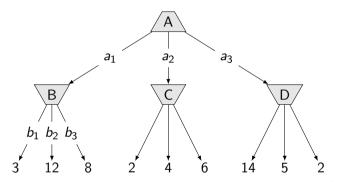
Uncertainty, Chance, and Utilities

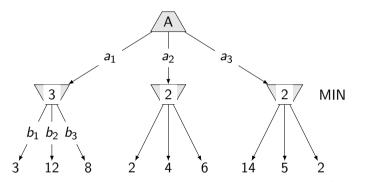
Tomáš Svoboda

Vision for Robots and Autonomous Systems, Center for Machine Perception Department of Cybernetics Faculty of Electrical Engineering, Czech Technical University in Prague

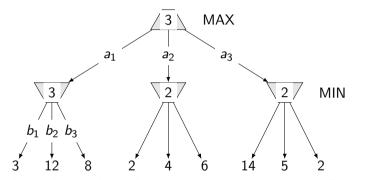
March 10, 2022



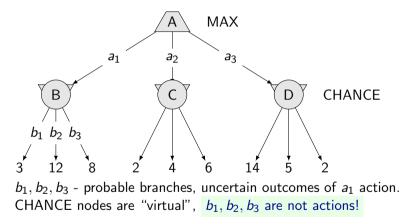
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Why? Actions may fail, ...



Video: Slipping robot. Vision for Robotics and Autonomous Systems, http://cyber.felk.cvut.cz/vras, https://youtu.be/kvEEHNyCHMs

A At home

tram bike car

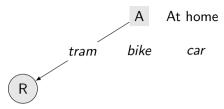
Random variable: Situation on rails R

 r_1 free rails

r₂ accident

 r_3 congestion

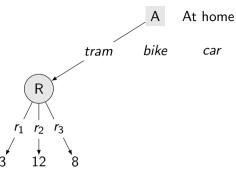
MAX/MIN depends on what the r_7 options and terminal numbers mean. The goal may be to get to work as fast as possible.



Random variable: Situation on rails R

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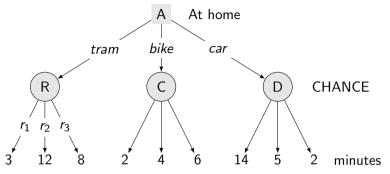




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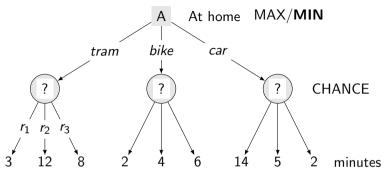
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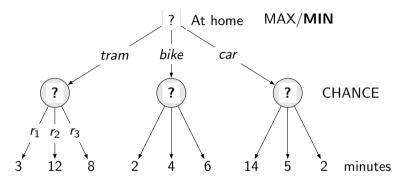
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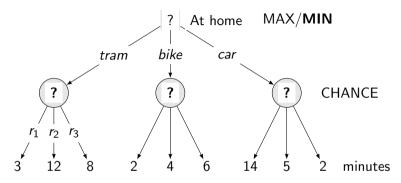
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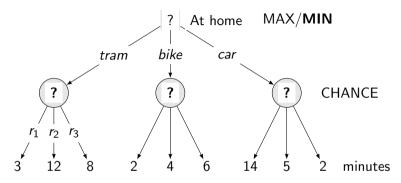
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- ► Calculate expected utilities . .
- i.e. take weighted average (expectation) of successors

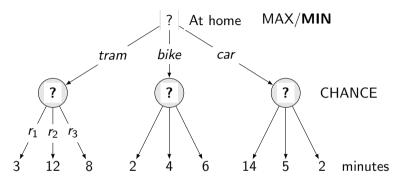


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Expectimax

function EXPECTIMAX(state) return a value

if IS-TERMINAL(state): return UTILITY(state)

if state (next agent) is MAX: return MAX-VALUE(state)

if state (next agent) is CHANCE: return EXP-VALUE(state)

end function

function MAX-VALUE(state) return value v

 $v \leftarrow -\infty$

```
for a in ACTIONS(state) do
```

```
v \leftarrow \max(v, \text{EXPECTIMAX}(\text{RESULT}(\text{state}, a)))
```

end for

end function

```
function EXP-VALUE(state) return value v

v \leftarrow 0

for all r \in random events do

v \leftarrow v + P(r) EXPECTIMAX(RESULT(state, r))

end for

end function
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Expectimax

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- Random variable an event with unknown outcome
- Probability distribution assignment of weights to the outcomes



- Random variable: R situation on rails
- Outcomes/events: r ∈ {free rails, accident, congestion}
- Probability distribution: P(R = free rails) = 0.3, P(R = accident) = 0.1, P(R = congestion) = 0.6

- always non-negative,
- sum over all possible outcomes is equal to 1.

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Few reminders from laws of probability, Probabilities:

always non-negative,

sum over all possible outcomes is equal to 1.

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How long does it take to go to work by tram?

- **•** Depends on the random variable R situation on rails with possible events r_1, r_2, r_3 .
- What is the expectation of the time?

$t = P(r_1)t_1 + P(r_2)t_2 + P(r_3)t_3$

Weighted average.

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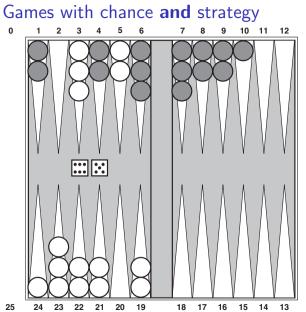
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How about the Reversi game?

- Is there any space for randomness?
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- Hope for chance when there is adversarial world Dangerous optimism .
 Assuming worst case even if it is not likely Dangerous pessimism.

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25

Random variable: Throwing two dice

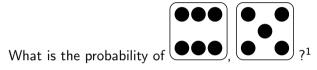
Do we care which die comes first?

What is the probability of , ? A 1/24 B 1/36 C 1/18 D 1/6

Source of dice images: https://flyclipart.com/dice-clipart-tool-rolling-dice-clipart-248574

Random variable: Throwing two dice

Do we care which die comes first?

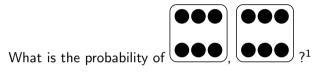


- A 1/24
- **B** 1/36
- C 1/18
- D 1/6

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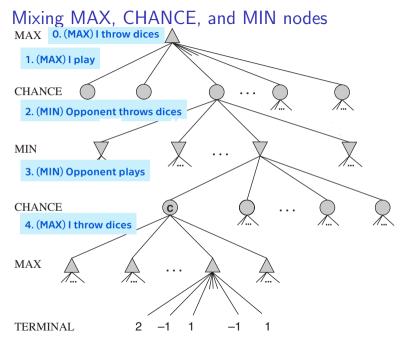
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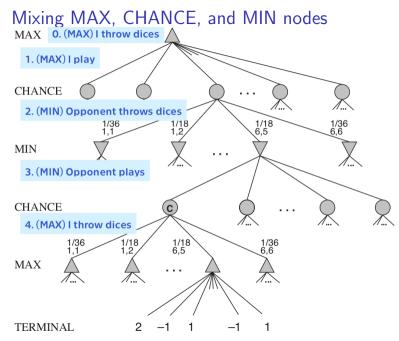
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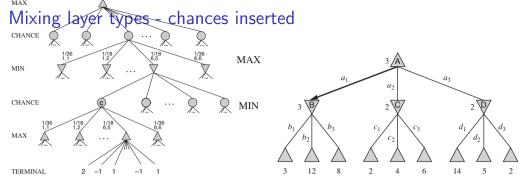
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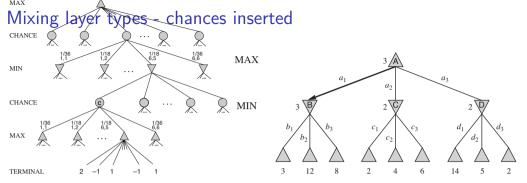


12 / 35



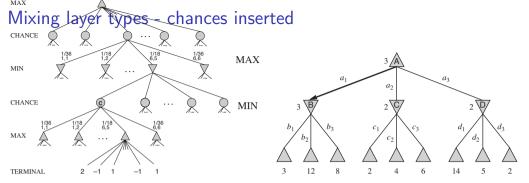
EXPECTIMINIMAX(s) =

 $\begin{cases} \text{UTILITY}(s, \text{MAX}) & \text{if } \text{IS-TERMINAL}(s) \\ \text{max}_{a}\text{EXPECTIMINIMAX}(\text{RESULT}(s, a)) & \text{if } \text{TO-PLAY}(s) = \text{MAX} \\ \text{min}_{a}\text{EXPECTIMINIMAX}(\text{RESULT}(s, a)) & \text{if } \text{TO-PLAY}(s) = \text{MIN} \\ \sum_{r} P(r)\text{EXPECTIMINIMAX}(\text{RESULT}(s, r)) & \text{if } \text{TO-PLAY}(s) = \text{CHANCE} \end{cases}$

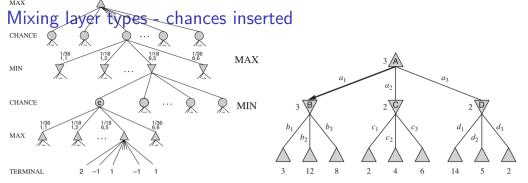


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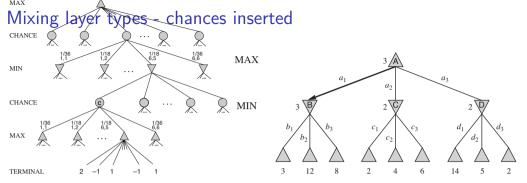
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```
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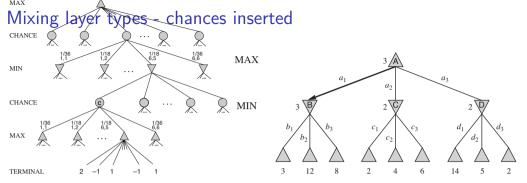
```
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```



Extra random agent that moves after each MAX and MIN agent

EXPECTIMINIMAX(s) =

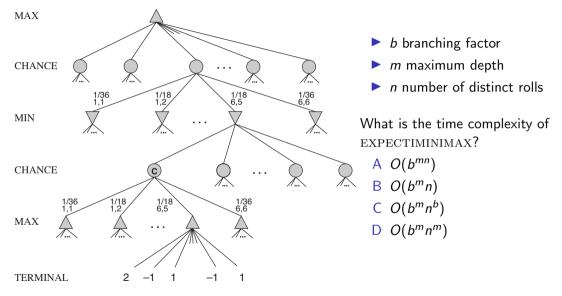
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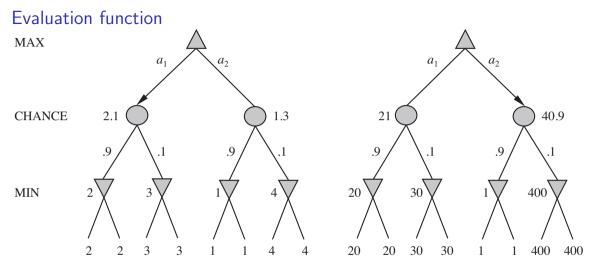


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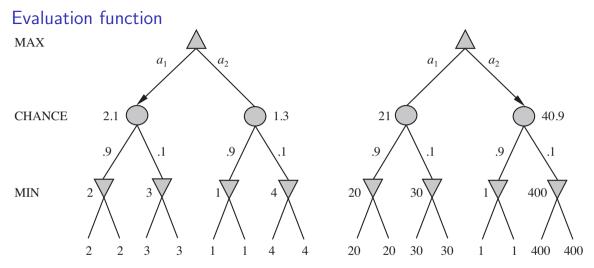
Mixing chance into min/max tree. How big is the tree going to be?



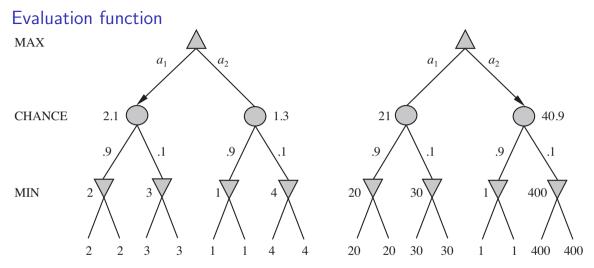


• Left: a_1 is the best. Right: a_2 is the best. Ordering of the (terminal) leaves is the same.

- Scale matters! Not only ordering
- Can we prune the tree? (lpha, eta like?)

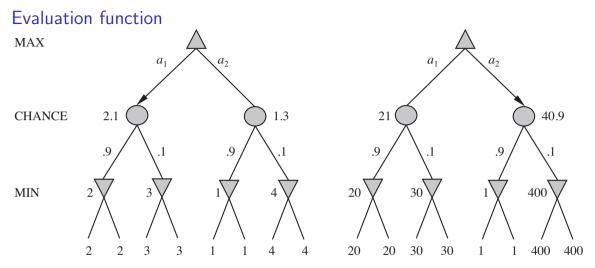


Left: a₁ is the best. Right: a₂ is the best. Ordering of the (terminal) leaves is the same.
 Scale matters! Not only ordering.
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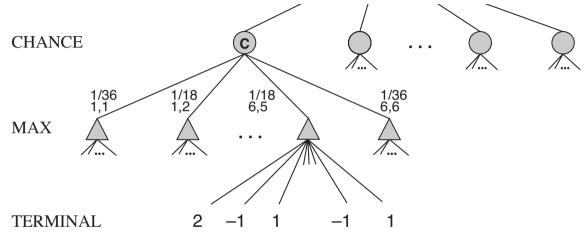
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- ▶ Left: a_1 is the best. Right: a_2 is the best. Ordering of the (terminal) leaves is the same.
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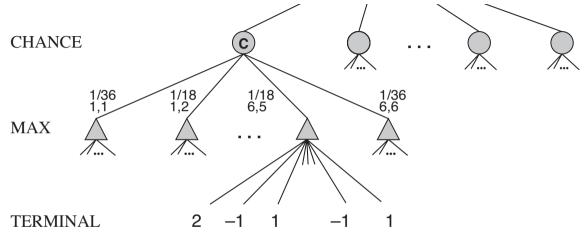
Pruning expectiminimax tree



Bounds on terminal utilities needed. Terminal values from -2 to 2.

Monte Carlo simulation for evaluation of a position (state).

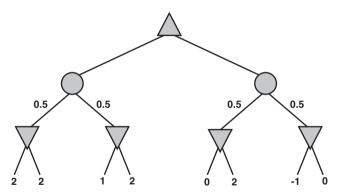
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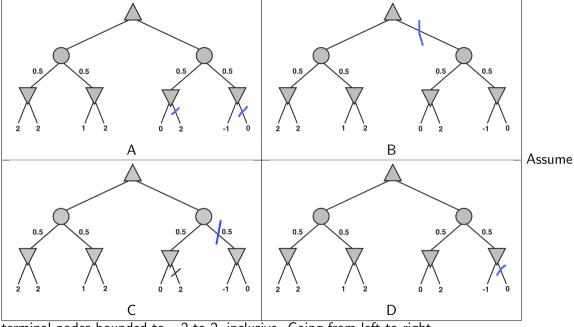


- **b** Bounds on terminal utilities needed. Terminal values from -2 to 2.
- Monte Carlo simulation for evaluation of a position (state).

Where to prune the Expectimax tree

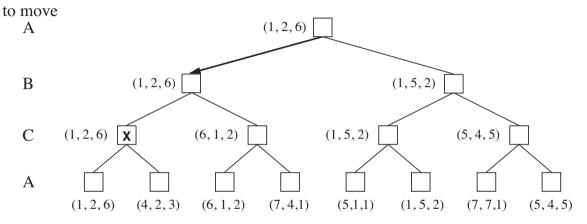
- Assume terminal nodes bounded to -2 to 2, inclusive
- ► Going from left to right.
- Which branches can be pruned out?





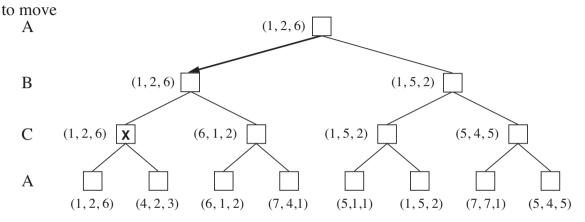
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Multi-player games



- Utility tuples
- Each player maximizes its own
- Coalitions, cooperations, competitions may be dynamic

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Uncertainty recap (enough games, back to the robots/agents)



Uncertain outcome of an action.

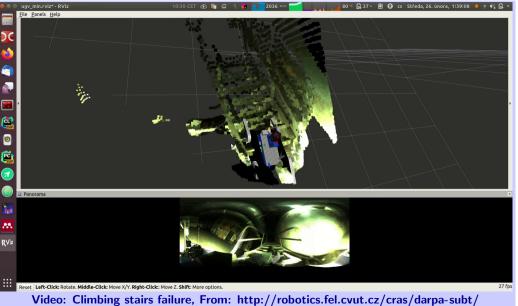
Robot/Agent may not know the current state!

Uncertainty recap (enough games, back to the robots/agents)



- Uncertain outcome of an action.
- Robot/Agent may not know the current state!

Uncertain outcome of an action



Uncertain, partially observable environment

- Current state s may be unknown, observations e
- Uncertain outcome, random variable RESULT(a)
- Probability of outcome s' given **e** is

 $P(\text{RESULT}(a) = s'|a, \mathbf{e})$

- Utility function U(s) corresponds to agent preferences.
- Expected utility of an action *a* given **e**:

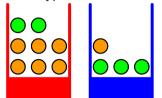
$$EU(a|\mathbf{e}) = \sum_{s'} P(\text{RESULT}(a) = s'|a, \mathbf{e})U(s')$$



About (conditional) probabilities

Two kind of boxes in a dark warehouse. State - box type color - is not directly observable.

- red box: 2 apples, 6 oranges
- blue box: 3 apples, 1 orange

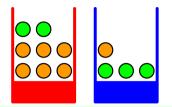


- Scenario: Pick a box at random. *Then* pick a fruit at random.
- (Frequent) questions:
 - What is the overall probability that the selection procedure will pick an apple?
 - Given that we have chosen an orange, what is the probability that it was from the blue box?

Example from Chapter 1.2 [1]

Picking fruits. What is the probability that ...?

- ▶ red box: 2 apples, 6 oranges
- blue box: 3 apples, 1 orange

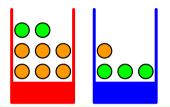


Procedure: Pick a box (say red box in 40% cases), then pick a fruit at random. Quiz 1: What is the probability that the selection procedure will pick an apple?

- A: 11/20
- **B**: 6/8
- C: 1/2
- D: Different value.

Picking fruits. What is the probability that ...?

- ▶ red box: 2 apples, 6 oranges
- ▶ blue box: 3 apples, 1 orange



Procedure: Pick a box (say red box in 40% cases), then pick a fruit at random. Quiz 2: Given that we have chosen an orange, what is the probability that it was from the blue box?

- A: 1/4
- **B**: 3/5
- C: 1/3

D: Different value.

Rational agent

Agent's expected utility of an action a given e:

$$EU(a|\mathbf{e}) = \sum_{s'} P(\text{RESULT}(a) = s'|a, \mathbf{e})U(s')$$

What should a rational agent do?

Is it then all solved? Do we know all what we need?

P(RESULT(a) = s'|a, e)
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$$\blacktriangleright P(\text{RESULT}(a) = s' | a, \mathbf{e})$$

► U(s')

Utilities



- ► Where do utilities come from?
- Does averaging make sense?
- Do they exist?
- What if our preferences can't be described by utilities?

Agent/Robot Preferences

► Prizes A, B

• Lottery: uncertain prizes L = [p, A; (1 - p), B]

Preference, indifference, .

- Robot prefers A over $B: A \succ B$
- Robot has no preferences: $A \sim B$
- ▶ in between: $A \succeq B$

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- **•** Robot prefers A over $B: A \succ B$
- Robot has no preferences: $A \sim B$
- ▶ in between: $A \succeq B$

Rational preferences

- Transitivity: $(A \succ B) \land (B \succ C) \Rightarrow (A \succ C)$
- Completeness: $(A \succ B) \lor (B \succ A) \lor (A \sim B)$
- Continuity: $(A \succ B \succ C) \Rightarrow \exists p \ [p, A; 1-p, C] \sim B$
- ▶ Substituability: $A \sim B \Rightarrow [p, A; 1 p, C] \sim [p, B; 1 pC]$. The same for \succ and \sim .
- Monotonocity: A ≻ B ⇒ (p > q) ⇔ [p, A; 1 − p, B] ≻ [q, A; 1 − q, B]. Agent must prefer a lottery with higher chance to win.
- Decomposability, compressing compound lotteries into one: [p, A; 1 - p, [q, B; 1 - q, C]] ~ [p, A; (1 - p)q, B; (1 - p)(1 - q), C]

Axioms of utility theory.

Motivation: if agent/robot violates an axiom \Rightarrow irrational agent/robot.

Rational preferences

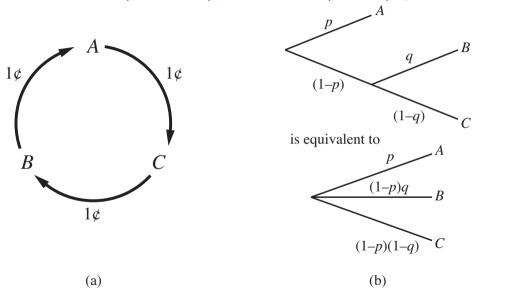
- Transitivity: $(A \succ B) \land (B \succ C) \Rightarrow (A \succ C)$
- Completeness: $(A \succ B) \lor (B \succ A) \lor (A \sim B)$
- Continuity: $(A \succ B \succ C) \Rightarrow \exists p \ [p, A; 1 p, C] \sim B$
- ▶ Substituability: $A \sim B \Rightarrow [p, A; 1 p, C] \sim [p, B; 1 pC]$. The same for \succ and \sim .
- Monotonocity: A ≻ B ⇒ (p > q) ⇔ [p, A; 1 − p, B] ≻ [q, A; 1 − q, B]. Agent must prefer a lottery with higher chance to win.
- Decomposability, compressing compound lotteries into one: [p, A; 1 - p, [q, B; 1 - q, C]] ~ [p, A; (1 - p)q, B; (1 - p)(1 - q), C]

Axioms of utility theory.

Motivation: if agent/robot violates an axiom \Rightarrow irrational agent/robot.

Transitivity and decomposability

Goods A, B, C and (nontransitive) preferences of an (irrational) agent $A \succ B \succ C \succ A$.



Maximum expected utility principle

Given the rational preferences (constraints), there exists a real valued function u such that:

$$u(A) > u(B) \Leftrightarrow A \succ B$$

 $u(A) = u(B) \Leftrightarrow A \sim B$

Expected utility of a Lotery L (outcomes s_i with probabilities p_i)

$$L([p_1, S_1; \cdots; p_n, S_n]) = \sum_i p_i u(S_i)$$

Proof in [5]. Is a utility *u* function unique?

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Human utilities

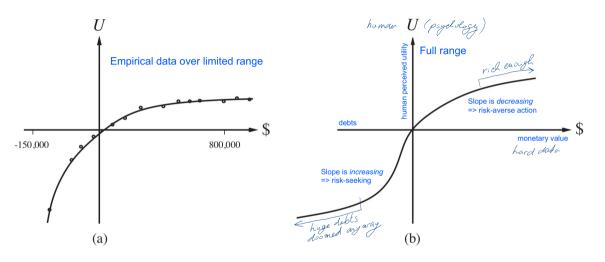


Utility of money

You triumphed in a TV show!

- a) Take \$1,000,000 ... or
- b) Flip a coin and loose all or win \$2,500,000

Utility of money: human psychology vs. hard data



References I

Some figures from [3], Chapters 5, 16. Human utilities are discussed in [2]. This lecture has been also greatly inspired by the 7th lecture of CS 188 at http://ai.berkeley.edu as it convenietly bridges the world of deterministic search and sequential decisions in uncertain worlds.

[1] Christopher M. Bishop.

Pattern Recognition and Machine Learning. Springer Science+Bussiness Media, New York, NY, 2006. https://www.microsoft.com/en-us/research/uploads/prod/2006/01/ Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf.

[2] Daniel Kahneman.

Thinking, Fast and Slow. Farrar, Straus and Giroux, 2011.

References II

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