive environment with $\xi - 1 \leqslant H \leqslant \xi$ not already in S_{used})
      IF (NOT FOUND) THEN (all of them have been used already)
        $\xi \leftarrow \xi + 1$ (we increment complexity artificially)
      ELSE
        BREAK REPEAT (we can exit the loop and go on)
      END IF
    END REPEAT
    $Reward \leftarrow V_{\mu}^{\pi} \| \tau$ (average reward until time-out τ stops)
    $\Upsilon \leftarrow \Upsilon + Reward$ (adds the reward)
    $\xi \leftarrow \xi + \xi \cdot Reward/2$ (updates the level according to reward)
    $\tau \leftarrow \tau + \tau/2$ (increases time)
    $S_{used} \leftarrow S_{used} \cup \{\mu\}$ (updates set of used environments)
  END WHILE
  $\Upsilon \leftarrow \Upsilon / |S_{used}|$ (averages accumulated rewards)
  RETURN Υ
END ALGORITHM

Instances and implementation

- Implementation of the anytime test requires:
  - To define an environment class *U* (e.g. a Turing-complete machine), where all the environments are balanced and reward-sensitive (or define a computable, preferably efficient, sieve to select them).
  - A complexity function (e.g., Kt^{max})
- Several environment classes may determine general or specific *performance* tests:
  - In [53] we have presented a Turing-complete environment class Λ which is balanced and reward-sensitive .
  - Other specific classes can be used to evaluate subfields of AI:
    - If *U* is chosen to only comprise static environments, we can define a test to evaluate performance on sequence prediction (for machine learning).
    - If *U* is chosen to be *games* (e.g. using the Game Description Language in the AAAI General Game Playing Competition), we have a test to evaluate performance on game playing.
    - Similar things can be done with the reinforcement learning competition, maze learning, etc.

Conclusions and future work

- Since the late 1990s, we have derived several general intelligence tests and definitions with a precise mathematical formulation.
  - Algorithmic Information theory (a.k.a. Kolmogorov complexity) is the key for doing that.
- The most important conclusions of this work are:
  - We have shaped the question of whether it is possible to construct an intelligence test which is universal, formal, meaningful and anytime.
  - We have identified the most important problems for such a test:
    - the notion of environment complexity and an appropriate distribution,
    - the issue that many environments may be useless for evaluation (not discriminative),
    - a proper sample of environments and time slots for each environment,
    - computability and efficiency,
    - time and speed for both agent and environment,
    - evaluation (reward aggregation) in a finite period of time,
    - the choice of an unbiased environment.

Conclusions and future work

- This proposal can obviously be refined and improved:
  - The use of balanced environments and the character of the anytime test suggest that for many (Turing-complete) environment classes, the measure is convergent, but this should be shown theoretically or experimentally.
  - Kt^{max} needs a parameter to be computable. Other variants might exist without parameters (e.g. using the speed prior).
  - The probability of social environments (other intelligent agents inside) is almost 0. A complexity measure including other agents could be explored.
- Implementation:
  - Currently implementing an approximation to the test using the environment class Λ.
  - Also considering to implement an approximation using the GDL (Game Description Language) as environment class.
- Experimentation:
  - On AI agents (e.g. RL Q learning, AIXI approximations, etc.), humans, non-human animals, children.