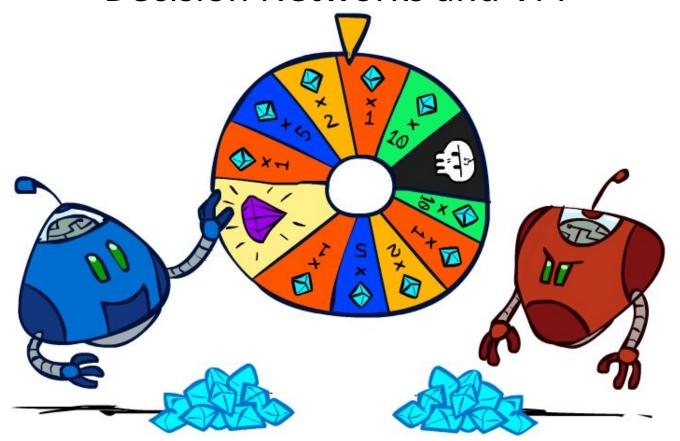
## CS 188: Artificial Intelligence

**Decision Networks and VPI** 



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University of California, Berkeley

### **Rational Preferences**

The Axioms of Rationality





#### Rational Preferences

#### The Axioms of Rationality

```
Orderability:
     (A > B) \lor (B > A) \lor (A \sim B)
Transitivity:
     (A > B) \land (B > C) \Rightarrow (A > C)
Continuity:
     (A > B > C) \Rightarrow \exists p [p, A; 1-p, C] \sim B
Substitutability:
     (A \sim B) \Rightarrow [p, A; 1-p, C] \sim [p, B; 1-p, C]
Monotonicity:
     (A > B) \Rightarrow
          (p \ge q) \Leftrightarrow [p, A; 1-p, B] \ge [q, A; 1-q, B]
```

#### What's the implication?

# MEU Principle

- Theorem [Ramsey, 1931; von Neumann & Morgenstern, 1944]
  - Given any preferences satisfying the previous constraints, there exists a real-valued function U such that:



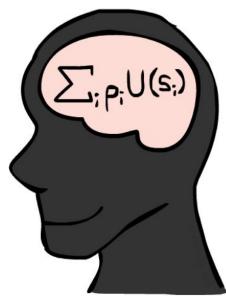
### MEU Principle

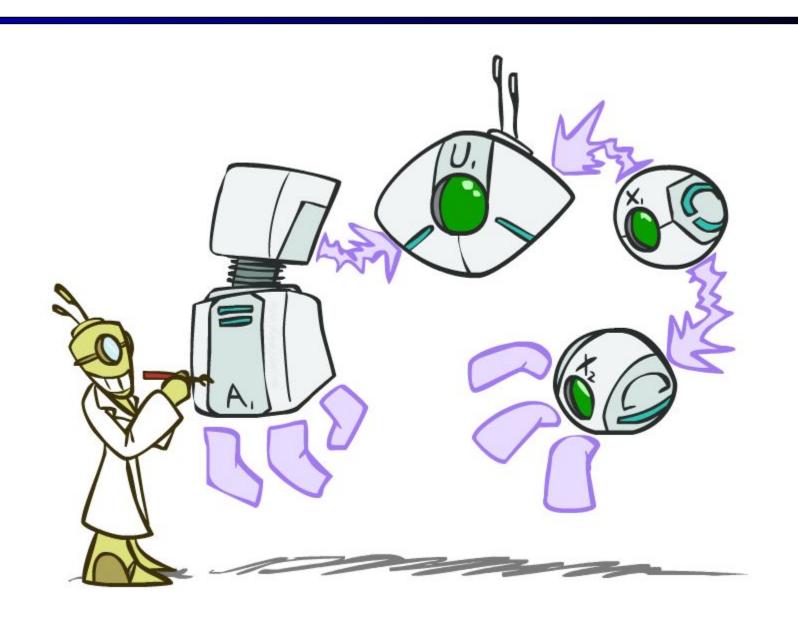
- Theorem [Ramsey, 1931; von Neumann & Morgenstern, 1944]
  - Given any preferences satisfying the previous constraints, there exists a real-valued function U such that:

$$U(A) > U(B) \Leftrightarrow A > B \text{ and } U(A) \sim U(B) \Leftrightarrow A \sim B$$
  
 $U([p_1, S_1; \dots; p_n, S_n]) = p_1 U(S_1) + \dots + p_n U(S_n)$ 



A rational agent chooses the action that maximizes expected utility





In its most general form, a decision network represents information about

- Its current state
- Its possible actions
- The state that will result from its actions
- The utility of that state

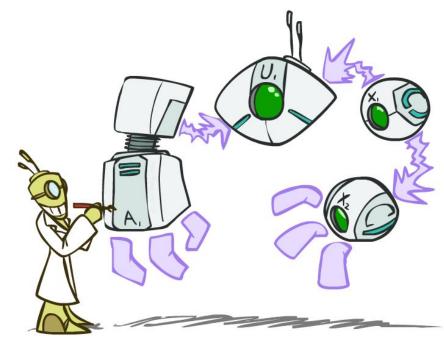
Decision network = Bayes net + Actions + Utilities

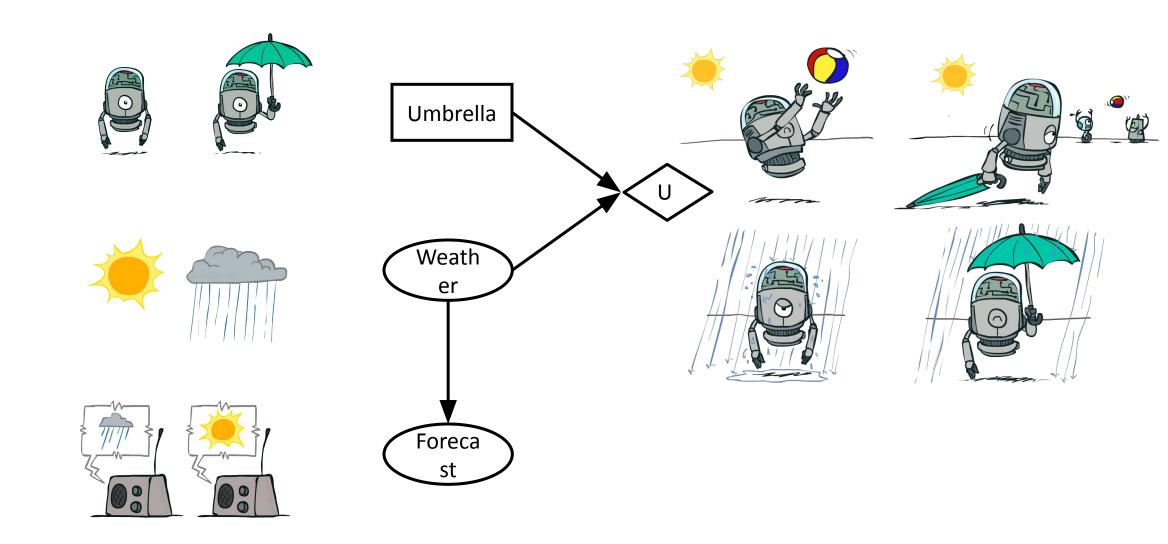


 Action nodes (rectangles, cannot have parents, will have value fixed by algorithm)

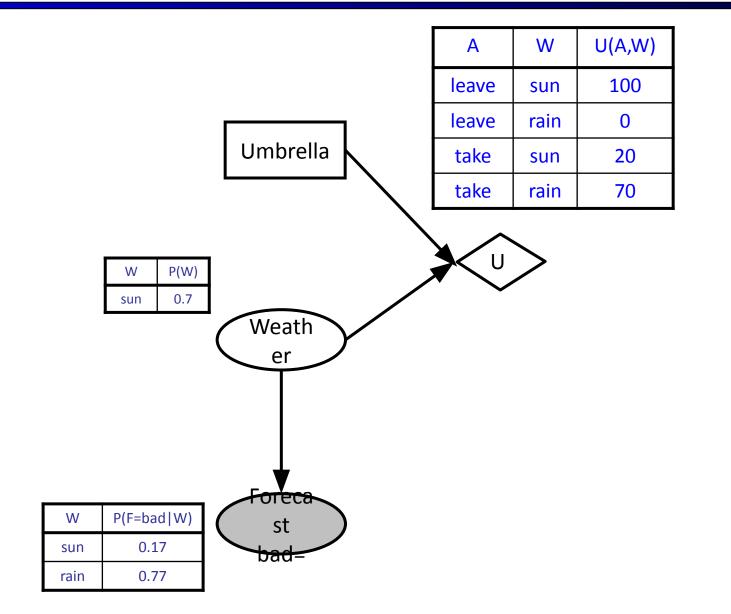


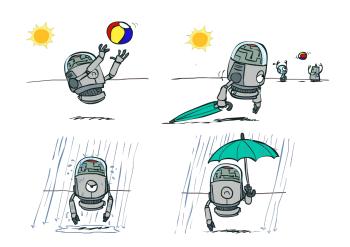
Utility nodes (diamond, depends on action and chance nodes)

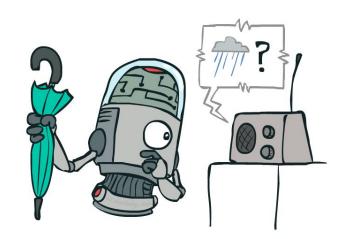




# Example: Take an umbrella?







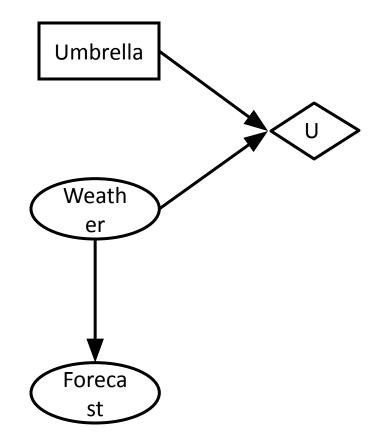
Bayes net inference!

Decision network = Bayes net + Actions + Utilities

Action nodes (rectangles, cannot have parents, will have value fixed by algorithm)

Utility nodes (diamond, depends on action and chance nodes)

- Decision algorithm:
  - Fix evidence *e*
  - For each possible action a
    - Fix action node to a
    - Compute posterior P(W|e,a) for parents W of U
    - Compute expected utility  $\sum_{\mathbf{w}} P(\mathbf{w} | \mathbf{e}, a) U(a, \mathbf{w})$
  - Return action with highest expected utility



## Example: Take an umbrella?

Bayes net inference!

- Decision algorithm:
  - Fix evidence e
  - For each possible action a
    - Fix action node to a
    - Compute posterior P(W|e,a) for parents W of U
    - Compute expected utility of action  $a: \sum_{w} P(w | e, a) U(a, w)$
  - Return action with highest expected utility

Umbrella = leave

$$EU(leave|F=bad) = \sum_{w} P(w|F=bad) U(leave,w)$$

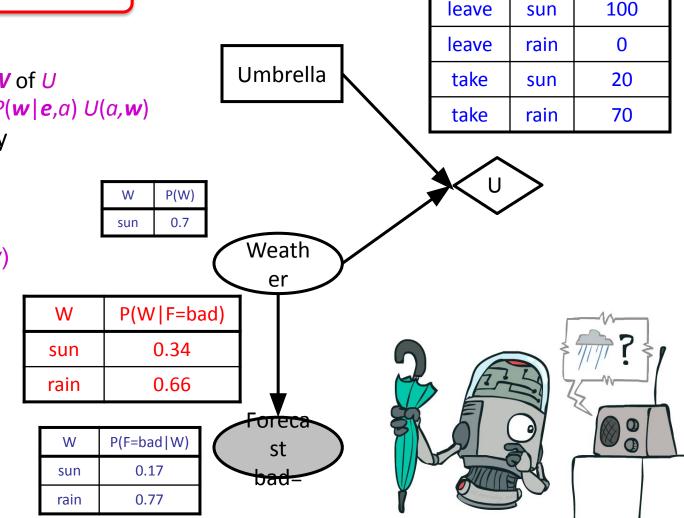
$$= 0.34 \times 100 + 0.66 \times 0 = 34$$

Umbrella = take

$$EU(take|F=bad) = \sum_{w} P(w|F=bad) U(take,w)$$

$$= 0.34 \times 20 + 0.66 \times 70 = 53$$

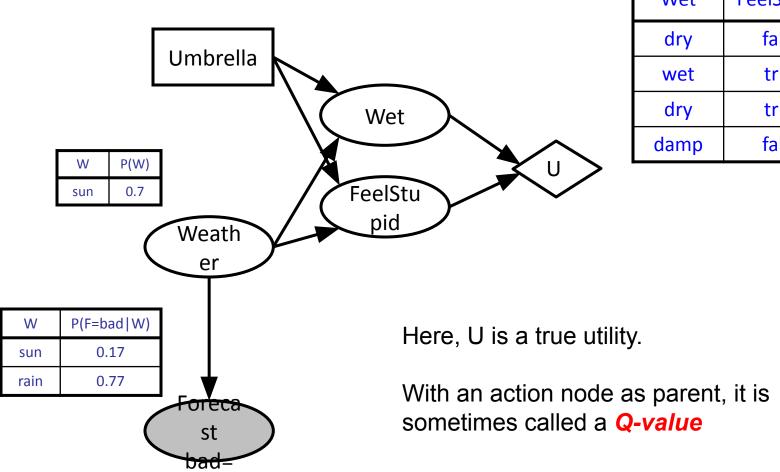
Optimal decision = take!



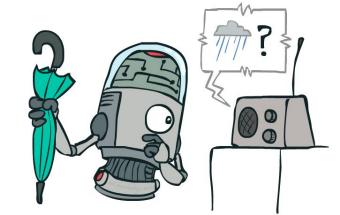
U(A,W)

W

#### Decision network with utilities on outcome states



Wet	FeelStupid	U
dry	false	100
wet	true	0
dry	true	20
damp	false	<b>7</b> 0



## Value of Information

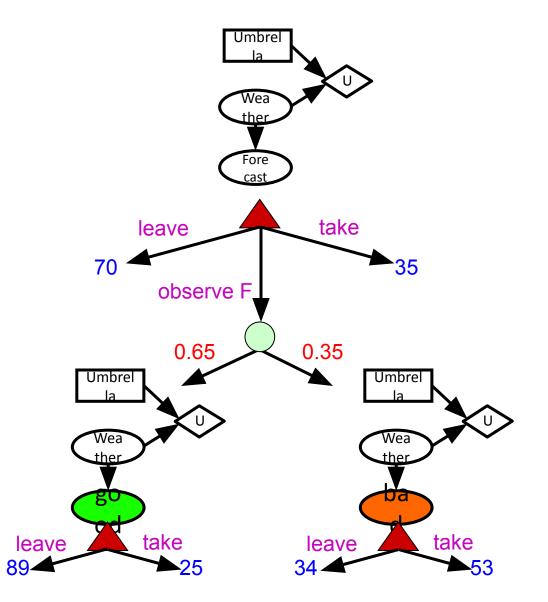


#### Value of information

- Suppose you haven't yet seen the forecast
  - EU(leave | ) = 0.7x100 + 0.3x0 = 70
  - EU(take | ) = 0.7x20 + 0.3x70 = 35
- What if you look at the forecast?
- If Forecast=good
  - | EU(leave | F=good) = 0.89x100 + 0.11x0 = 89
  - $\blacksquare$  EU(take | F=good) = 0.89x20 + 0.11x70 = 25
- If Forecast=bad

Bayes net inference!

- EU(leave | F=bad) = 10 + 0.66x0 = 34
- EU(take | F=bad -34x20 + 0.66x70 = 53
- P(Forecast) = <0.65,0.35>
- Expected utility given forecast
  - = 0.65x89 + 0.35x53 = 76.4
- **Value of information** = 76.4-70 = 6.4



#### Value of information contd.

- General idea: value of information = expected improvement in decision quality
   from observing value of a variable
  - E.g., oil company deciding on seismic exploration and test drilling
  - E.g., doctor deciding whether to order a blood test
  - E.g., person deciding on whether to look before crossing the road
- Key point: decision network contains everything needed to compute it!
- $VPI(E_i \mid e) = \left[\sum_{e_i} P(e_i \mid e) \max_a EU(a \mid e_i, e)\right] \max_a EU(a \mid e)$

#### **VPI** Properties

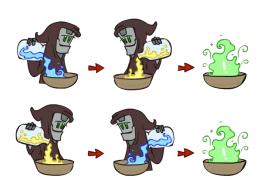
VPI is non-negative!  $VPI(E_i | e) \ge 0$ 



VPI is not (usually) additive:  $VPI(E_i, E_j | e) \neq VPI(E_i | e) + VPI(E_j | e)$ 



VPI is order-independent:  $VPI(E_i, E_j | e) = VPI(E_j, E_i | e)$ 

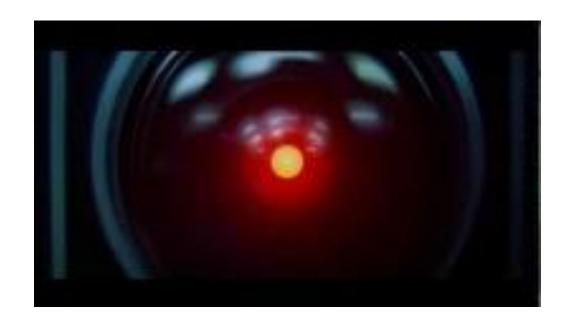


### Decisions with unknown preferences

- In reality the assumption that we can write down our exact preferences for the machine to optimize is false
- A machine optimizing the wrong preferences causes problems



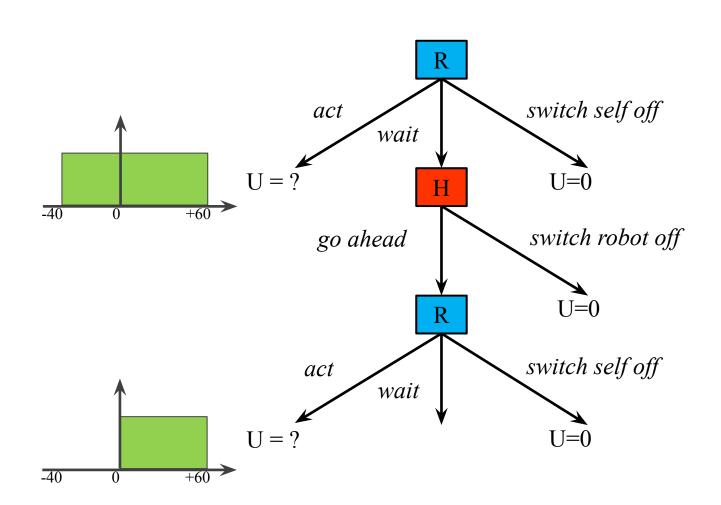
I'm sorry, Dave, I'm afraid I can't do that



### Decisions with unknown preferences

- In reality the assumption that we can write down our exact preferences for the machine to optimize is false
- A machine optimizing the wrong preferences causes problems
- A machine that is explicitly uncertain about the human's preferences will defer to the human (e.g., allow itself to be switched off)

# Off-switch problem (example)



$$EU(act) = +10$$

$$EU(wait) = (0.4 * 0) + (0.6 * 30) = +18$$

# Off-switch problem (general proof)

- $EU(wait) = \int_{-\infty}^{0} P(u) \cdot 0 \ du + \int_{0}^{+\infty} P(u) \cdot u \ du$
- Obviously  $\int_{-\infty}^{0} P(u) \cdot u \ du \le \int_{-\infty}^{0} P(u) \cdot 0 \ du$
- Hence  $EU(act) \leq EU(wait)$