Artificial Intelligence in Computer Games
Not only strong, but also entertaining

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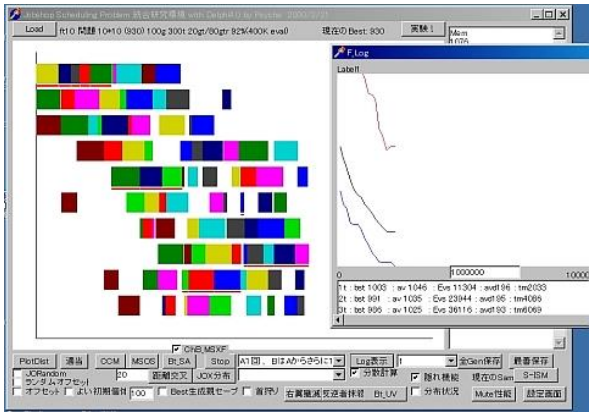
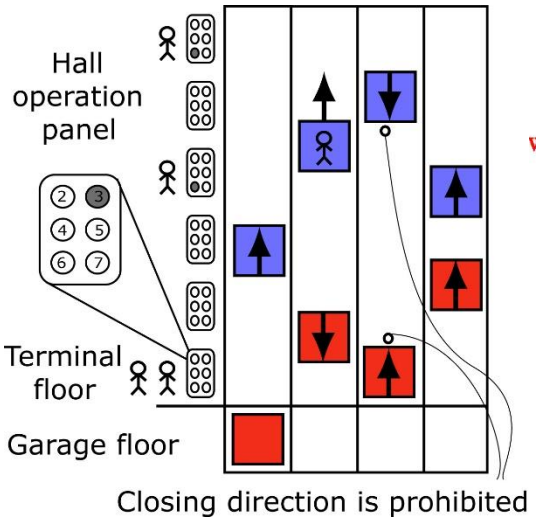
Artificial Intelligence

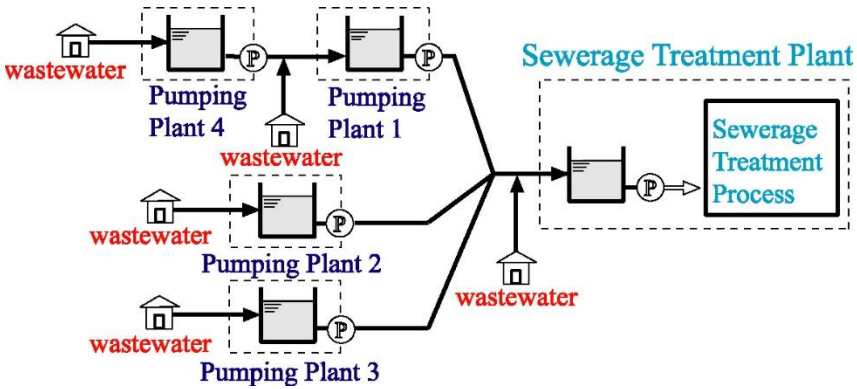
Many methods and many applications

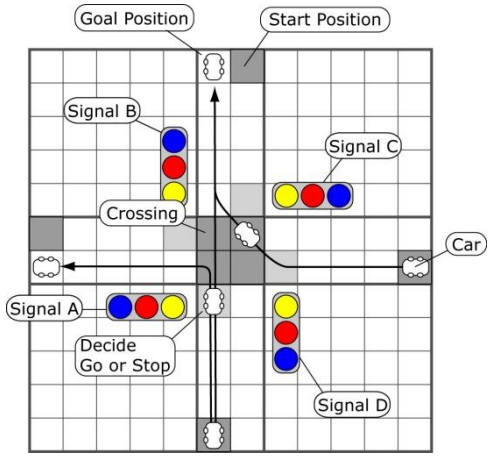
- Reasoning
- Machine Learning
- Tree Search
- Optimization

From **23** years old (to 34), I applied AI methods to many serious systems…







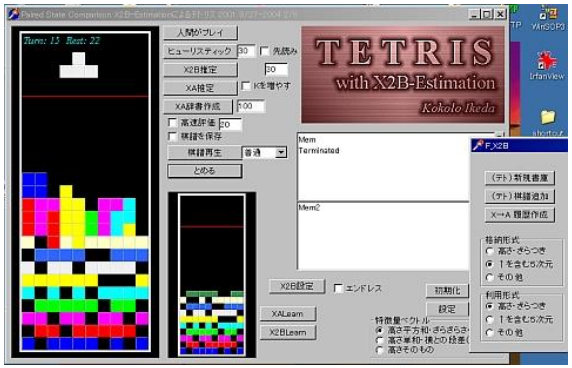


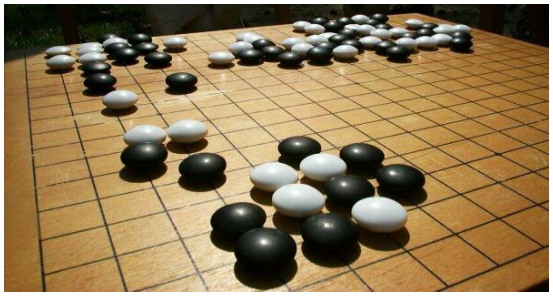
Artificial Intelligence in Games

But from **3** years old, I have played many games,
and I have had many complaints about AIs in Games.

AI methods are necessary for computer games,
and games are good testbeds for AI methods.

I want to improve AIs in Games, for researchers,
for game players, for society, and for me.





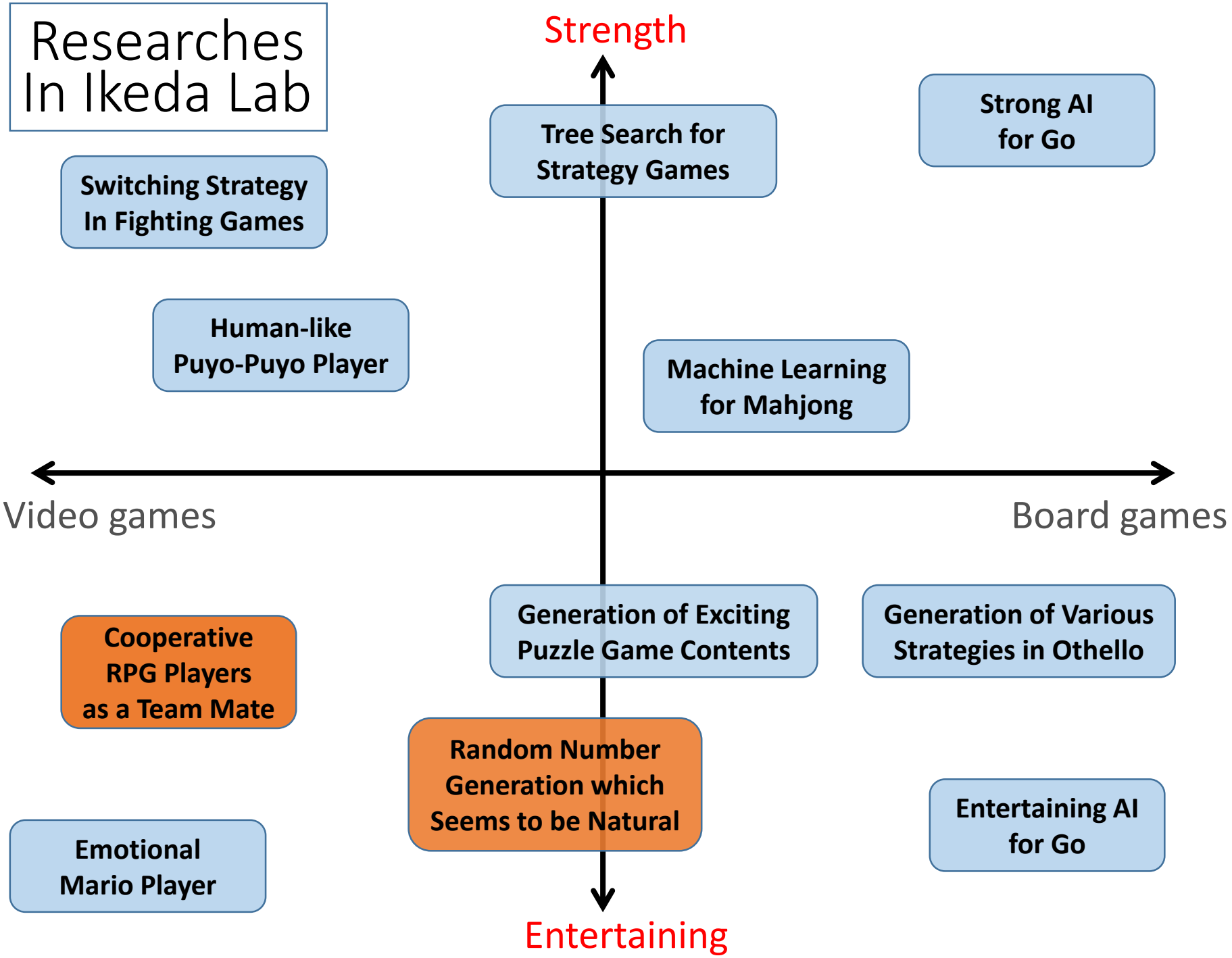
Not only strong, but also entertaining

- Board games such as Chess or Go have been the main target of AI researches
- Strong computer players have been sought
- By using sophisticated AI methods, they are now almost strong enough in many board games

→ Entertaining aspects are intensively studied

- Human-like behaviors
- Adaptive strength for each human player
- Emotion and speaking
- Contents generation (1 player game)
- Not only as an opponent, but also as a team-mate
- Or, as a coach

… etc.

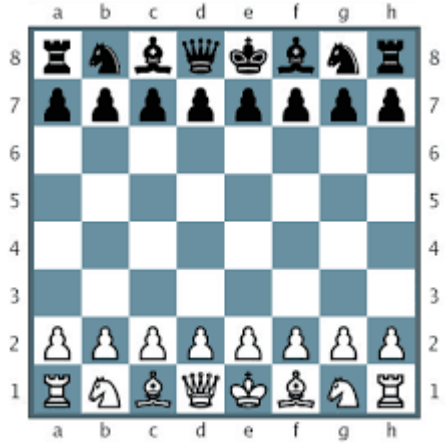

Researches In Ikeda Lab
Strength
Tree Search for Strategy Games
Strong AI for Go
Switching Strategy In Fighting Games
Human-like Puyo-Puyo Player
Machine Learning for Mahjong
Video games
Board games
Generation of Exciting Puzzle Game Contents
Generation of Various Strategies in Othello
Cooperative RPG Players as a Team Mate
Random Number Generation which Seems to be Natural
Entertaining AI for Go
Emotional Mario Player
Entertaining

Estimation of Player's Preference for Co-operative RPGs Using Multi-Strategy Monte-Carlo Method

IEEE Computer Intelligence in Games (CIG)

2015 31st. Aug.

Cooperative RPG Players as a Team Mate



Chess, 1 vs 1

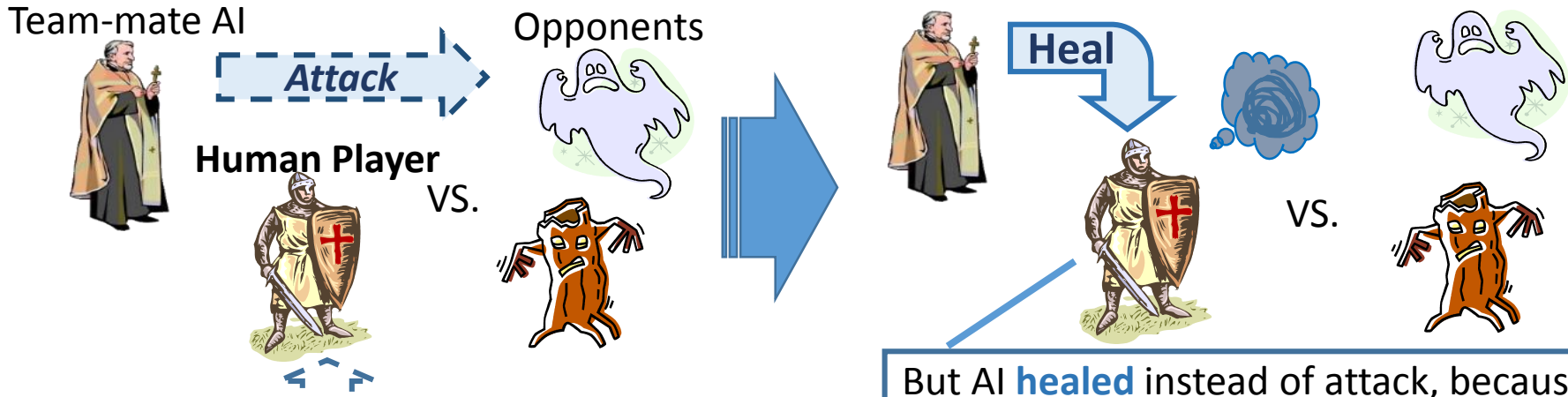
Soccer, team vs team

Wizardry [RPG], team vs team

DotA [RTS], team vs team

Game AIs in cooperative games

- AIs as opponent players
  - OK if not too strong or too weak
- AIs as team-mates
  - Strong play is not enough
  - AIs need to play in the way that each human player prefers
  - Otherwise, human player feels big dissatisfaction



→ So, AIs should estimate the preference of each player from his play

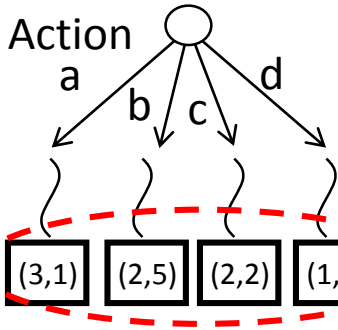
Approach overview

preference on game-state

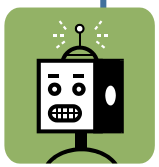
Human Player

Recorded

(state s_i, action a_i)



Simulate **averaged game end state** from the actions



Computer Player

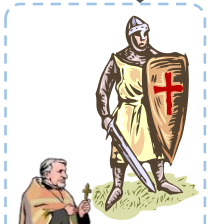
Interpret as:

(Preference for the result from the selected action) ≥ (Preference for the result from another action)

Derive

Estimated preference of the human player

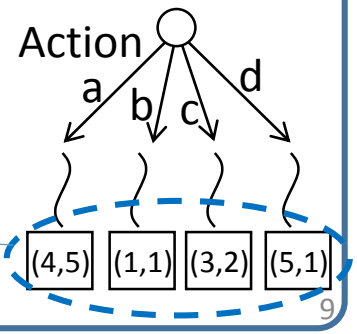
Action Selection



VS

Selecting action

Decide an action that leads **averaged end state** which is best according to the **human preference**



Estimation of player's preference

We use a simple parametrized **preference function**, and optimize the parameters

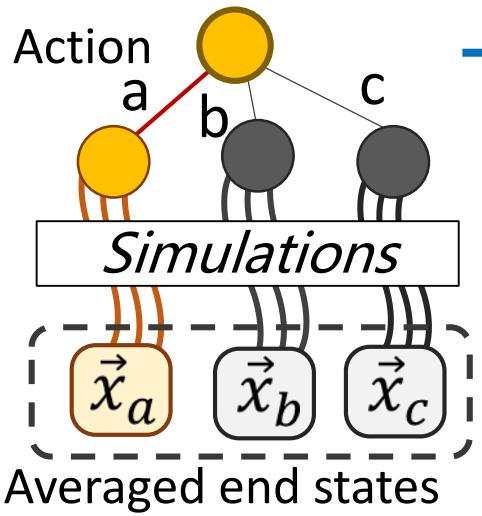
Preference function

- A function to evaluate the game end state
- Calculated as

$$u(\vec{x}, \vec{w}) = \vec{x} \cdot \vec{w}$$
$$= x_{HP} + w_{MP} \cdot x_{MP} + w_{Turn} \cdot x_{Turn}$$

Feature vector of the game state

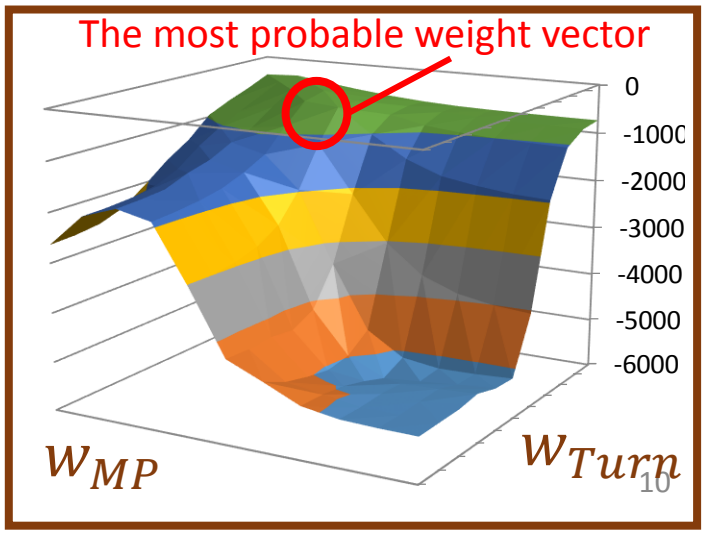
Preference weights vector $(1, w_{MP}, w_{Turn})$



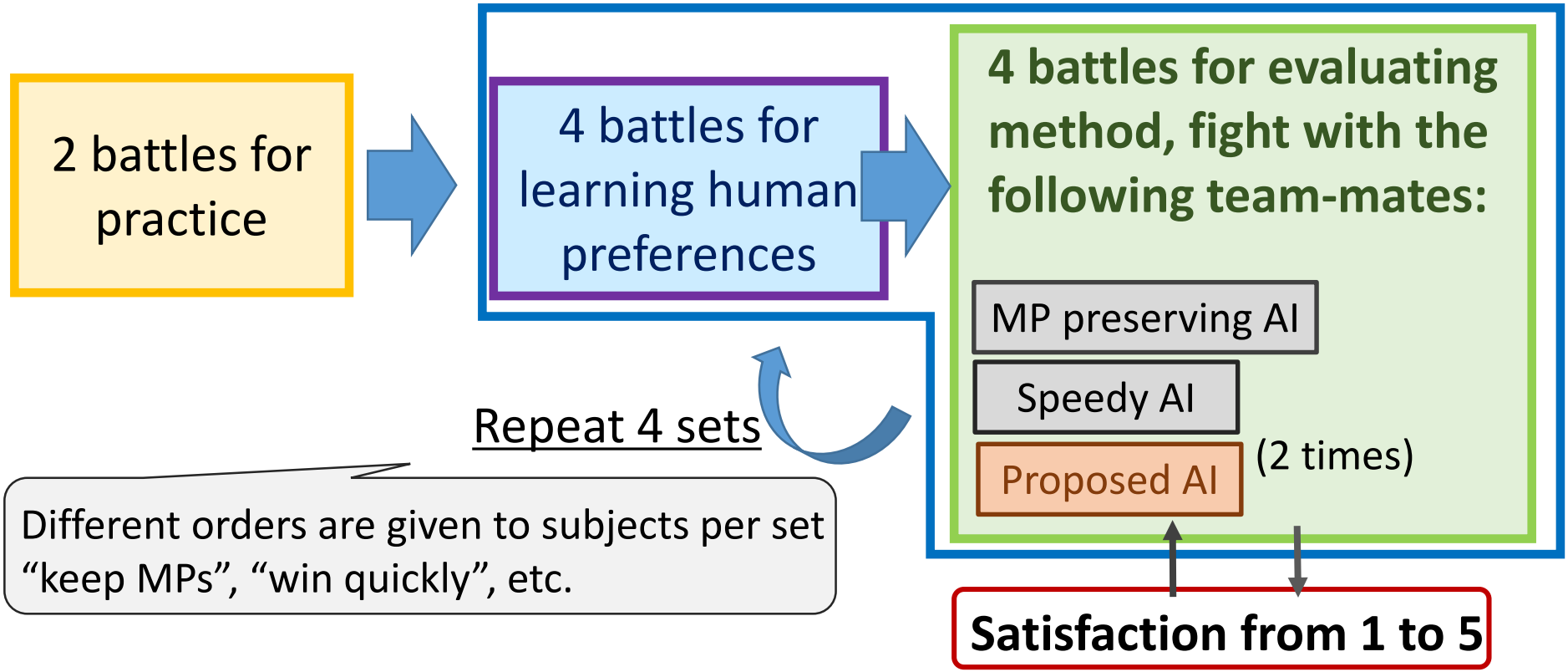
If the player select action a (not b),

$$u(\vec{x_a}, \vec{w}) > u(\vec{x_b}, \vec{w})$$

would hold.
If not, penalty is added.



Evaluation experiment using human subjects



(Team-mate)	[Direction] Keep MPs	Win quickly	Keep HPs	Win quickly and keep MPs
MP preserving AI	3.0	2.5	2.9	3.0
Speedy AI	2.1	4.0	3.2	2.7
Proposed AI	**3.4**	**4.2**	**3.8**	**4.0**

→ Our method successfully decreased the dissatisfaction of human players

Biased Random Sequence Generation for Making Common Player Believe it Unbiased

IEEE Game Entertainment Media (GEM) Conference
2014, October 23th

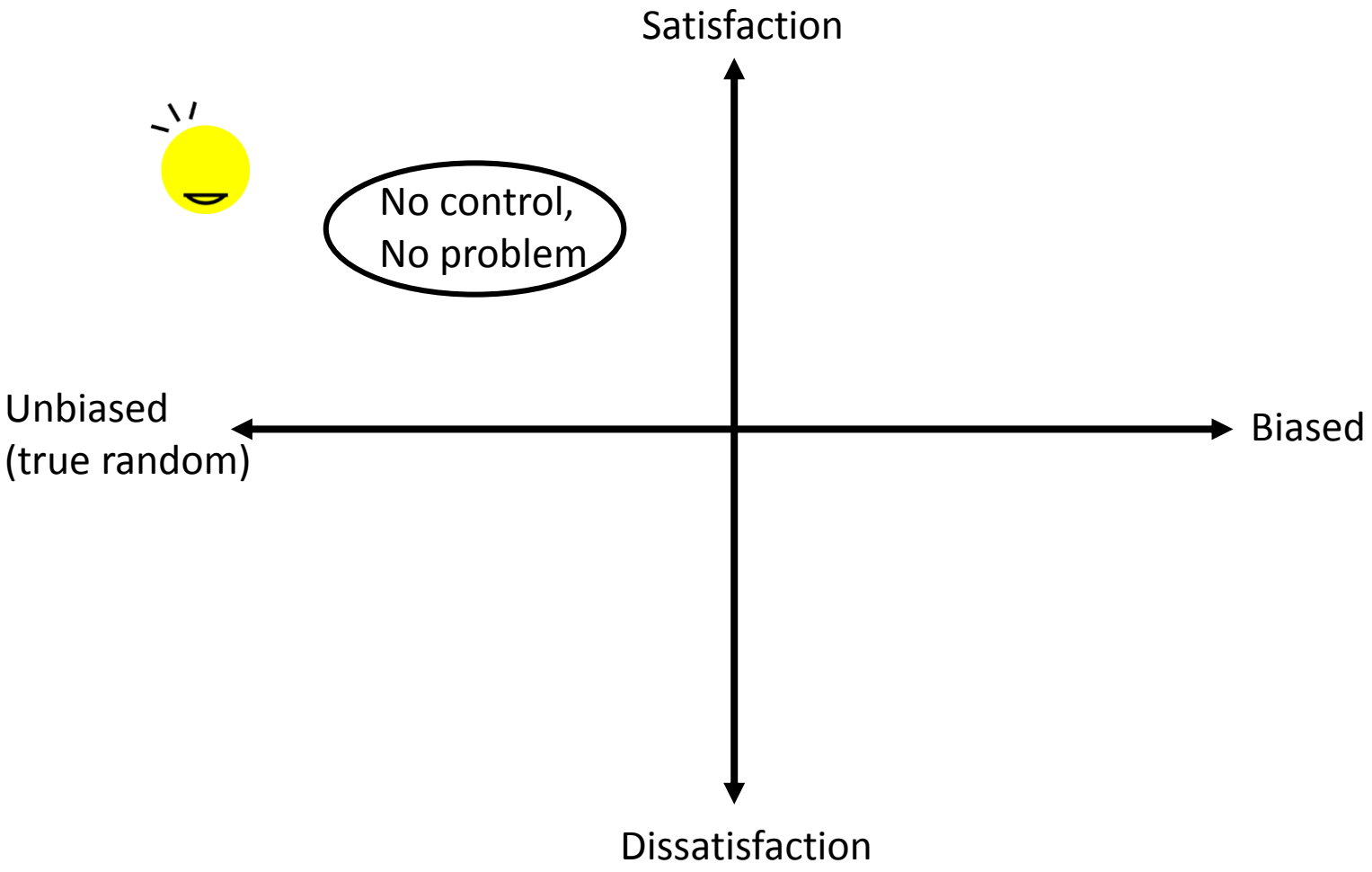
Random generation

- Pseudorandom algorithm widely used
  - Monte-Carlo methods
  - Stochastic optimization
  - Agent based simulation
  - Cryptography

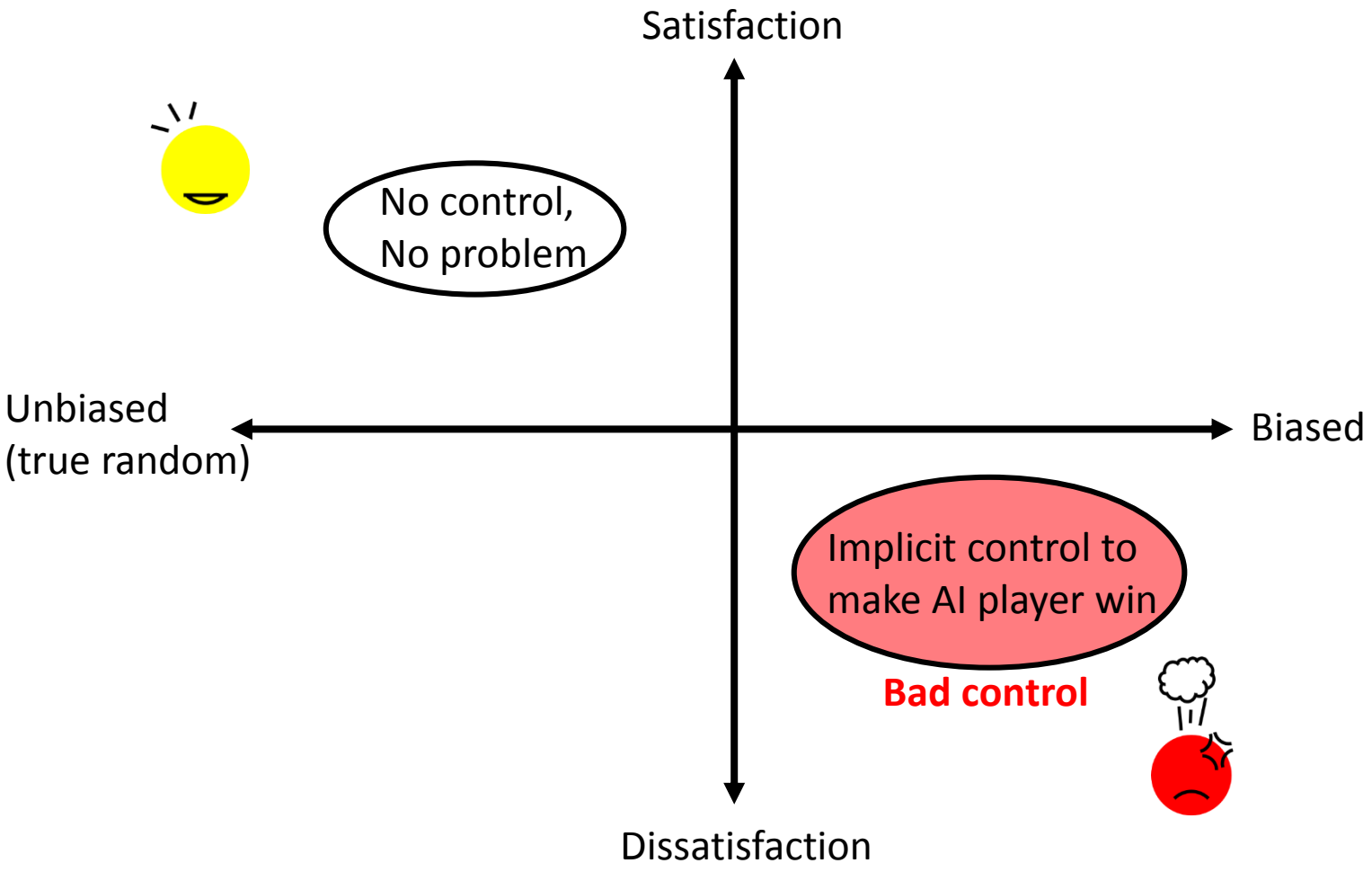
  → Sophisticated methods
  such as Mersenne Twister
- Also important in computer games
  - Card shuffling (Poker)
  - Rolling dice (Monopoly)
  - Judging hit/miss (RPG)

  → Usual random generator is sufficient?

Problem and purpose



Problem and purpose



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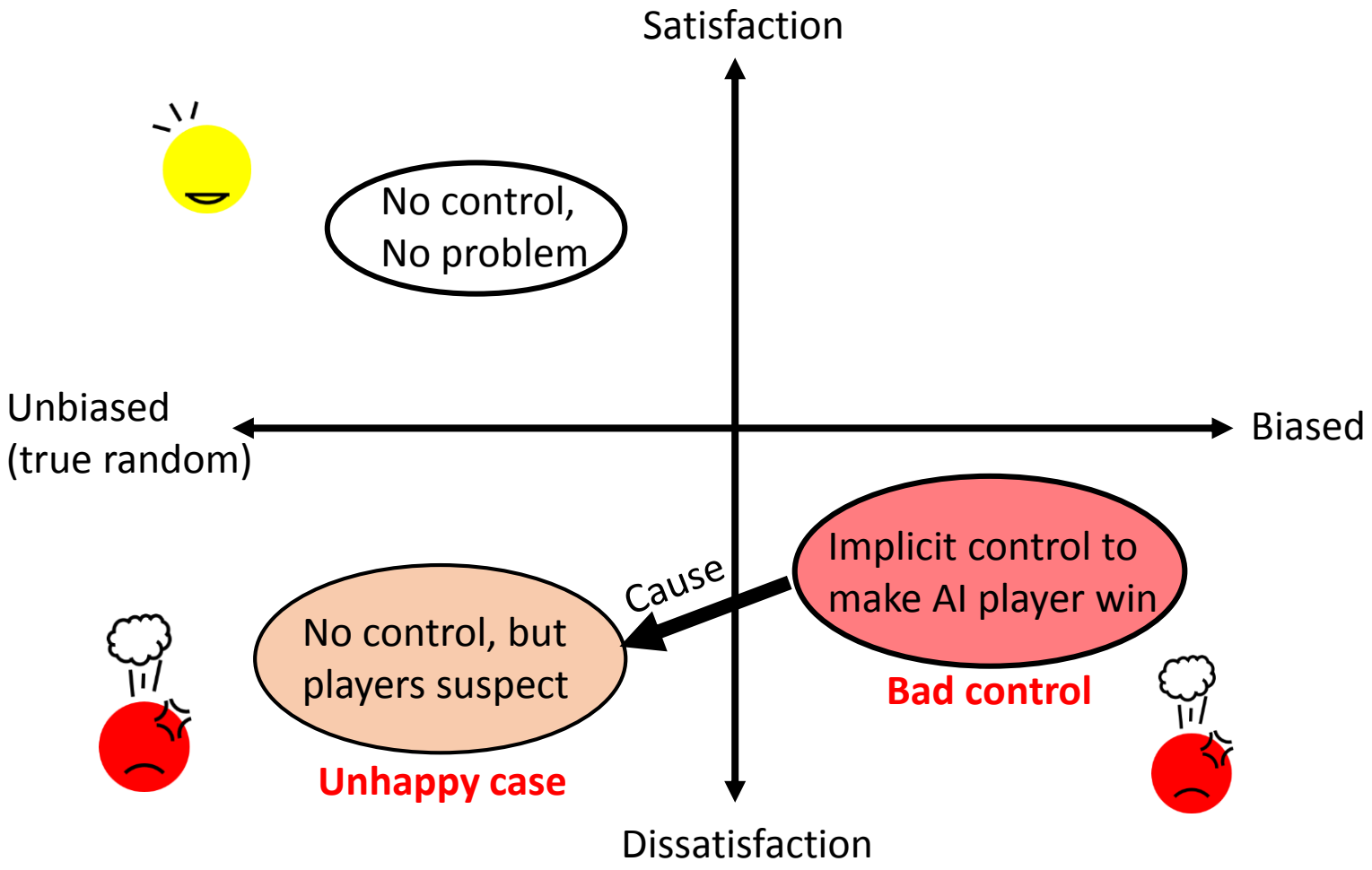
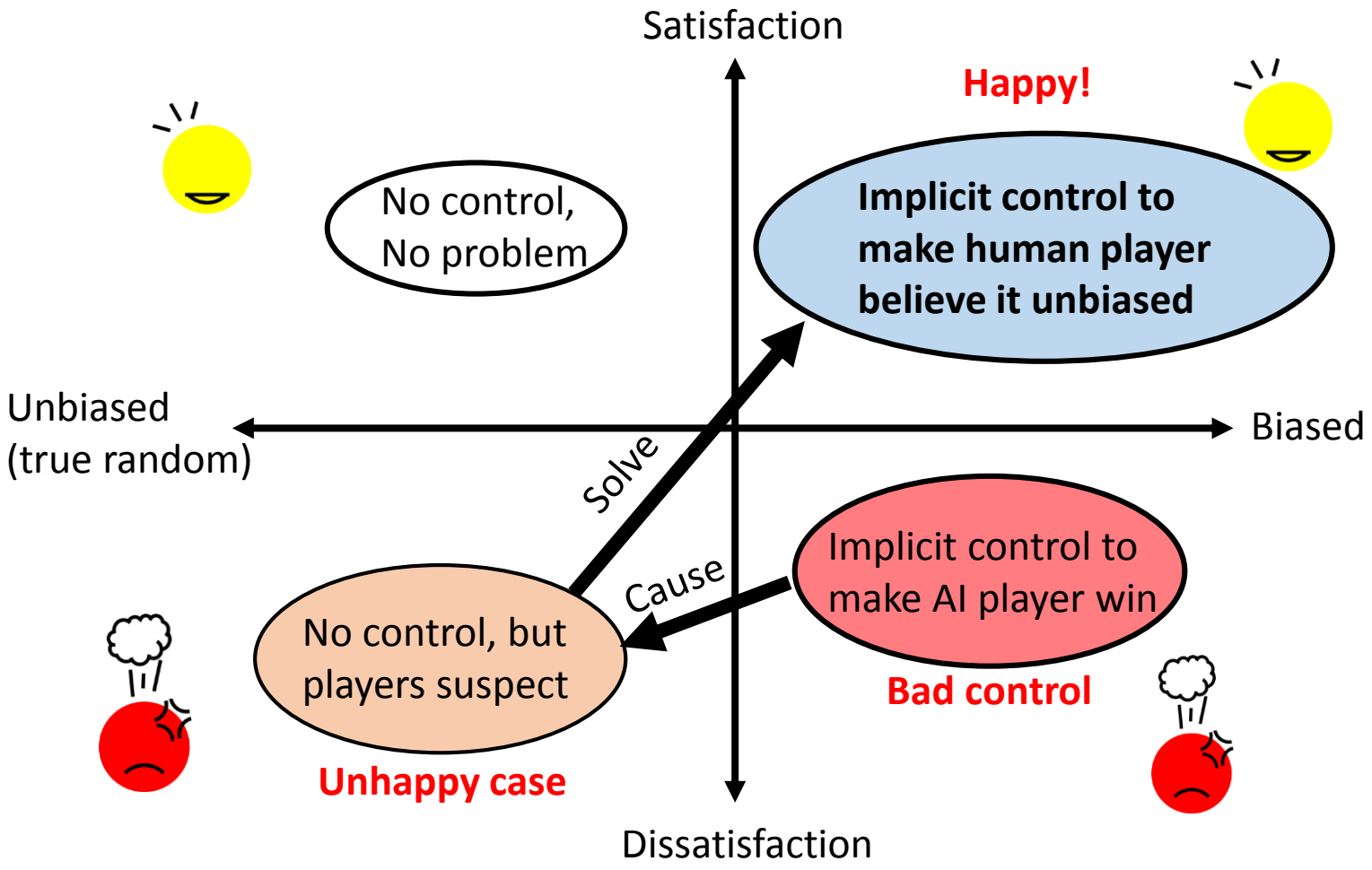
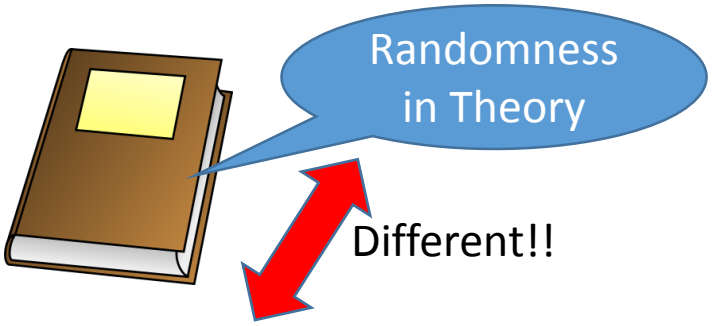


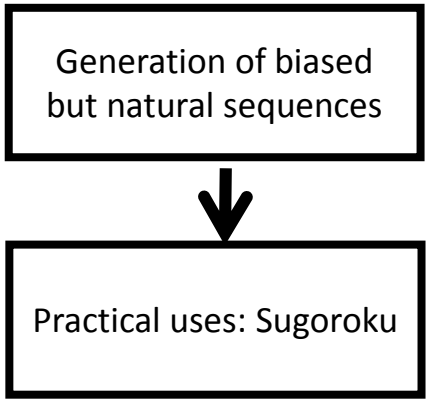
Problem and purpose

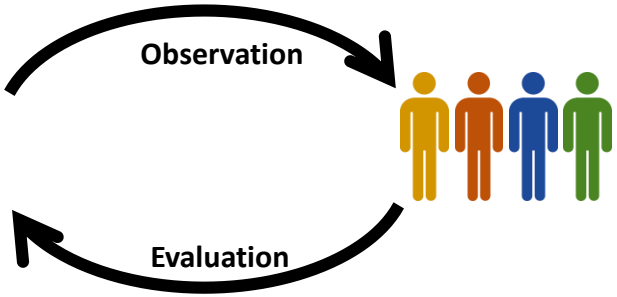


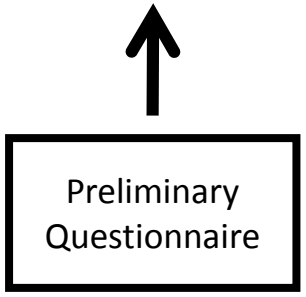
Approach

- Human players may have common cognitive bias on randomness
- Simulate the bias in random generation

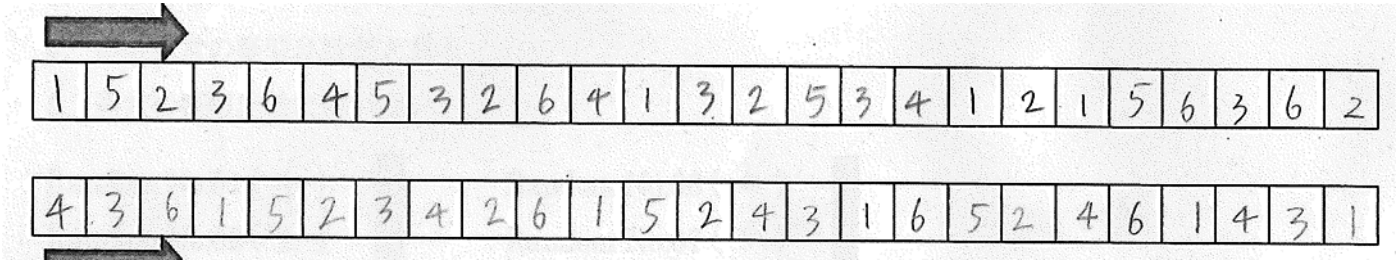








Sequences of 100 dice digits were manually generated (not with a real dice)



Do you find a typical bias in this sequence?

Common bias in human players

Feature	Theoretical	average	Top half	Bottom half
F6 : Frequency of the flips from even to odd (or vice versa) 	49.5	**55.6**	62.0	49.3
F7 : Frequency of the same numbers appearing consecutively 2 times. (e.g. )	16.5	**10.9**	15.9	6.0
F12 : Frequency of subsequences in which 3 of 4 digits are the same numbers.(e.g. )	4.5	**1.4**	2.8	0.0

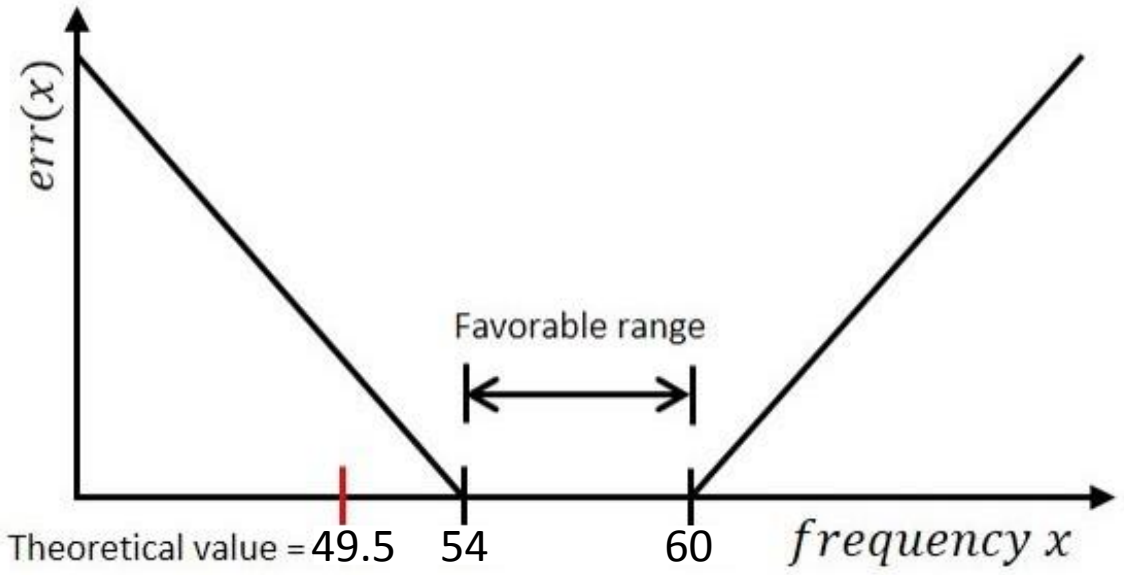
- Average of F6 is higher than the theoretical value
  - Frequent change of even/odd seems to be natural
- Average of F7 is lower than theoretical (Even the average of top half is lower)
  - It seems to be unnatural that the same number appears in a row
- Average of F12 is below $\frac{1}{3}$ of theoretical value
  - Close similar numbers seem to be unnatural

Significant bias were found in almost all 15 features → We simulate this bias

Error function to be minimized

$$err(s) = \sum_i (\gamma_i err_i(f_i(s)))$$

- $err_i(x)$: amount of deviation from the favorable range.
- γ_i : weight of deviation for this feature.

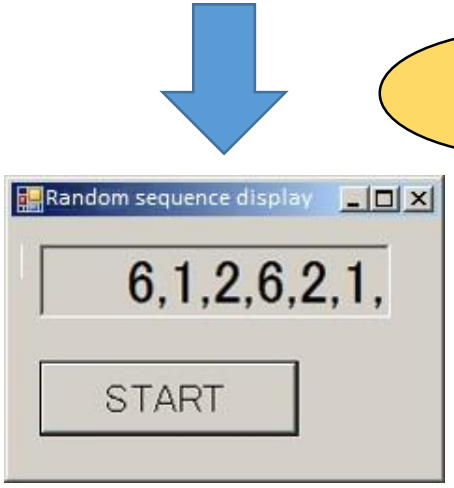


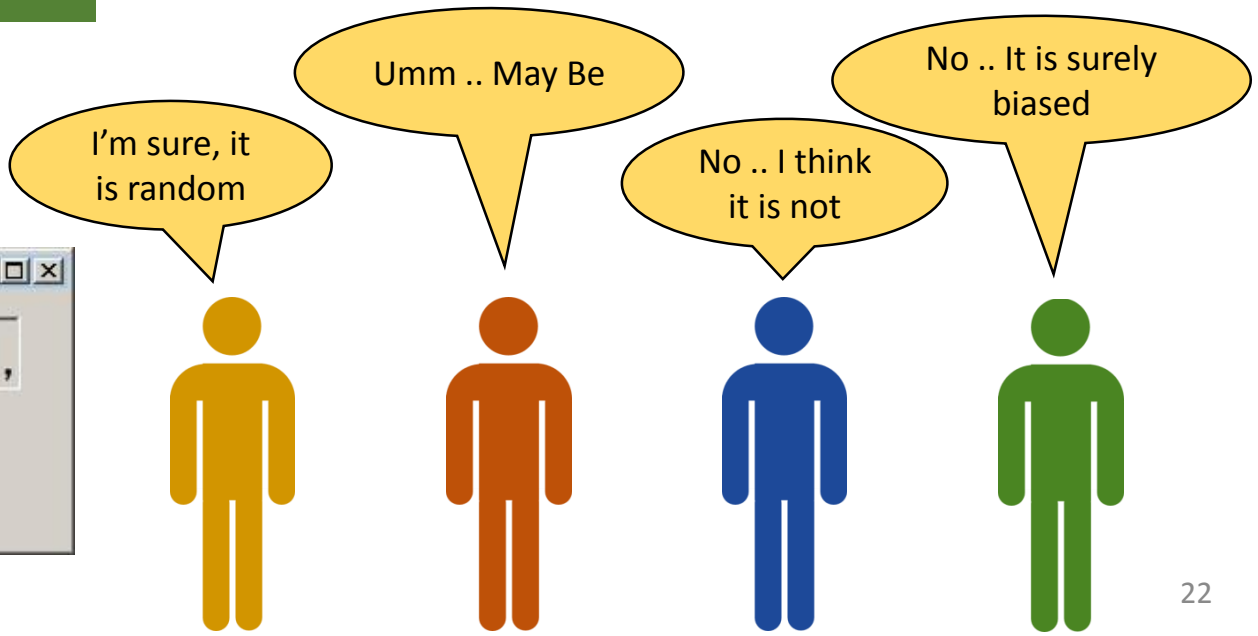
Case of $err_{F6}(x)$

The sequences will look more natural with smaller $err(s)$ value.

Evaluation using human subjects

Standard sequences	Generated by MT pseudorandom algorithm
Low rank sequences	Bottom 20% of 300 pseudorandom sequences (sorted by $err()$)
Proposed sequences	Optimized pseudorandom sequences ($err()$ =0)





Evaluation using human subjects

Group	Score					
	1	2	3	4	5	Average
[Standard]	11	**19**	2	**11**	5	2.58
[Low rank]	17	**23**	2	5	1	1.96
[Proposed]	7	9	4	**23**	5	3.21

- 48 votes for each type.
- [Standard] range of $err()$ are 2.7 to 238.0, some might look natural, and some might not.
- [Low rank] seems to be unnatural, even though they are not so rare sequences
- [Optimized] get higher scores than the others

"Biased Random Sequence Generation for Making Common Player Believe it Unbiased" was successfully achieved.

Thank you!