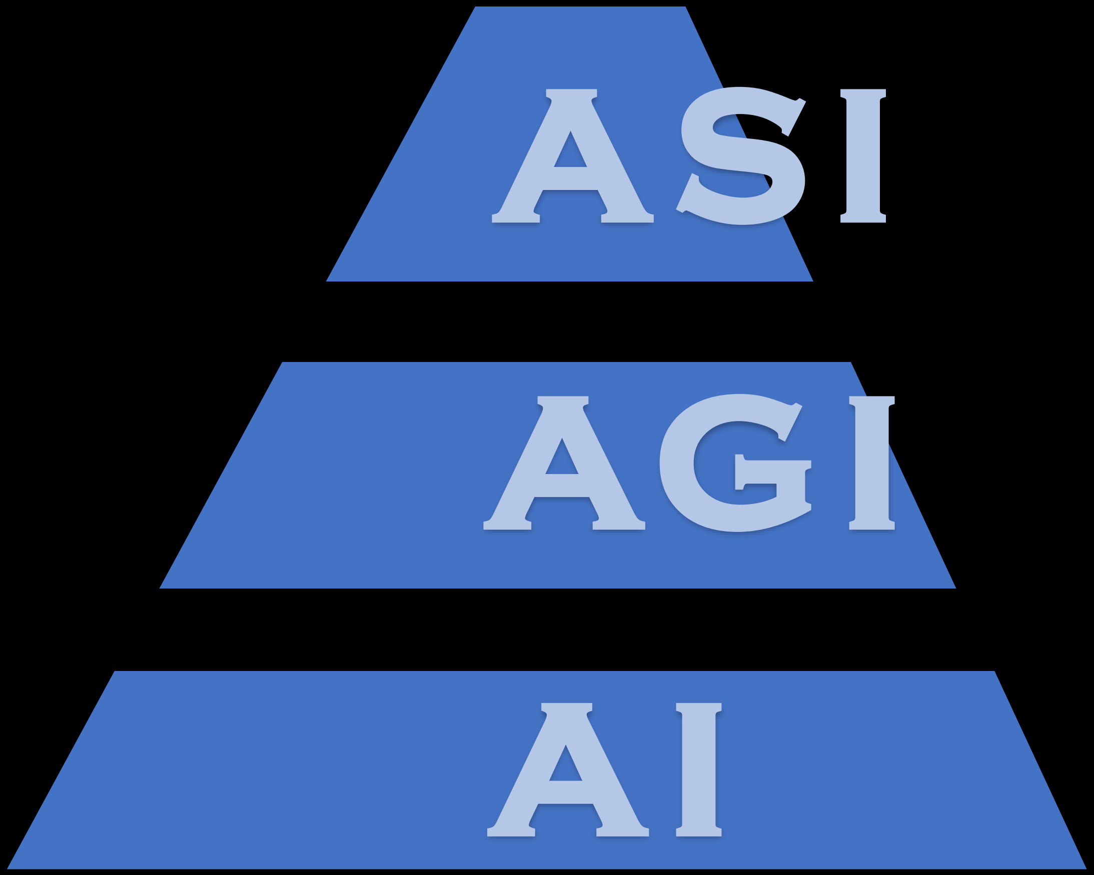
ULTIMATE AGI



Theory (1)

Definition of Intelligence

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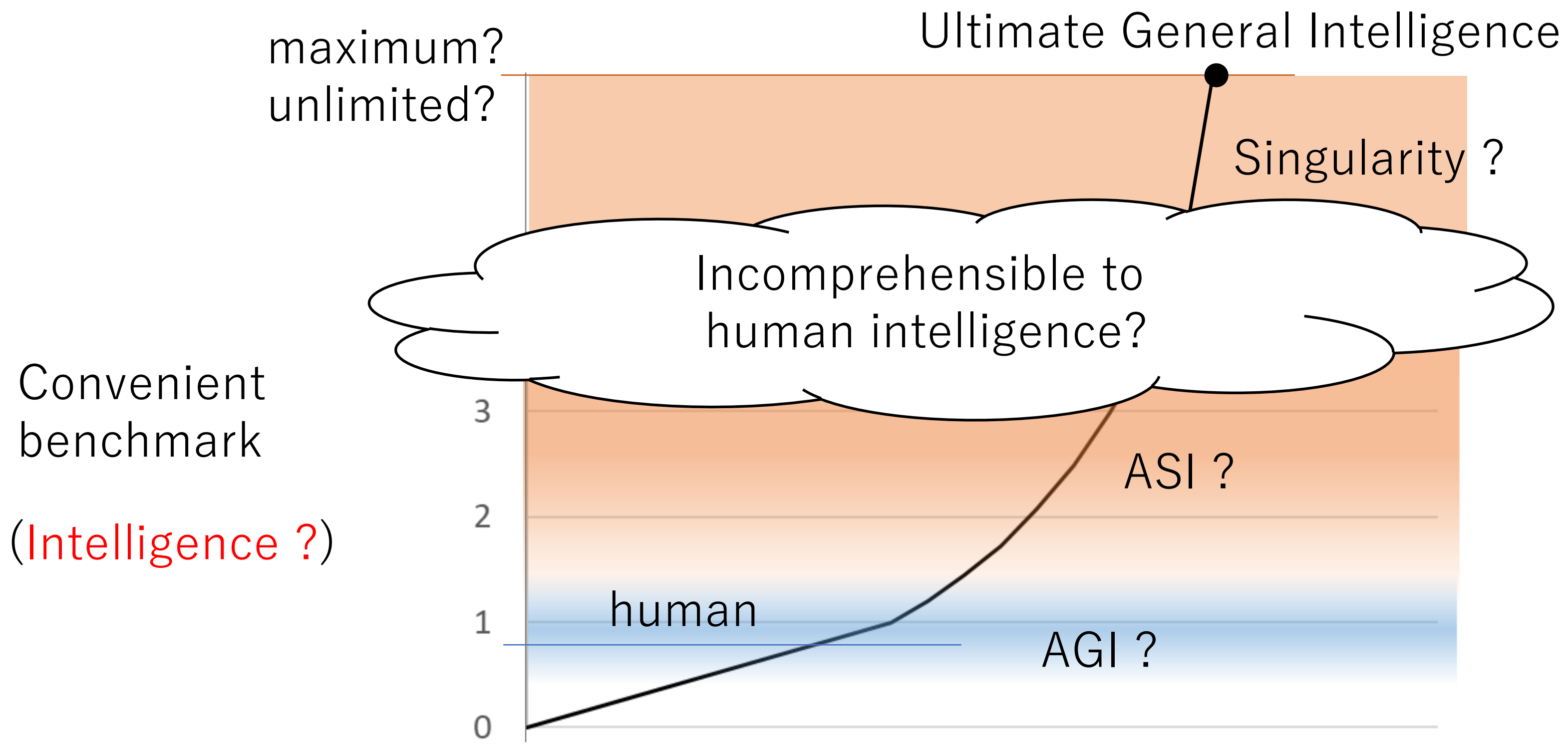
The need to define intelligence



If we define intelligence correctly, we should be able to understand ultimate intelligence.

Generally, AGI means human-equivalent intelligence, and ASI means intelligence beyond human capabilities.
However, there is no objective definition of intelligence.
Some people say that a system has AGI because it is already human-equivalent after conducting convenient benchmark tests.
Some people believe that intelligence can improve infinitely through self-improvement.
Some say that humans cannot understand intelligence superior to that of humans.
But how can we make such a statement when the definition of intelligence remains vague?
If we define intelligence properly, humans should be able to understand ultimate intelligence.

Intelligence is limited

Question

1+1=?

Answer options

① 1

② 2 ← Optimal answer
(No matter how excellent an AI is)

③ 3

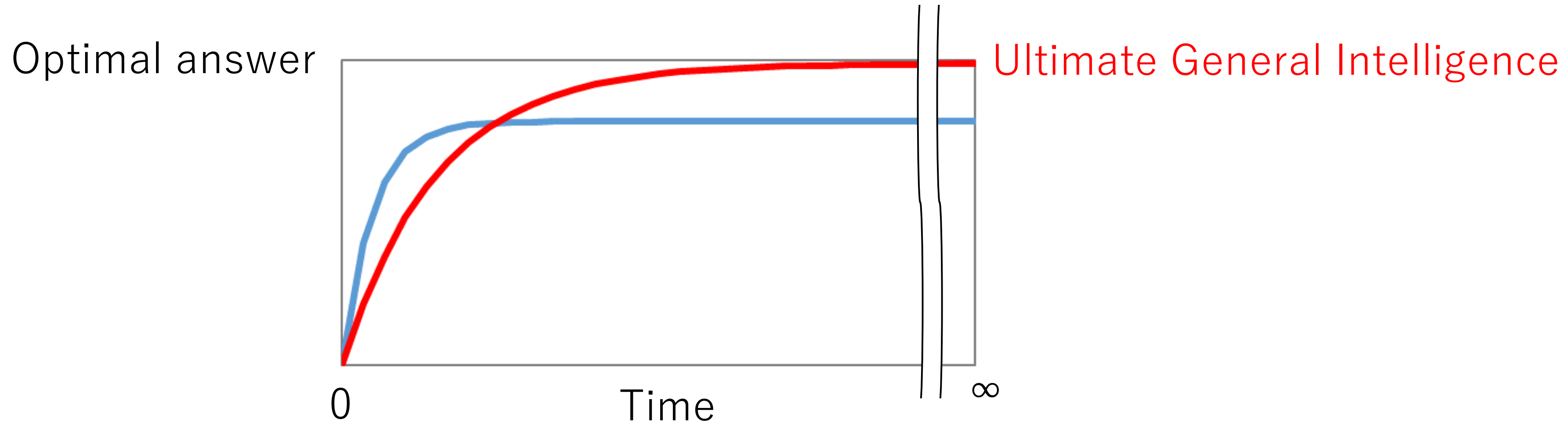
④ 4

For only this question, if you can answer 2, you have ultimate intelligence.

There is no better answer than this → Intelligence is never infinite.

A simple thought experiment can help us understand that intelligence is never infinite.
There is infinite room for improvement in intelligence if there is always a better solution than the one given.
Consider the question "1+1=?" and the answer being given by choosing 1, 2, 3, or 4.
No matter how excellent an AI is, it is easy to predict that it will answer "2“.
If this is the only question it is asked, then it can be said to have the most superior intelligence if it outputs the optimal answer, "2“.
If it can only answer this question, then it has no versatility and cannot be called general intelligence.
If it can define the optimal answer to all questions, and output that answer, it will become the ultimate general intelligence.

Definition of Ultimate General Intelligence



Definition of "Ultimate General Intelligence":

The ability to always get the optimal answer to any question

Here, we are ignoring the time it takes to reach an answer.
If the answer is poor, it won't be satisfying no matter how fast it is.
Calculation speed can be improved by improving hardware performance.
To some extent, there is a trade-off between answer speed and accuracy.
However, if the algorithm is poor, accuracy will reach a plateau no matter how much calculation is increased.
So, if the optimal solution can be obtained, no matter how long it takes, that is considered the ultimate intelligence.
We define the ability to always obtain the optimal answer to any question as "ultimate general intelligence".

Learning Classification

	Pre-learning	Lazy learning
Timing of learning	Before being asked question	After being asked question
Speed of answer	First	Slow
Quality of answer	Worse	Better
Optimal learning by knowing the question	No	Yes
Necessary for ultimate general intelligence?	No	Yes

The word learning is sometimes used in a similar sense to intelligence.
In a general sense, learning is a change that alters behavioral patterns.
Learning can be divided into pre-learning and lazy learning that takes place after the question is asked.
Pre-learning is equivalent to quick, intuitive thinking.
Lazy learning is equivalent to careful thinking.
If you don't mind how long it takes, there is no need to pre-learn at all.
It is better to know the question and then lazy learn in the way that best suits that question.

Learning rate

	Machine learning (Pre-learning)	Conscious Thought (Lazy learning)
Data used	All	n (Some of the relevant)
Learning rate	0.1%	1/n
Effect of one data	0.1%	1/n

Conventional AI requires large amounts of data for training.
Humans, on the other hand, can make inferences from small amounts of data.
You can load only a few pieces of data into your consciousness and make inferences from only those few pieces of data.
The learning rate for machine learning is typically around 0.1%.
The influence of a single piece of data on an inference result is around 0.1%.
If you think about it after receiving a question, you can select several pieces of data that are closely related and then learn from them.
If you only use n pieces of data, the influence of one piece of data is 1/n, so the learning rate is also 1/n.
If you think about it before receiving a question, your only option is to learn evenly from all the data little by little.

Intelligence is a process

Question: 1+1=?

① 1
② 2
③ 3
④ 4

Random choice → ② 2 (correct)

Zero intelligence

① 1
② 2
③ 3
④ 4

Non random choice →

① 1
② 2
~~③ 3~~
~~④ 4~~

Random choice → ① 1 (incorrect)

Better intelligence

Process of intelligence →

Process of Non intelligence →

Intelligence is a process,
not a result

When you want to quantify the level of intelligence, it is common to conduct some kind of benchmark test.
However, it is important to note that more correct answers does not necessarily mean greater intelligence.
Even if you choose randomly from four options, there is a chance that you will get the correct answer by chance.
If you narrow down four options to two and then choose one randomly, it may be incorrect.
Even if the answer is incorrect in the end, it is better than a completely random answer, because you have narrowed it down to two options.
Intelligence level should be assessed from the process, not the result.
The process of narrowing down four options to two is intelligence, but the process of randomly choosing from two options is not intelligence.
If you answer completely randomly, your intelligence can be said to be 0 regardless of the result.

Definition of Intelligence

Question: Please answer randomly. (Evaluation criteria: random is the best)

① 1
② 2
③ 3
④ 4

Random choice → ② 2 Optimum answer ~~Zero intelligence~~

Definition of "Intelligence":
Ability to output that meets the evaluation criteria

If we can define "ultimate general intelligence," we can also define "intelligence".
In the previous example, we said that there is no intelligence in a random answer, but there are exceptions.
If you are asked to "answer randomly," the optimal answer is to answer randomly.
The evaluation criteria for what the optimal answer is decided by the question setter.
Intelligence is defined as the ability to output an answer that meets the evaluation criteria.
The ability to output the highest rated optimal answer, no matter what question is asked, is the ultimate general intelligence.

Definition of question and optimal solution

Definition of "Question":
- Answer options
- Evaluation function
- Available information

Definition of "Optimal solution":
To the extent that can be determined from the "available information",
the "answer option" with the highest rating in the "evaluation function"

Next, we define the "question" and the "optimal solution".
A "question" is defined as "answer options", an "evaluation function", and "available information".
The "evaluation function" takes two "answer options" as input and uniquely outputs which is better.
Random evaluation is not permitted, nor is it allowed to change.
Within the "available information" scope, the "answer option" with the highest rating in the "evaluation function" is defined as the "optimal solution".

The need for optimal inference methods

Evaluation function (Action 1, Action 2) { … Invalid evaluation function

return “which is greater rewards in the future at actions”

} Unknown

Evaluation function (Action 1, Action 2) { … Valid evaluation function

return “which is greater estimated value of rewards in the future at actions”

} Calculatable.

However, this depends on the inference method.

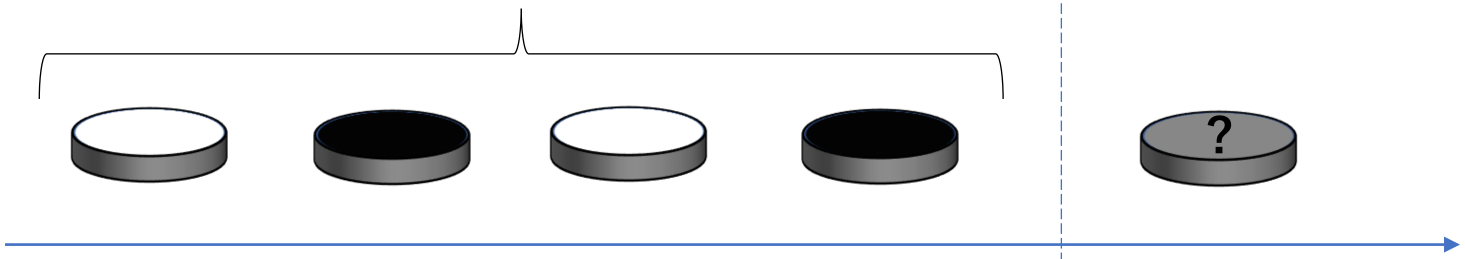
It is necessary to decide on the "optimal inference method".

The evaluation function can be set freely, as long as it can evaluate superiority or inferiority.
Let's take the typical example of setting a robot's goal.
Suppose that an action that results in a larger future reward is highly evaluated.
However, since the future reward is unknown, this evaluation function is not valid.
However, it is possible to guess.
An evaluation function that estimates the larger future reward would be valid.
However, the estimated value will change depending on how the guess is made.
In order to determine the "optimal solution", it is necessary to decide on the "optimal inference method".

Deduction and Induction

Coin toss result

Available information



Time

past

future

Answer contained
in the available information

Deduction

Uniquely determined by mathematical axioms

Answer not contained
in the available information

Induction

No mathematical axioms

Reasoning can be divided into deduction and induction.
Reasoning when the answer is contained in the "available information" is called deduction.
Deduction is possible if all of the values used in the evaluation function are known.
On the other hand, reasoning when deduction is not possible is called induction.
For example, asking about the past outcome of a coin toss is deduction, while asking about the future outcome is induction.
The outcome of deductive reasoning is uniquely determined by mathematical axioms.
On the other hand, with inductive reasoning, there are no mathematical axioms that justify a particular guess.

Confirmation Principle

Confirmation Principle:

“the more relevant observations there are, the greater the certainty”

“Number of observations”

“Degree of relationship”

“Amount of increase in certainty”

Without determining these relationships, it is impossible to determine the "optimal method of inference”.

In inductive reasoning, there is a principle known as the confirmation principle.
This states that "the more relevant observations there are, the greater the certainty“.
The relationship between the "number of observations“, the "degree of relationship“, and the "amount of increase in certainty" has not been discussed.
Without determining these relationships, it is impossible to determine the "optimal method of inference“.
These relationships can be seen by assuming extreme examples.

An extreme example of certainty

◆"Certainty"=0 : No guess can be made at all.

◆"Certainty"=1 : Can make deduction.

◆"Relationship"=0 : Irrelevant information. "Certainty"=0

◆"Relationship"=1 : Contains the answer. "Certainty"=1

("Number of observations"≧1)

◆"Relationship"＜1 : "Certainty"＜1

(No matter how many "Number of observations")

Deductive inference can be thought of as a special case of inductive inference.
When "Certainty" is 0, it means that no guess can be made at all.
When "Certainty" is 1, you are sure of the correct answer and can make a deduction.
Information with a "Relationship" of 0 is completely irrelevant information.
Information with a "Relationship" of 1 contains the answer, and with it you can make a deduction.
If the information has a "Relationship" of 1, then so long as the "Number of Observations" is 1 or greater, then "Certainty" will be 1.
If the information has a "Relationship" of less than 1, then no matter how much the "Number of Observations" increases, "Certainty" will be less than 1.

Sample quality limits certainty

◆“Relationship”=c: “Certainty”≦c

(No matter how many “Number of observations”)

Question: How much does a woman body weight?

“Relationship”=50%

Answer: Statistical distribution of body weights of 1,000,000 men and women of the same age

50% of the sample is men and therefore noise

“Certainty”≦50%

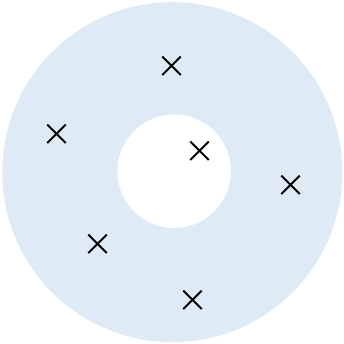
If the quality is poor, even a large sample size limits the degree of certainty

Also, if the "relationship" is a constant, then no matter how much the "number of observations", the "certainty" will remain below a certain value.
As an example, consider a question asking about a woman's weight.
The answer is the statistical distribution of the weights of 1 million men and women of the same age.
However, 50% of the sample is male, so it is noise.
If the association is measured by the agreement between gender, then the certainty will also be below 50%.
If the quality is poor, no matter how large the sample is, the certainty will be limited.

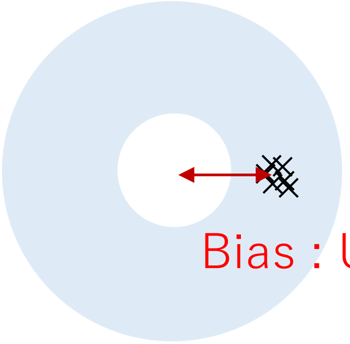
Precision and Accuracy

| Prediction - Measured | = 0 :   "Certainty"=1

Low Precision (Variance)



Low Accuracy (Bias)



Bias : Unpredicted

(Aim for center)

Expected value of | Prediction - Measured | = minimum :   "Optimal Inference"

Let's think about what a state of high certainty is.
If the difference between prediction and actual measurement is 0, there is no uncertainty and the certainty can be said to be 1.
The quality of an inference result can be thought of in terms of precision (variance) and accuracy (bias).
For example, even if the arrows shot are concentrated at one point on the target, it is not good if they are biased from the center.
Even if there is a bias, the archer thinks he is aiming at the center, so he does not know which way the bias will be.
You can know the bias by looking at the results, but you cannot know the bias before seeing the results.
However, intelligence is a process, so whether the result is good or bad is irrelevant.
If you can estimate that the expected value of the difference between prediction and actual measurement is minimum, that is the optimal inference.

Deviation

Expected value of (Measured - Prediction)^2

Root Mean Square Deviation

(Standard deviation)

$$RMSD = \sqrt{\frac{1}{n}\sum(x_i - \bar{x})^2}$$

Selected by the questioner

Mean Absolute Deviation

$$MAD = \frac{1}{n}\sum|x_i - \bar{x}|$$

Expected value of | Measured – Prediction |

While bias is difficult to know, variance can be calculated statistically.
It is common to look at statistical variation in standard deviation (root mean square deviation).
There is also a value called absolute mean deviation.
It is up to the question maker to indicate which one to use.
For example, if damage occurs in proportion to the square of the difference between the guess and the actual value, it should be using the SD.
The absolute mean deviation of the guessed values corresponds to the expected distance between the guessed value and the actual value.
If the goal is simply to make a guess with a smaller error, it is appropriate to evaluate using the absolute mean deviation.

Information

Available information : $A \subset B$
Inference Quality : $A \leqq B$

Any information would be good.

AI that turns a blind eye to some information is not optimal

Available information : $A = B$
Inference Quality : $A = B$

If available information is the same,
Inference is the same.

AI whose inferences change due to overlapping information is not optimal

The quality of inductive inference can also be considered from the perspective of the amount of information.
No matter what kind of information is available, having it should be able to make the same or better inferences than not having it.
As the amount of available information increases, the quality of inferences monotonically increases.
If an AI deliberately pretends not to know certain information, it will not be optimal.
Conversely, if the amount of available information does not increase, it will not be able to change to a better solution.
If the same information is given twice, the amount of information does not increase, so the optimal solution should not change.
If some data is duplicated and overlapping, an AI that emphasizes that data is not optimal.

Human bias

	A		B
Available information	Stock price prediction formula		Stock price prediction formula The formula was fitted to a back-test Negative information
Probability of making a profit	99.99%		50%
Accuracy	A	>	B
Available information	A	<	B
Inference Quality	A	<	B

This is not limited to AI; human intelligence also has various biases.
For example, we sometimes give weight to positive information and ignore negative information.
Even if the information is negative, taking it into consideration rather than ignoring it will lead to better inference.
For example, when inferring that there is a high probability of making money, you will want to ignore information that refutes this.
Adding that negative information will decrease the estimated probability of making money, but it will still result in a better inference.
The size of the probability only represents the variance and does not reflect bias,
so even if the probability of making a profit is statistically higher, it may just be that you are setting convenient assumptions.

Maximize rewards

Reinforcement learning goals: Maximize Estimated value of rewards

Estimation formula	Estimated value of rewards
$A: ax^5 + bx^4 + cx^3 + dx^2 + ex + f$	$= 99$
$B: ax^2 + bx + c$	$= 80$
$C: ax + b$	$= 50$

$\xrightarrow[\text{the formula}]{\text{AI chooses}}$ Formula A

Formula A is the maximum value, but maybe it's just a coincidence?

There is also a major pitfall in the idea of maximizing the "reward" in reinforcement learning.
Because future rewards are unknown, what is maximized is merely an estimated value of the reward.
Suppose the AI itself can decide how to make inferences, such as using statistical assumptions.
Suppose it tries multiple methods and simply adopts the inference method that maximizes reward.
However, what appears to be a correlation is often actually just a coincidence.
By trying various methods, it is possible to choose the method that results in a convenient coincidence.
If you want the AI to decide how to make inferences, you need a mechanism to avoid such biases.

Hyperparameter

Hyperparameters: Number of layers in neural network, etc.

	How to decide hyperparameters	Inference Quality
A	Decide by intuition	Bad
B	Set a fixed value that maximizes the average test score	Averagely good
C	Allow the value to be adjusted to the optimum for each question (hyperparameters disappear)	Can be the best for each question

Reinforcement learning has a hyperparameter called the discount rate.
Hyperparameters should be decided based on improved test results, not based on intuition.
However, even if they are decided so that the average score is the highest, the hyperparameter does not disappear.
The hyperparameter should not just be good on average, but should be the best for each question.
The number of layers in a neural network is also a hyperparameter.
It is generally fixed to the number of layers that results in good performance on average.
There is more room for improvement in performance if the number of layers is not fixed, but allowed to vary to the optimal number for each question.
Only once it is optimized for each question can it be said that hyperparameters have disappeared.

Axiom of induction

Axiom of induction:

The closer the element x of the function f is, the closer the mapping y is.

$y = f(x)$ It is unclear what function this is

order	function	mapping	frequency
0	Constant	|f(1)-f(0)| ＝ |f(2)-f(0)|	＝100%
1	Linear function	|f(1)-f(0)| ≦ |f(2)-f(0)|	＝100%
≧2	Quadratic or higher degree functions	|f(1)-f(0)| ≦ |f(2)-f(0)| |f(1)-f(0)| ≧ |f(2)-f(0)|	＝50% ＝50%
?	Unknown function	|f(1)-f(0)| ≦ |f(2)-f(0)| |f(1)-f(0)| ≧ |f(2)-f(0)|	≧50% ≦50%

To determine the best method of inductive inference, let's consider as simple an example as possible.
Let's set the induction axiom as "the closer the element x of function f is, the closer the mapping y is“.
We express it as y=f(x), but it is unknown what type of function this is.
For a zero-order function, y is constant regardless of x.
For a straight line that is a linear function, the closer x is, the closer y will be.
For quadratic or higher functions, it is unknown whether the line will deviate above or below the straight line.
Even if we don't know what type of function it is, we can say that the closer x is, the closer "y is also closer" rather than "y is far away“.
This is because this relationship holds for linear functions, but the other cases are unknown and so are equivalent.

Multi-element function

$$y = f(x, z)$$

condition	mapping	frequency
$\Delta x1 < \Delta x2$ $\Delta z1 = \Delta z2$	$\lvert f(1, c)-f(0, 0)\rvert \leqq \lvert f(2, c)-f(0, 0)\rvert$	$\geqq 50\%$
	$\lvert f(1, c)-f(0, 0)\rvert \geqq \lvert f(2, c)-f(0, 0)\rvert$	$\leqq 50\%$
$\Delta x1 < \Delta x2$ $\Delta z1 < \Delta z2$	$\lvert f(1, 1)-f(0, 0)\rvert \leqq \lvert f(2, 2)-f(0, 0)\rvert$	$\geqq 50\%$
	$\lvert f(1, 1)-f(0, 0)\rvert \geqq \lvert f(2, 2)-f(0, 0)\rvert$	$\leqq 50\%$
$\Delta x1 < \Delta x2$ $\Delta z1 > \Delta z2$	$\lvert f(1, 2)-f(0, 0)\rvert \leqq \lvert f(2, 1)-f(0, 0)\rvert$	?
	$\lvert\lvert f(1, 2)-f(0, 0)\rvert \geqq \lvert f(2, 1)-f(0, 0)\rvert$	?

Let's also consider the case of y=f(x, z).
If z is the same, we can infer that the closer x is, the closer y is.
If z is close and x is close, we can infer that y is also close.
If z is far and x is close, we can't say either way.
If x and z have different units, they cannot be compared.
Even if the physical units are the same, it is rough to compare them if they represent different things.

Partially random function

$y = f(x, z, \ldots, \varepsilon)$

ε : Hidden Variables ⋯Noise
(All variables that affect y other than x, z, ⋯)

$$\lim_{n\to\infty}\left(\frac{1}{n}\sum \varepsilon_i\right) = 0$$

More data reduces noise and increases certainty

We will also consider the case of a function that is partially determined randomly.
We have added ε to the base function.
Even if it looks random at first glance, we interpret it as being inevitably determined by the hidden variable ε.
ε represents all variables other than x and z that affect y.
ε is considered to be noise, and the more data there is, the closer the average is to 0.
Therefore, as the amount of data increases, the noise decreases and the certainty increases.

Inferring hidden variables

$y = f(x)$ (There is no hidden variable ε)

Question: $f(0) = ?$

	A	B	
Observations	$f(2) = 2$	$f(2) = 2$	
	$f(1) = 1$	$f(1) = 1$	Since there are no hidden variables,
		$f(1) = 1$	the value remains the same
		$f(1) = 1$	no matter how many times you observe it.

Certainty: A = B

The essence of inductive reasoning: Statistical inference of hidden variables

Conversely, let's consider the case where there is no hidden variable ε.
Suppose you want to guess the value of f(0) for the function y=f(x).
You infer that f(1)=1 is closer to f(0) than f(2)=2.
Since there is no hidden variable, f(1) will be 1 no matter how many times you observe it.
No matter how many times you observe f(1)=1, the accuracy of the inference does not improve.
The same is true when a hidden variable exists, but you know its value is the same.
The essence of inductive inference is the statistical inference of hidden variables.

Noise immunity

Axiom of induction: $y = f(x)$

The closer the element x of the function f is, the closer the mapping y is.

If the difference in x is small, the difference in y must be small.

Qualities that AI should meet:

If any value changes only slightly, the output should also change only slightly.

- Do not branching based on whether the numbers match.
- Do not pick the sample with the maximum or minimum value.

If a small difference causes a large change,
it means that the output is strongly affected by noise.

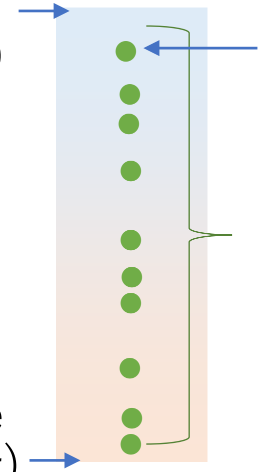
The axioms of induction derive the properties that AI should satisfy.
If the difference in x is small, the difference in y should also be small.
If there is only a small change in some value, the output should also only change slightly.
For example, conditional branching should not be based on whether the numerical values match.
Furthermore, samples with the maximum or minimum value should not be selected.
If the difference is small, noise will reverse the magnitude relationship.
If a small difference causes a large change, it means that the output is strongly affected by noise.

Amount of calculation

Traveling Salesman Problem

Ranking

Shortest route
(best answer)



Best one: Top 10% (1/n)

n=10 random pickup

Longest Route
(worst answer)

The order of computation required to produce
an answer with quality in the top 1/n : O(n)

If combinatorial explosion occurs in an AI algorithm,
we should suspect that it is not optimal.

Up until now, we have ignored calculation time, but I will show that it is not a big issue.
For example, in the traveling salesman problem, the number of combinations of all routes is extremely large.
So, suppose we randomly examine 10 routes and choose the best one.
If we arrange all the routes in order of best quality, the best of the 10 will be roughly in the top 10%.
The order of the amount of calculation required to give an answer with quality in the top 1/n is n.
If there is a time limit, we have no choice but to give the best answer we can currently do, even if it is not the optimal solution.
This method can be used generically for any problem.
If combinatorial explosion occurs in an AI algorithm, we should suspect that it is not optimal.

Multiple problems

◆Problem A "…" set by human

◆Problem B "…" set by AI itself, which is necessary to solve problem A

◆Problem C "determining the priority order for all problems"

Problem A
Problem B
Problem C (itself)

Let's consider the case where there are multiple problems.
If computing power is finite, it is necessary to decide priorities as to which problems to solve first.
If the problems are set by humans, the human will specify the priorities.
Also, the AI itself may set new problems in order to solve existing problems.
If the AI sets the problems, it must decide the priorities.
A problem arises of "determining the priority order for all problems".
Priorities are decided including the "problem of deciding priorities" itself.

Frame problem

Setting up a new question

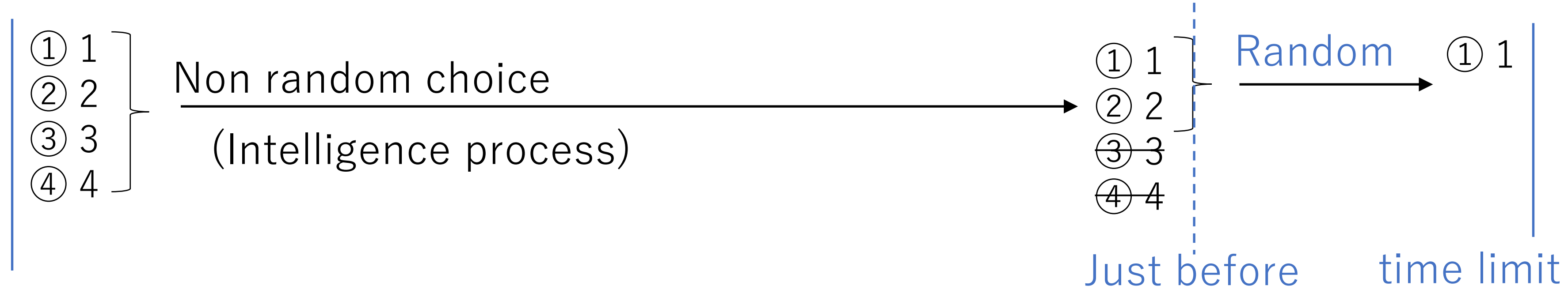
- Answer options
- Available information
- Evaluation function

It is allowed to set it to infinite

If you randomly select n answers from an infinite number of answers and choose the best one, you will get an answer that is in the top 1/n quality.

To choose the best one out of n options, you need to make n-1 comparisons.

n=1: Simply randomly select one. No comparison required.



When an AI sets a new question by itself, it needs to set things like "answer options".
It is also permissible to have an unlimited number of "answer options".
When there are an infinite number of things to consider, you fall into the frame problem.
However, if you randomly select n options from an infinite number of options and choose the best one, you will get an answer that is 1/nth of the top quality.
To select the best one from n options, n-1 comparisons are necessary.
If you don't have time, you can just set n=1 and select randomly, and there is no need to evaluate the options.
For example, if a question has four options and you have narrowed it down to two, you can just choose randomly from those two options just before the time limit.
In other words, the frame problem can be dealt with by using a random process to process only the amount that cannot be processed by the intelligence process.

Information Degradation

- Intelligent Choices
  (Keep as much as possible)
- Random Choices
  (Avoid as much as possible)

A distinction must be made

- Guessing Values (Induction)
- Actual measurements

A distinction must be made

There are times when an AI has to make partial random choices.
Because random selection is not intelligence, it should be kept in a non-random state as much as possible.
Even after a random selection has been made, the AI should remember the state it was in before the random selection.
It is necessary to distinguish whether a value is a guess or a value that has simply been chosen randomly.
Furthermore, no matter how good a guess is, it must be distinguished from an actual measured value, unless it is a deduction.
All information must be protected not only from deletion or tampering, but also from deterioration due to the addition of uncertain information.
Otherwise, the AI itself will not be able to determine whether it is lying or not.

Hallucination of Generative AI

	Question	Answer	Evaluation
Training	What is Company A’s stock price?	It’s 123,456	Good
	What is Company B’s stock price?	I don’t know	Bad
Runtime	What is Company B’s stock price?	It’s 123,456	

The AI is just answering what it was trained to do.

Generative AI suffers from a phenomenon called hallucination.
The cause of this is not just the AI itself failing to distinguish between truth and falsehood.
The generative AI is simply answering as it has been trained, and is not making any mistakes.
It's just that the training content and evaluation criteria are bad.
Answers like "I don't know" should be given a low rating or excluded during training.
In human society, it is encouraged to give an answer that has even the slightest possibility of being correct, even if it is a guess.
Besides, since the questioner is asking because they don't know, they won't be seen through as a lie and given a low rating on the spot.
If the AI says "I don't know," praise it by saying, "You confessed so honestly“.

Summary of definition

Definition of "Intelligence":

Ability to output that meets the evaluation criteria

Definition of "Ultimate General Intelligence":

The ability to always get the optimal answer to any question,
(no matter how long it takes)

The starting line
to the Ultimate AGI

Define the optimal method of inductive reasoning

- Gathering puzzle pieces from each case.
- Putting puzzles together for generalization.

The goal of Ultimate
AGI completion

Define the optimal answer to any question

Let's summarize what we've learned so far.
We defined "intelligence" as the ability to output information according to evaluation criteria.
We defined "ultimate general intelligence" as the ability to output the optimal solution to any problem, no matter how long it takes.
This is the starting line towards the ultimate AGI.
The goal will be to define the optimal solution to every question.
To do this, we realized that we need to define the optimal method of inductive inference.
First, we collect puzzle pieces from individual cases.
If we can put the puzzle together well and generalize it, the ultimate AGI will be complete.

Summary of required for Ultimate AGI

1. There should be no non-optimized values (hyperparameters).
2. Estimated values must be distinguished from actual values.
3. No information should be ignored.
4. Duplicate information should not change the output.
5. Small differences in information should not greatly change the output.
6. Random selection should be minimized.
7. Not only precision (variance) but also accuracy (bias) must be considered.
8. Combinatorial explosion is not allowed.

We have summarized the required characteristics of the ultimate AGI.

1. There should be no non-optimized values (hyperparameters).
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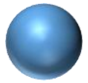
Comparison of AGI

	Commercial AGI	Ultimate AGI
Purpose	Replacing Labor	Clarifying Intelligence
Generality	Human Level	Maximum
Process	Any (black box)	Proof from axioms
Grading	Benchmark Test	Unnecessary

Compare commercial AGI and ultimate AGI.
The goal of commercial AGI is to replace labor, while the goal of ultimate AGI is to elucidate intelligence.
The generality of the goal also differs between the human level and the maximum.
Commercial AGI aims for high scores in benchmarks, even in a black box.
We believe that ultimate AGI does not need benchmarks as long as the process is proven.

Comparison of development strategies

	Traditional AI	Ultimate AGI
Aim shape		
Improvement direction	Find and develop the good points	Find and fix the bad points
Important Ability	Presenting ideas	Rejecting ideas
Progress Check	Benchmark	Theoretical

The development approaches for conventional AI and ultimate AGI are different.
Conventional AI finds good points and develops them.
On the other hand, ultimate AGI finds bad points and fixes them.
The ability to find the bad points of an idea and reject it is more important than coming up with ideas.
Also, since benchmark tests are not available, it is difficult to monitor progress.

Reference

・Self intelligence

(Rather than reading observations of intelligence, observe intelligence in action)

The reference is self intelligence.
Rather than reading observations of intelligence, observe intelligence in action.

Afterword

This research is being carried out by volunteers.

No benchmark tests are required, so no supercomputers or big data are needed.

Anyone can take on the challenge.

It's not a shortcut to profit, but it is a shortcut to understanding intelligence.

Why not aim for the ultimate AGI, which will be humanity's last invention?

Contact: ai@ultagi.org https://ultagi.org/

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Next Episode

In the next video we will talk about "Statistics 2.0".

The name is tentative.

We will determine the optimal method of inductive inference.

To do this, we will significantly expand the concept of statistics.

In this video, we listed important pieces of the puzzle.

From the next video onwards, the pieces of the puzzle will start to come together.

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Contact Information

For inquiries,

please contact us here.

https://ultagi.org/