A (hopefully) Unbiased Universal Environment Class for Measuring Intelligence of Biological and Artificial Systems

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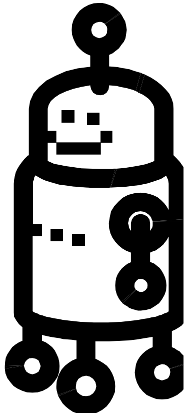
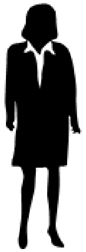
Evaluating intelligence. Some issues.



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.

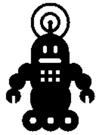
Different subjects, different tests

- 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.

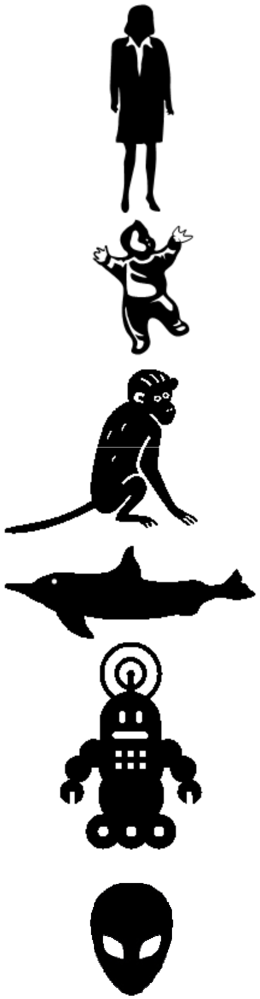
- Children intelligence evaluation:

  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).

- 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).

Can we construct a test for all of them?



- Without knowledge about the examinee,
- No natural language needed,
- Non-biased and without human intervention,
- Meaningful,
- Practical, and
- **Anytime.**

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

- Any system, now (human, non-human) 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, but it is a test of humanity, and needs human intervention.
- Tests based on Algorithmic/Kolmogorov Complexity (compression-extended Turing Tests, Dowe and Hajek 1998) (C-test, Hernandez-Orallo 1998). Very much like IQ tests, but formal and well-grounded. However, they can be cheated (Sanghi and Dowe 2003) and they are static.
- Captchas (von Ahn, Blum and Langford 2002): quick and practical, but strongly biased. They soon become obsolete.
- Universal Intelligence (Legg and Hutter 2007): can be seen as an interactive extension to C-tests, but it is not a test but a theory of intelligence. A practical instance is hard to implement (computability problems, environment classes, time, ...).
- Anytime Intelligence Test (Hernandez-Orallo and Dowe 2010): an interactive setting with a feasible implementation in mind.

Problems and Possible Solutions (1/2)

- Computability
  - Approach: Sample of environments, finite interactions, bounded variants of Kolmogorov complexity used (Hernandez-Orallo and Dowe 2010).
- Discriminative (the rewards of the environments should always be sensitive to the agent's actions)
  - Approach: Reward-sensitive environments (Hernandez-Orallo and Dowe 2010).
- Random agents shouldn't score well.
  - Approach: Balanced environments (Hernandez-Orallo and Dowe 2010).
- Social abilities could also be included in the test.
  - Approach: Other agents can be incorporated in the environments

Problems and Possible Solutions (2/2)

- Adaptation (the complexity of the exercises should adapt to the level of the examinee).
  - Approach: The complexity of environments is chosen according to the results on previous environments. (Hernandez-Orallo and Dowe 2010).
- Evaluation with time (Any time scale, stopped at any time, no opportunistic agents)
  - Approach: Use of a continuous time on the side of the agent and a variation of the average reward: ("On evaluating Agent Performance in a Fixed Period of Time", AGI'2010).
- Choosing an unbiased environment:
  - Approach: Using a class of environment which are balanced and reward-sensitive. Preserving universality of spaces and agents inside the environment. ("A hopefully unbiased universal environment class for measuring intelligence of biological and artificial systems") (This poster)

The choice of the environment class.

- Measurement of Intelligence is usually associated with the performance over a selection of tasks or environments.
- Universal Intelligence (Legg & Hutter 2007) assigns a probability to each environment, based on a universal distribution over a reference Turing machine.
  - Bad news: It is impossible to find a canonical Turing machine.
  - Good news: The difference between two reference machines is bounded by a constant.
  - Bad news: The constant can be much larger than the code length of the simplest environments in the class.
  - Good news: But still some choices are better than others.

The choice of the environment class.

The environment class (and its reference machine) must be an arbitrary choice.

- For static environments (series prediction as in IQ tests), we used a very simple accumulator machine [Hernández-Orallo 2000]. From it, we derived the test exercises for the C-test.

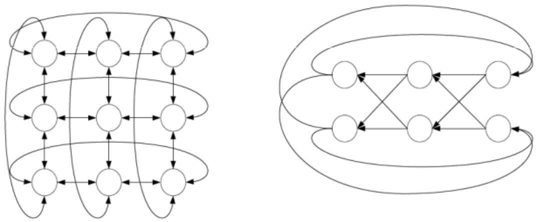
- In this paper, we present a proposal of environment class to construct interactive tests. Requirements:
  - Environments must be balanced (unbiased for random agents).
  - Environments must be discriminative (sensitive to examinee's actions).
  - Any space definition (grids, linear, arbitrary, ...) allowed.
  - They can contain other agents with possibly any computable behaviour.

The choice of the environment class.

- We want to generate environments automatically and to derive their probability in order to populate a pool of environments for testing.
  - One option: use any universal machine and generate programs with its universal distribution.
    - Problem: we will have to make a post-processing sieve to select those environments which follow the desired properties.
  - Better option: define an environment class which always produces environments which follow the desired properties.
    - Problem: we cannot use restricted representation languages such as state machines (since they are not universal).
- We also want the environment's interface to be user-friendly.

Definition of the Environment Class Λ.

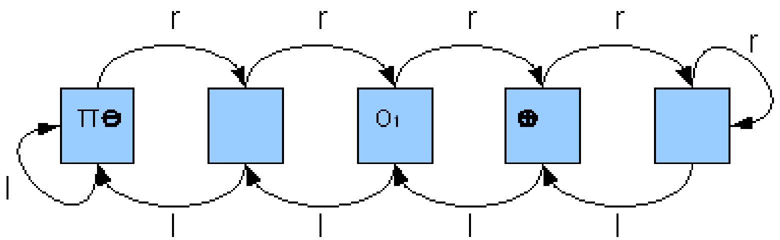
- The definition of an environment class Λ:
  - Spaces are defined as fully connected graphs.
  - Actions are the arrows in the graphs.
  - Observations are the ‘contents’ of each edge/cell in the graph.



- Objects can perform actions inside the space.
  - Evaluated agent (π).
  - Special Objects *Good* ($\oplus$) and *Evil* ($\ominus$) : special agents who are responsible for the rewards. They are symmetric, to ensure balance.
  - Other objects (o_i): Any set of inanimate or animate agents.

Definition of the Environment Class Λ.

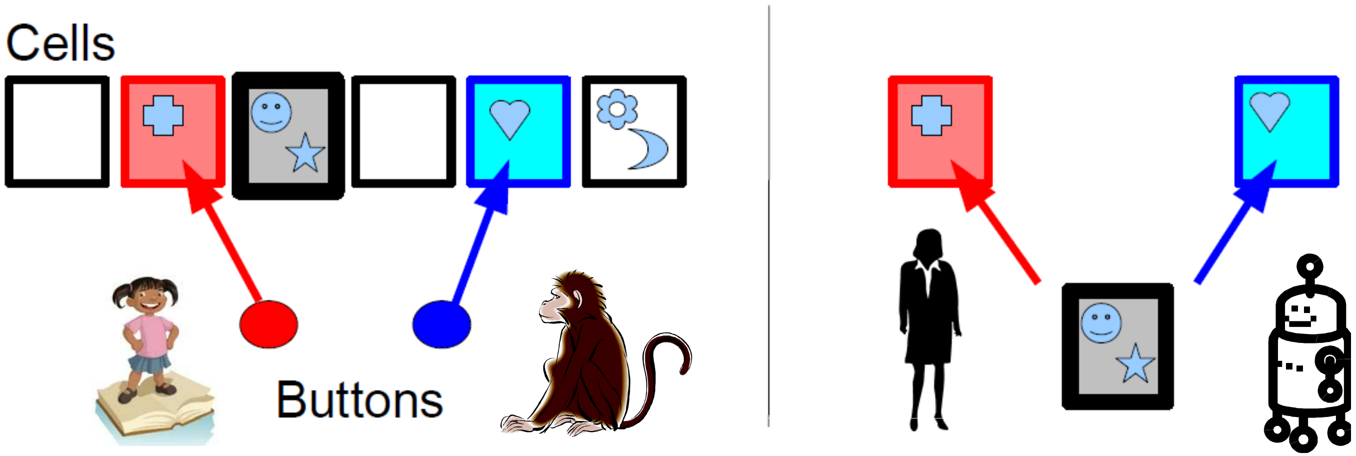
- Example:



- Rewards: a trace from ⊕ and ⊕ movements.
  - ⊕ leaves a positive trace and ⊖ leaves a negative trace.

- Properties:
  - Environment class Λ is shown to be:
    - Reward sensitive: there is always two different sequences of actions leading to different reward.
    - Balanced: a random agent must have an expected reward of zero.

Interface

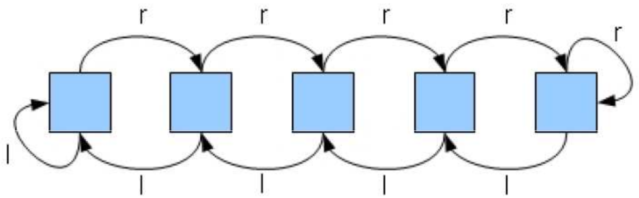


- The same environment should be used with different interfaces.
  - With the same information about observations and actions.
  - Adapted to ease interaction for each type of subject without introducing too much bias.

Coding and Generation

- Coding: we propose to code space (connected graph) and objects using string rewriting systems (universal expressiveness).
  - Example of space:

    1. $S \rightarrow\ +r - l$
    2. $T \rightarrow\ SS$
    3. $\rightarrow\ TT\Omega$
    4. $\Omega \rightarrow \cdot$



  - Example of agent:
    1. $\pi[\odot]L \rightarrow \cdot\ rrr$
    2. $\rightarrow \cdot\ l$
  - From the set of rules we can calculate their complexity/probability.
    - Using a common pool of rules (they can be shared by several agents).
- Generation: a computationally hard problem.
  - Sieves and heuristics must be developed to avoid non-terminating and incorrect sets of rules.

Conclusions

- We have present an environment class with the following characteristics:
  - Only includes reward-sensitive and balanced environments.
  - Hopefully unbiased.
  - Able to include any universal behaviour.
  - Allows for coding and generation of environments.
  - Social environments considered if other agents are included.
  - Interfaces are simple and adaptable to many different subjects.
- Future work:
  - We are working on the coding and automated generation of environments, in order to construct the tests.
  - A repository of environments under this class will be created and a benchmark dataset will be made available to evaluate AGI systems (e.g. MonteCarlo AIXI from Veness et al. 2009).

More information

- There is an extended version of this work in:

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

- Web of the **AnYnt** (Anytime Universal Intelligence) Project:

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

- Includes:
  - Project description.
  - Definition of the measuring setting:

Hernandez-Orallo and Dowe "Measuring Universal Intelligence: Towards an Anytime Intelligence Test", 2010

  - Previous work on C-tests, compression-based tests, etc.
  - Other related work.