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Quality-time-complexity universal intelligence measurement

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Abstract

Purpose – With development of machine learning techniques, the artificial intelligence systems such as crowd networks are becoming more and more autonomous and smart. Therefore, there is a growing demand to develop a universal intelligence measurement so that the intelligence of artificial intelligence systems can be evaluated. This paper aims to propose a more formalized and accurate machine intelligence measurement method.

Design/methodology/approach – This paper proposes a quality–time–complexity universal intelligence measurement method to measure the intelligence of agents.

Findings – By observing the interaction process between the agent and the environment, we abstract three major factors for intelligence measure as quality, time and complexity of environment.

Practical implications – In a crowd network, a number of intelligent agents are able to collaborate with each other to finish a certain kind of sophisticated tasks. The proposed approach can be used to allocate the tasks to the agents within a crowd network in an optimized manner.

Originality/value – This paper proposes a calculable universal intelligent measure method through considering more than two factors and the correlations between factors which are involved in an intelligent measurement.

Keywords Turing test, Agent-environment framework, Algorithmic information theory, Kolmogorov complexity, Universal intelligence

Paper type Research paper

1. Introduction

1.1 Background and related work

With development of machine learning techniques, the artificial intelligence systems such as crowd networks are becoming more and more autonomous and smart. Therefore, to evaluate the intelligence of artificial intelligence systems, the universal intelligence measurement is needed. The current intelligence measurement methods can be classified as the human IQ test and the measurement of machine intelligence. IQ test mainly through people's perception of knowledge, text and graphics and understanding to test the intelligence of individuals. The machine intelligence can be measured based on human



discrimination, problem benchmark, task response theory estimation and algorithmic information theory (Hernandez-Orallo, 2014; Solomonoff, 2009).

In a crowd network, a number of intelligent agents are able to collaborate with each other to finish a certain kind of sophisticated tasks (Prpic and Shukla, 2016). How to allocate the tasks to the agents in an optimized manner is the primary concern of a crowd network. As agents obtain different abilities (e.g. profession and reliability), the optimized task allocation should perform based on the evaluation of agents' abilities. However, the agents are inherently heterogeneous for they operate within a hybrid space including information space, physical space and awareness space and such hybrid space varies with profession and tasks of corresponding agents. Therefore, it is not feasible to evaluate the ability of agent in a comprehensive manner.

Performing intelligence measurement on agents is one of the feasible way to evaluate the ability of agents partially. The research of intelligent measurement can be dated back to 1950 when Turing Test was proposed by Turing (1950). In recent years, a number of intelligent measurement methods have been proposed in Oppy and Dowe (2003); Longo (2009); Mahoney (1999); Gibson (1998); Masum *et al.* (2002); Alvarado *et al.* (2001); Smith (2006). However, according to the results of these papers, all the proposed methods have the following drawbacks:

- None of these methods are comprehensive enough to make the measurements by considering more than two factors include reward quality, timeliness and complexity of the environment.
- Most of these methods (Oppy and Dowe, 2003; Mahoney, 1999; Masum *et al.*, 2002; Alvarado *et al.*, 2001; Smith, 2006) do not evaluate the correlations between factors that are involved in an intelligent measurement. Hence, the effectiveness of the selected factors cannot be proved.

1.2 Summary of content and contributions

In this paper, we propose an intelligent measure approach for intelligent machines such as the agents in crowd network. We name the approach as quality–time–complexity (QTC) intelligent measure approach, as it can perform intelligent measurement by considering three factors: test complexity, rewards quality and timeliness. We proved that there are correlations between the reward quality and the two other factors. The intelligence of an intelligent agent is quantified through calculating the expected accumulative reward quality of the agent.

The rest of the paper is organized as follows. In Section 2, we briefly introduce the agent-environment framework for conducting intelligent test and then introduce the three factors for intelligence measure. In Section 3, the correlations between the reward quality and the two other factors are evaluated. Then the QTC intelligent measure approach is introduced in detail. In Section 4, we prove the effectiveness of our approach by implementing a famous intelligent measure test. We conclude the paper in Section 5.

2. Agent-environment framework for conducting intelligent test

There are two steps for measuring the intelligence of an agent. The first step is conducting intelligent test on the agent so that the outcome of the test can be collected for further analysis. The second step is using intelligent measure approach to analyze the information collected from the intelligent test. In this paper, we conduct intelligent tests based on a widely accepted agent-environment framework. The detail of agent-environment framework

and its implementation is introduced in this section. Agent-environment framework is a widely accepted framework which provide a guideline to conduct intelligent test. As shown in [Figure 1](#), there are three components in this framework: An agent, an environment and a goal ([Legg and Hutter, 2006](#)). Agent is an intelligent entity who are taking the test. The goal is the task assigned to the agent during the test. The goal of a test is predefined by the test designer and should be informed to the agent before the test. The environment is a space to control the agent, it can provide rewards to the agent based on the agents' actions. During the test, the agents interact with a dynamic environment to maximize the predefined reward. In particular, the agent can send an action signal to the environment and receive a reward corresponded to the current action from the environment. Such test can be regarded as an interactive process between agent and environment and a certain information can be collected by observing the process.

3. Quality–time–complexity intelligence measuring model

In this section, we first analyze the correlations between the reward quality and the two other factors. And next, we will introduce our QTC intelligent measure model in detail.

3.1 Major factors for measuring intelligence

By observing the interaction process between the agent and the environment, we abstract three major factors which determine the performance of agent during the intelligent test as follows:

- (1) *Reward* is a sequence of the reward which are derived based on the actions taken by the agent, and it is quantified by calculating the expected accumulated reward (EAR) of the reward sequence.
- (2) *Time* is the timestamp of the rewards which can represent the timeliness of the agents' actions.
- (3) *Environment* is the complexity of the test environment, which can be computed and these environments can adjust based on evaluating the agents' actions.

To evaluate the correlation among the three factors, we conducted two experiments with seven agents involved. In the first experiment, we performed the same intelligent test on four agents. During the tests, we observe the variation of EAR obtained the tested agent by progressively increase the complexity of environment. The result of the first experiment (see [Figure 2](#)) indicate that although the EARs of the four agents change with different patterns when the complexity of environment increases, all of them converge when the complexity of environment are above 21. In the second experiment, we performed the same intelligent test on three agents. The third agents in this experiment was configured invokes random

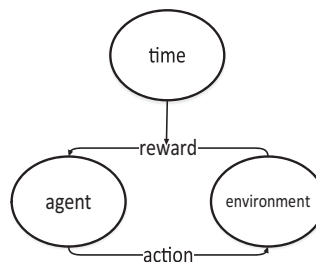


Figure 1.
The interaction
between the agent
and the environment

actions. The result (see Figure 3) shows that the three EARs are all increase with time. Moreover, the EARs of the first two agents converge as numbers of interactions increase. Based on the results of the two experiments, we model the correlations of the three factors as a diagram shown in Figure 4. As shown in the figure, time and complexity of environment both correlate with the reward factor, as the EAR converges when time and complexity of environment increase to a certain threshold.

After analyzing the relationship between them, our next question is how to calculate the EAR.

3.2 The reward for each interaction

As the goal of intelligent measure is to calculate the value of the reward, our first task is to calculate the reward for each interaction. According to the intelligent test designed in Legg and Hutter (2006), a complete interaction between the agent and the environment include two steps:

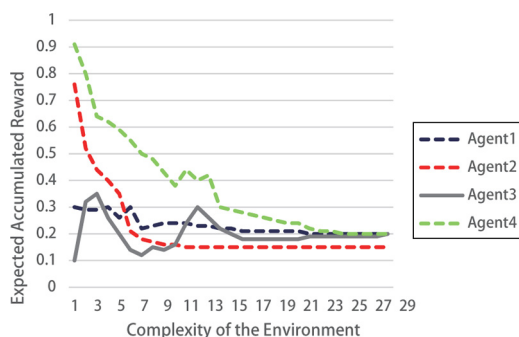


Figure 2. Expected accumulated reward vs the complexity of the environment

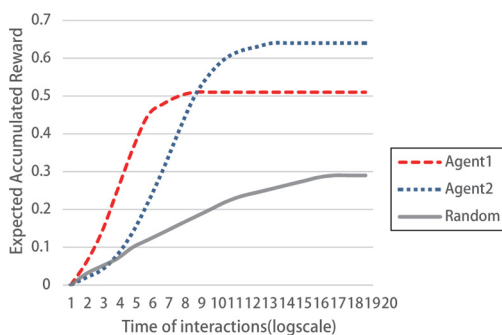


Figure 3. Expected accumulated reward vs the time of interactions

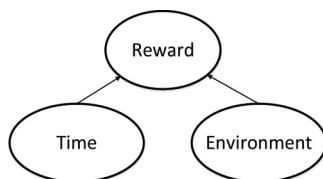


Figure 4. Correlations between the three major factors for intelligent measure

- (1) The agent sends an action to the environment.
- (2) The environment evaluates the action and returns a reward to the agent.

For instance, in the Turing test, a complete interaction includes a question asked by the agent and an answer responded by a human.

In an intelligent test where the finite number of interactions occurs within a finite time period, we define the reward R_i of interaction i as:

$$R_i(t) = \left(1 + \frac{1}{mt}\right)^t \quad (1)$$

where m is the complexity of environment, t is the time when the action i is invoked. This equation is designed according to the trend shown in [Figures 2](#) and [3](#).

When duration an intelligent test is infinite long so that $t \rightarrow \infty$, the limit value of R_i is:

$$\lim_{t \rightarrow \infty} R_i = \lim_{t \rightarrow \infty} \left(1 + \frac{1}{mt}\right)^t = e^{\frac{1}{m}} \quad (2)$$

The result in (1) is a constant when conforms the convergences shown in [Figure 2](#) and [Figure 2](#). Hence, such result proves the correctness of (1).

The complexity of environment m can be calculated according to the algorithm information theory by using Levins Kt complexity ([Li and Paul, 2008](#); [Levin, 1973](#)) as follows:

$$m(p, \pi) = \min\{l(p) + \log \text{time}(\pi, p)\} \quad (3)$$

where p represents the action, π represents the agent.

By substituting (3) into (1), the reward R_i of interaction i can be calculated as:

$$R_i(t) = \left(1 + \frac{1}{m_{p_i}t}\right)^t \quad (4)$$

3.3 Intelligence measuring model

In this paper, we measure the intelligence of agent π by calculating the EAR obtained by agent π within a predefined period t . Hence, the objective of intelligence measure model is to accurately calculate the EAR. According to the intelligence measuring model introduced in ([Hernandez-Orallo and David, 2010](#)), the calculation of EAR can be based on the sum of the average rewards obtained by agent π within a predefined period t (defined as V_μ^π). The equation to calculate V_μ^π as follows:

$$V_\mu^\pi := E\left(\sum_{i=1}^n R_i\right) = \frac{1}{n_i} \sum_{i=1}^{n_i} \left(1 + \frac{1}{m_{p_i}t}\right)^t \quad (5)$$

where n_i is the total number of interactions, μ is the identity of environment.

Based on (5), we derived the EAR from ([Legg and Venes, 2013](#)):

$$Y := \sum_{\mu \in E} 2^{-k(\mu)} V_\mu^\pi \quad (6)$$

By substituting (5) into (6), we can obtain the value of the EAR as:

$$\Upsilon := \frac{1}{n_i} \sum_{\mu \in E} 2^{-k(\mu)} \sum_{i=1}^{n_i} \left(1 + \frac{1}{m_{p_i} t}\right)^t \quad (7)$$

where the environment μ belongs to the environment set E which includes all computable reward bounded environments, and $K(s^2)$ is the Kolmogorov complexity.

By combining (1) to (7), we can eventually propose our intelligence measure model as:

$$\Upsilon(t; \theta) := \frac{1}{n_i} \sum_{\mu \in E} 2^{-k(\mu)} \sum_{i=1}^{n_i} \left(1 + \frac{1}{m_{p_i} t}\right)^t \quad (8)$$

$$\text{s.t. } t > t_0 \quad (9)$$

$$m_{p_i}, n_i \in N^+ \quad (10)$$

where $\theta = (\mu, \pi)^T$ is the parameters of EAR, μ is the identity of environment.

4. The results analysis of the model

In this section we implement our proposed intelligent model and then conduct an experiment to evaluate the performance of our model.

4.1 The algorithm of quality–time–complexity universal intelligence measurement

The implementation of our proposed model is described by the following pseudocode:

Algorithm 1 Universal Intelligence Test

Input: t (the time of the interaction), p (interactive behavior)

Output: a realnumber (the rewards of the interaction between the agent and the environment)

- 1: Calculate complexity of environment m based on (2).
- 2: Calculate the reward for action R_i based on (3).
- 3: Calculate the expected sum of the rewards V_μ^π based on (4).
- 4: Calculate the Expected accumulated reward Υ based on (6).
- 5: **return** $\Upsilon(t; \theta)$

Based on the pseudocode introduced above, we performed a simulation to visualize the correlation between the expected cumulated reward, time and the complexity of environment.

According to the simulation result shown in [Figure 5](#), it can be seen that the expected cumulated reward increases with time and decreases significantly as the complexity of the environment increases.

4.2 Experimental analysis

In this section, an example of implementing the proposed intelligent measure is introduced in detail. Consider a test setting where a chimpanzee (the agent) can press one of the three buttons ($A = \{B1, B2, B3\}$). Rewards can be either giving the agent a banana or giving nothing ($R = \{0,1\}$). The observation set is derived from an environment where a ball must be put into one of the three cells ($O = \{C1, C2, C3\}$). We start the test by giving a banana to the chimpanzee which indicate that the first reward is 1. The observations are randomly

generated with a uniform distribution with respect to O so that the rewards are determined accordingly. The behavior patterns of the agents are designed as follows.

The first chimpanzee π_1 are much more likely to press button $B1$, i.e. $\pi_1(B_1|X)$ for all sequences X . Consequently, the performance of π_1 in this test is:

$$E(V_{\mu}^{\pi_1}) = E_{n_i \rightarrow \infty} \left(\frac{\sum_{k=1}^{n_i} R_k^{\mu, \pi_1}}{n_i} \right) = \frac{2}{4} \lim_{n_i \rightarrow \infty} \frac{n_i}{n_i} + \frac{2}{4} \lim_{n_i \rightarrow \infty} \frac{0}{n_i} = \frac{1}{2} \quad (11)$$

The second chimpanzee (π_2) behaves randomly. Hence the performance of π_2 is:

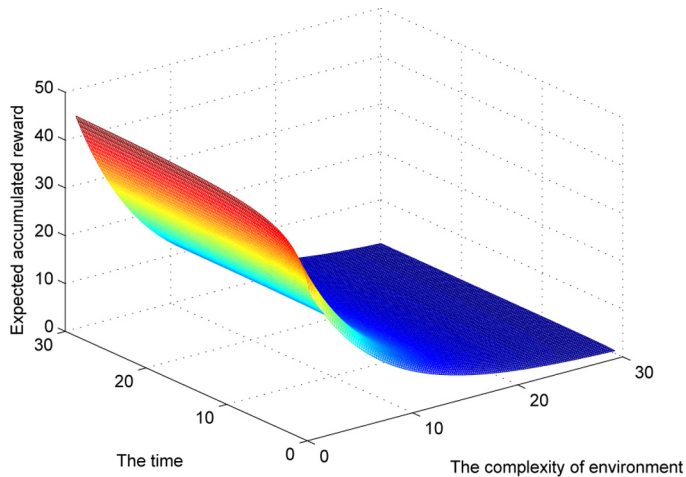
$$E(V_{\mu}^{\pi_2}) = E_{n_i \rightarrow \infty} \left(\frac{\sum_{k=1}^{n_i} R_k^{\mu, \pi_2}}{n_i} \right) = \frac{3}{3} \left(\frac{2}{4} \lim_{n_i \rightarrow \infty} \frac{n_i}{n_i} + \frac{1}{4} \lim_{n_i \rightarrow \infty} \frac{-n_i}{n_i} + \frac{1}{4} \lim_{n_i \rightarrow \infty} \frac{-n_i}{n_i} \right) = 0 \quad (12)$$

By comparing the performance between the two agents, we can conclude that agent π_1 is better than agent π_2 during this test.

5. Conclusion and future work

Traditional human intelligence and machine intelligence are difficult to be described by the form of intelligence in the current environment and have great limitations. In this paper, we propose a universal intelligent measure approach: quality–time–complexity intelligence measure approach. We abstract three major factors for intelligence measure as quality, time and complexity of environment. Correlation of the three factors is estimated by conducting two experiments so that the intelligence measure mode can be designed accordingly. Based on the intelligent measure model, we can quantify the intelligence of an agent by calculating the EAR achieved by the agent during an intelligent test. In future, we plan to design and implement a set of comprehensive experiments to evaluate the performance of our measurement model.

Figure 5. This figure shows the relationship between the three major factors of intelligent measurement, where x -axis represents the complexity of environment, y -axis represents the time, z -axis represents the EAR, EAR increases with time and decreases with the complexity of the environment



References

- Alvarado, N., Adams, S.S., Burbeck, S. and Latta, C. (2001), "Project Joshua blue: design considerations for evolving an emotional mind in a simulated environment", *Proceedings of the 2001 AAAI Fall Symposium Emotional and Intelligent II: The Tangled Knot of Social Cognition*.
- Gibson, E. (1998), "Linguistic complexity: locality of syntactic dependencies", *Cognition*, Vol. 68 No. 1, pp. 1-76.
- Hernndez-Orallo, J. (2014), "AI evaluation: past, present and future", arXiv preprint arXiv:1408.6908.
- Legg, S. and Hutter, M. (2006), "A formal measure of machine intelligence", arXiv preprint cs/0605024.
- Legg, S. and Veness, J. (2013), "An approximation of the universal intelligence measure", *Algorithmic Probability and Friends: Bayesian Prediction and Artificial Intelligence*, Springer, Berlin Heidelberg, pp. 236-249.
- Levin, L.A. (1973), "Universal sequential search problems", *Problemy Peredachi Informatsii*, Vol. 9, pp. 115-116.
- Li, M. and Paul, M.B. (2008), *An Introduction to Kolmogorov Complexity and Its Applications*, Springer-Verlag, New York, NY, p. 3.
- Longo, G. (2009), "Turing and the imitation game impossible geometry", *Parsing the Turing Test*, Springer, Berlin, pp. 377-411.
- Mahoney, M.V. (1999), "Text compression as a test for artificial intelligence", AAAI/IAAI: 970.
- Masum, H., Christensen, S. and Oppacher, F. (2002), "The turing ratio: metrics for open-ended tasks", *Proceedings of the 4th Annual Conference on Genetic and Evolutionary Computation*, Morgan Kaufmann Publishers, pp. 973-980.
- Oppy, G. and Dowe, D. (2003), available at: <https://seop.illc.uva.nl/entries/turing-test/>
- Prpic, J. and Shukla, P. (2016), "Crowd science: measurements, models, and methods", *49th Hawaii International Conference on IEEE System Sciences (HICSS), 2016*, pp. 4365-4374.
- Smith, W.D. (2006), "Mathematical definition of intelligence (and consequences)", Unpublished report.
- Solomonoff, R.J. (2009), "Algorithmic probability: theory and applications", *Information Theory and Statistical Learning*, Springer, New York, NY, pp. 1-23.
- Turing, A.M. (1950), "Computing machinery and intelligence", *Mind*, Vol. 59 No. 236, pp. 433-460.

Further reading

- Gurland, J. and Sethuraman, J. (1994), "Measuring universal intelligence: towards an anytime intelligence test", *Artificial Intelligence*, Vol. 174 No. 18, pp. 1508-1539.

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