CS 480

Introduction to Artificial Intelligence

November 10, 2022

Announcements / Reminders

- **Follow Week 12 TO DO List**
- **Written Assignment #03 due on ~~Sunday (11/06/22)~~ Thursday (11/10) at 11:00 PM CST**
- **Programming Assignment #02 due on Sunday (11/20/22) at 11:00 PM CST**
- **Quiz #03 posted due on Sunday (11/13/22) at 11:00 PM CST**
- **Grading TA assignment:**

  https://docs.google.com/spreadsheets/d/1ExS0bKnGt_fdf4LHa3YS1qRA7-Iq4xqXVjfSAPMaGVk/edit?usp=sharing

- **UPDATED Final Exam date:**
  - **December 1st, 2022 (last week of classes!)**
    - **Ignore the date provided by the Registrar**

Plan for Today

- **Decision Networks**

Decision Theory

- Decisions: every plan (actions) leads to an outcome (state)
- Agents have preferences (preferred outcomes)
- Preferences $\rightarrow$ outcome utilities
- Agents have degrees of belief (probabilities) for actions

Decision theory = probability theory + utility theory

Decision Theory

- Decisions: every plan (actions) leads to an outcome (state)
- Agents have preferences (preferred outcomes)
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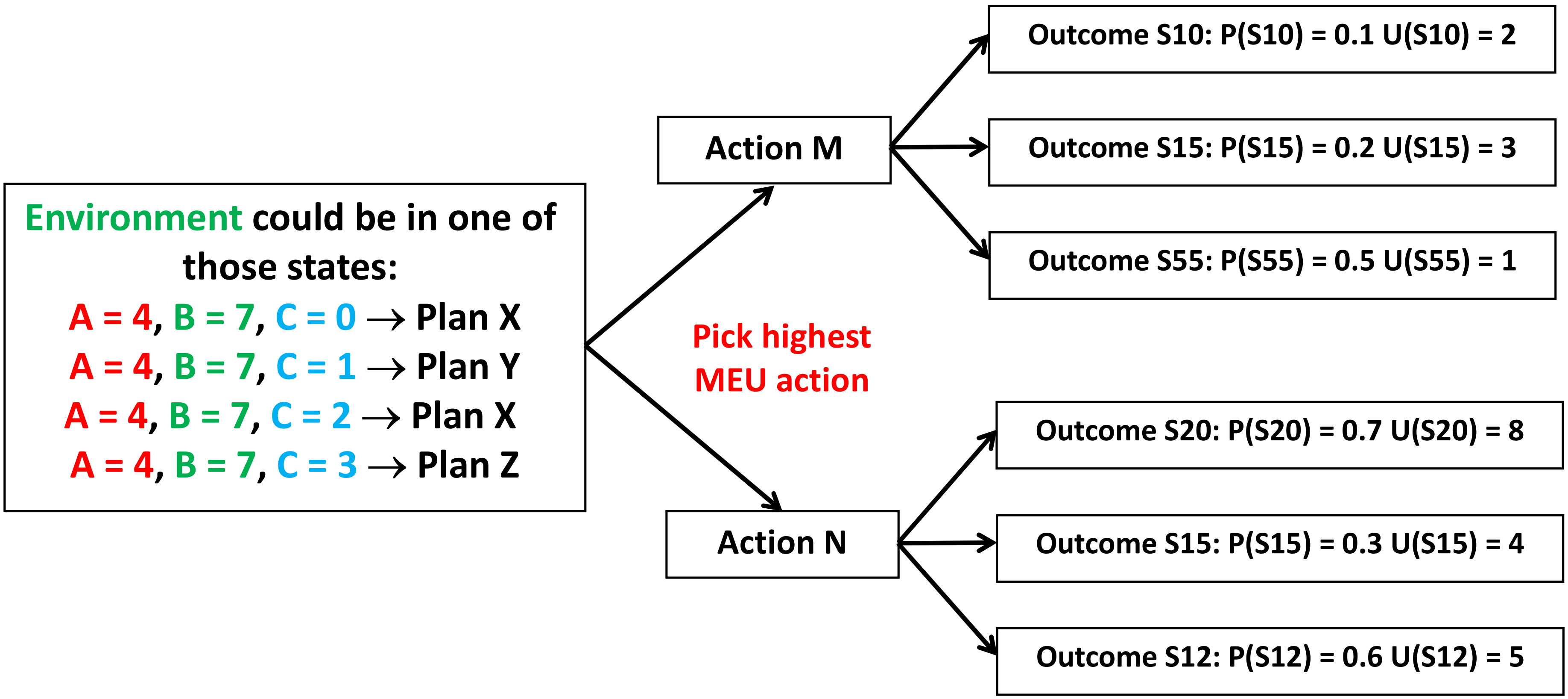
- Agents have degrees of belief (probabilities) for actions

Decision theory = $\underbrace{\text{probability theory}}_{\text{BELIEFS}}$ + $\underbrace{\text{utility theory}}_{\text{DESIRES}}$

Maximum Expected (Average) Utility

$$MEU(M) = P(S10) * U(S10) + P(S15) * U(S15) + P(S55) * U(S55)$$



$$MEU(N) = P(S20) * U(S20) + P(S15) * U(S15) + P(S12) * U(S12)$$

Agents Decisions

Recall that agent ACTIONS change the state:

- **if we are in state** s
- **action** a **is expected to**
- **lead to another state** s' **(outcome)**

Given uncertainty about the current state s **and action outcome** s' **we need to define the following:**

- **probability (belief) of being in state** s**:** $P(s)$
- **probability (belief) of action** a **leading to outcome** s'**:** $P(s' \mid s, a)$

Now:

$$P(s' \mid s, a) = P(\textsc{Result}(a) = s') = \sum_s P(s) * P(s' \mid s, a)$$

State Utility Function

Agent's preferences (desires) are captured by the Utility function $U(s)$**.**

Utility function assigns a value to each state s **to express how desirable this state is to the agent.**

Expected Action Utility

The expected utility of an action a given the evidence is the average utility value of all possible outcomes s' of action a, weighted by their probability (belief) of occurence:

$$\mathrm{EU}(a) = \sum_{s'} \sum_{s} \mathrm{P}(s) * \mathrm{P}(s' \mid s, a) * \mathrm{U}(s') \;=\; \sum_{s'} \mathrm{P}(Result(a) = s') * \mathrm{U}(s')$$

Rational agent should choose an action that maximizes the expected utility:

$$\text{chosen action} \;=\; \underset{a}{\operatorname{argmax}}\ \mathrm{EU}(a)$$

How Did We Get Here?

Let's start with relationships (and related notation) between agent's preferences:

- **agent prefers** A **over** B**:**

$$A \;\square\; B$$

- **agent is indifferent between** A **and** B**:**

$$A \sim B$$

- **agent prefers** A **over** B **or is indifferent between** A **and** B **(weak preference):**

$$A \;\square\; B$$

The Concept of Lottery

Let's assume the following:

- **an action a is a lottery ticket**
- **the set of outcomes (resulting states) is a lottery**

A lottery L with possible outcomes $S_1, \ldots, S_n$ that occur with probabilities $p_1, \ldots, p_n$ is written as:

$$L = [p_1, S_1; p_2, S_2; \ldots ; p_n, S_n]$$

Lottery outcome S_i: atomic state or another lottery.

Lottery Constraints: Orderability

Given two lotteries A and B, a rational agent must either prefer one or else rate them as equally preferable:

Exactly one of $(A \succ B)$, $(B \succ A)$, or $(A \sim B)$ holds

Lottery Constraints: Transitivity

Given three lotteries A, B, **and** C, **if an agent prefers** A **to** B **AND prefers** B **to** C, **then the agent must prefer** A **to** C**:**

$$(A \succ B) \land (B \succ C) \Rightarrow (A \succ C)$$

Lottery Constraints: Continuity

If some lottery B **is between** A **and** C **in preference, then there is some probability** p **for which the rational agent will be indifferent between getting** B **for sure or some other lottery that yields** A **with probability** p **and** C **with probability** $1 - p$**:**

$$(A \succ B \succ C) \Rightarrow \exists p\ [p, A;\ 1-p, C] \sim B$$

Lottery Constraints: Substitutability

If an agent is indifferent between two lotteries A and B, then the agent is indifferent between two more complex lotteries that are the same, except that B is subsituted for A in one of them:

$$(A \sim B) \Rightarrow [p, A; 1-p, C] \sim [p, B; 1-p, C]$$

Lottery Constraints: Monotonicity

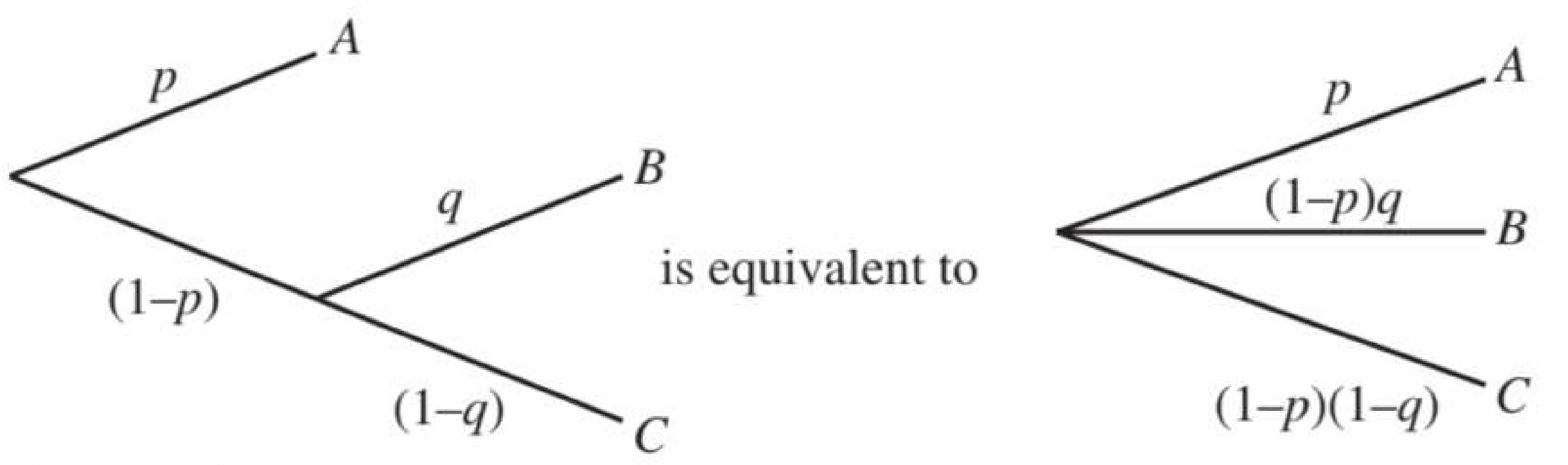
Suppose two lotteries have the same two possible outcomes, A and B. If an agent prefers A to B, then the agent must prefer the lottery that has a higher probability for A:

$$(A \succ B) \Rightarrow (p > q \Leftrightarrow [p, A;\ 1-p, B] \succ [q, A;\ 1-q, B])$$

Lottery Constraints: Decomposability

Compound lotteries can be reduced to smaller ones using the laws of probability:

[p, A; 1- p, [q, B; 1- q, C]] ~ [p, A; (1- p)*q, B; (1- p)*(1- q), C]



Preferences and Utility Function

An agent whose preferences between lotteries follow the set of axioms (of utility theory) below:

- **Orderability**
- **Transitivity**
- **Continuity**
- **Subsitutability**
- **Monotonicity**
- **Decomposability**

can be described as possesing a utility function and maximize it.

Preferences and Utility Function

If an agent's preferences obey the axioms of utility theory, then there exist a function U such that:

$U(A) = U(B)$ **if and only if** $(A \sim B)$

and

$U(A) > U(B)$ **if and only if** $(A \; \square \; B)$

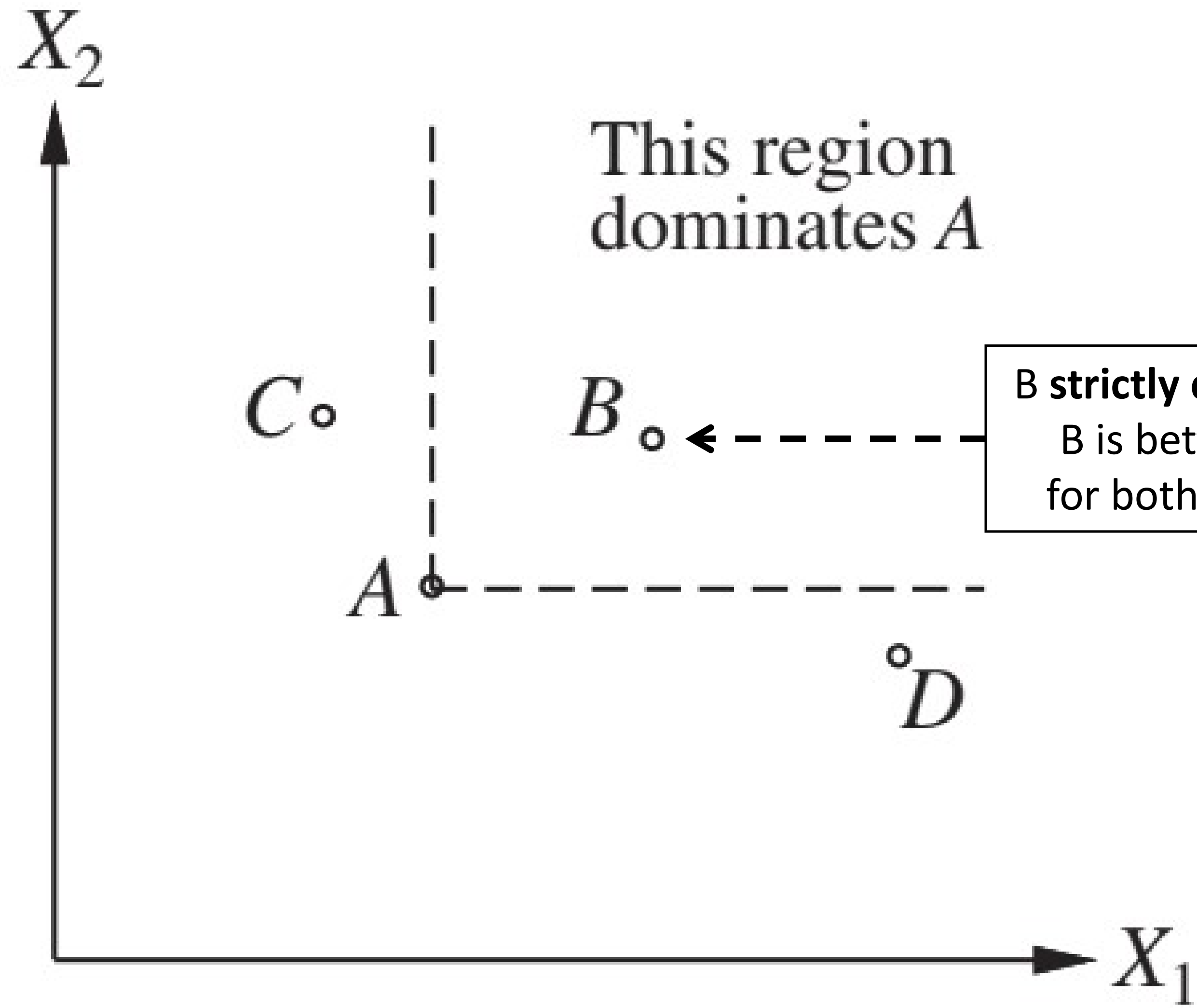
Multiattribute Outcomes

Outcomes can be characterized by more than one attribute. Decisions in such cases are handled by Multiattribute Utility Theory.

Attributes: $\mathbf{X} = X_1, \ldots, X_n$

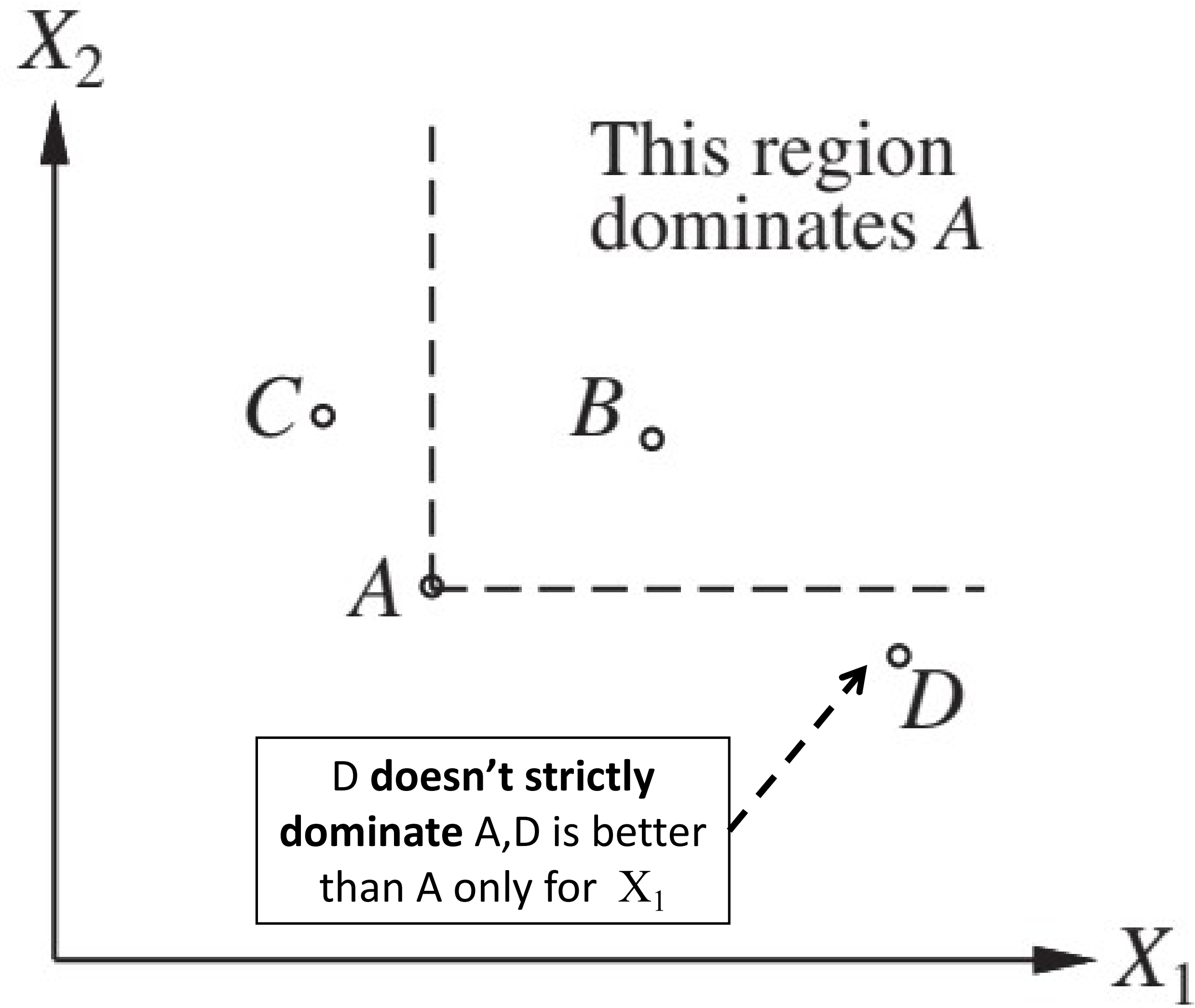
Assigned values: $\mathbf{x} = \langle x_1, \ldots, x_n \rangle$

Strict Dominance: Deterministic



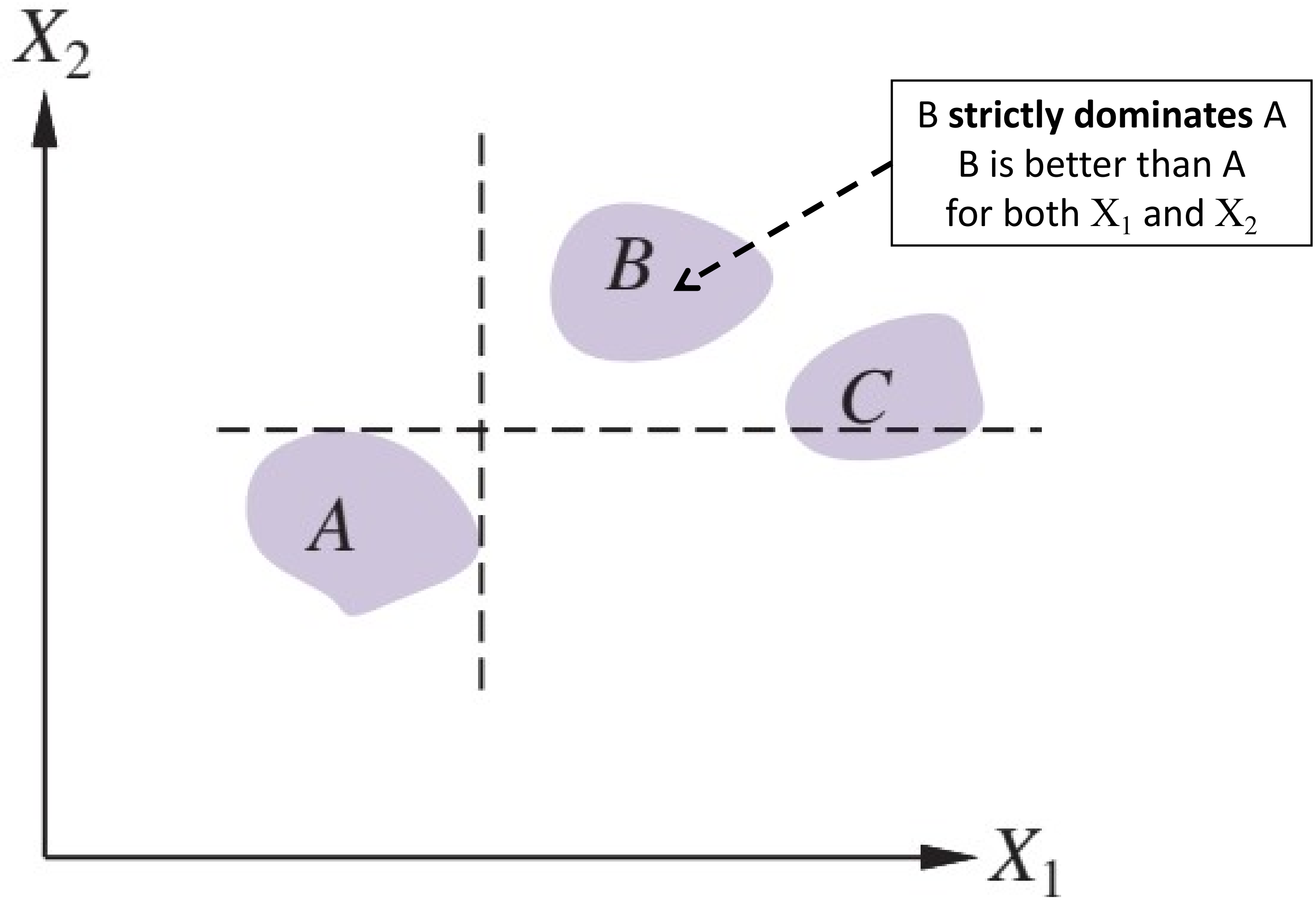
B **strictly dominates** A
B is better than A
for both X_1 and X_2

Strict Dominance: Deterministic

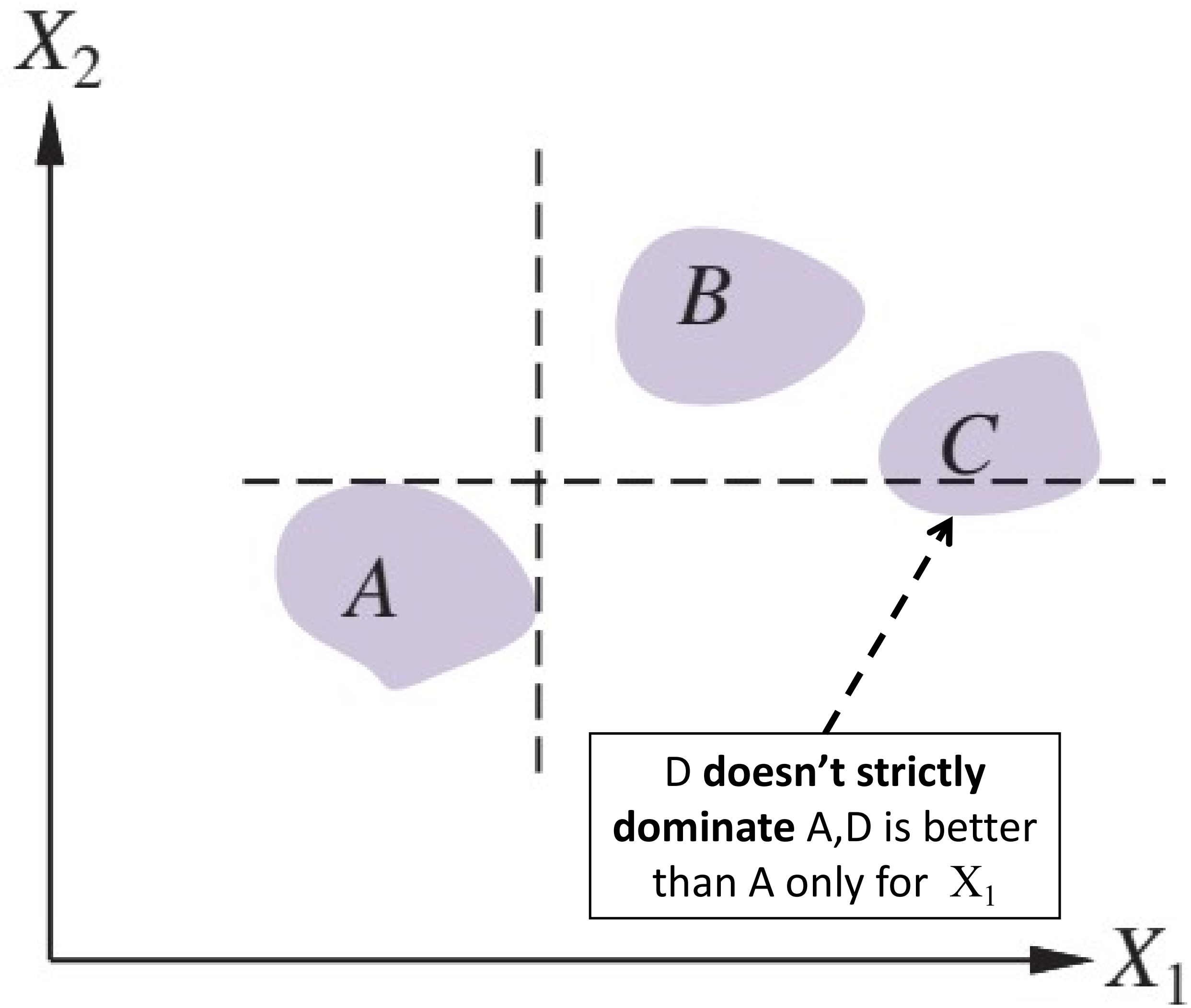


D **doesn't strictly dominate** A,D is better than A only for X_1

Strict Dominance: Uncertain



Strict Dominance: Uncertain



Decision Network (Influence Diagram)

Decision networks (also called influence diagrams) are structures / mechanisms for making rational decisions.

Decision networks are based on Bayesian networks, but include <u>additional nodes</u> that represent actions and utilities.

Decision Networks

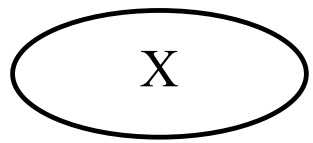
The most basic decision network needs to include:

- **information about current state** s
- **possible actions**
- **resulting state** s' **(after applying chosen action** a**)**
- **utility of the resulting state** $U(s')$

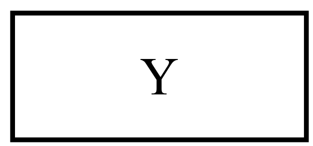
Decision Network Nodes

Decision networks are built using the following nodes:

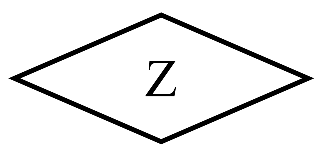
- **chance nodes:**



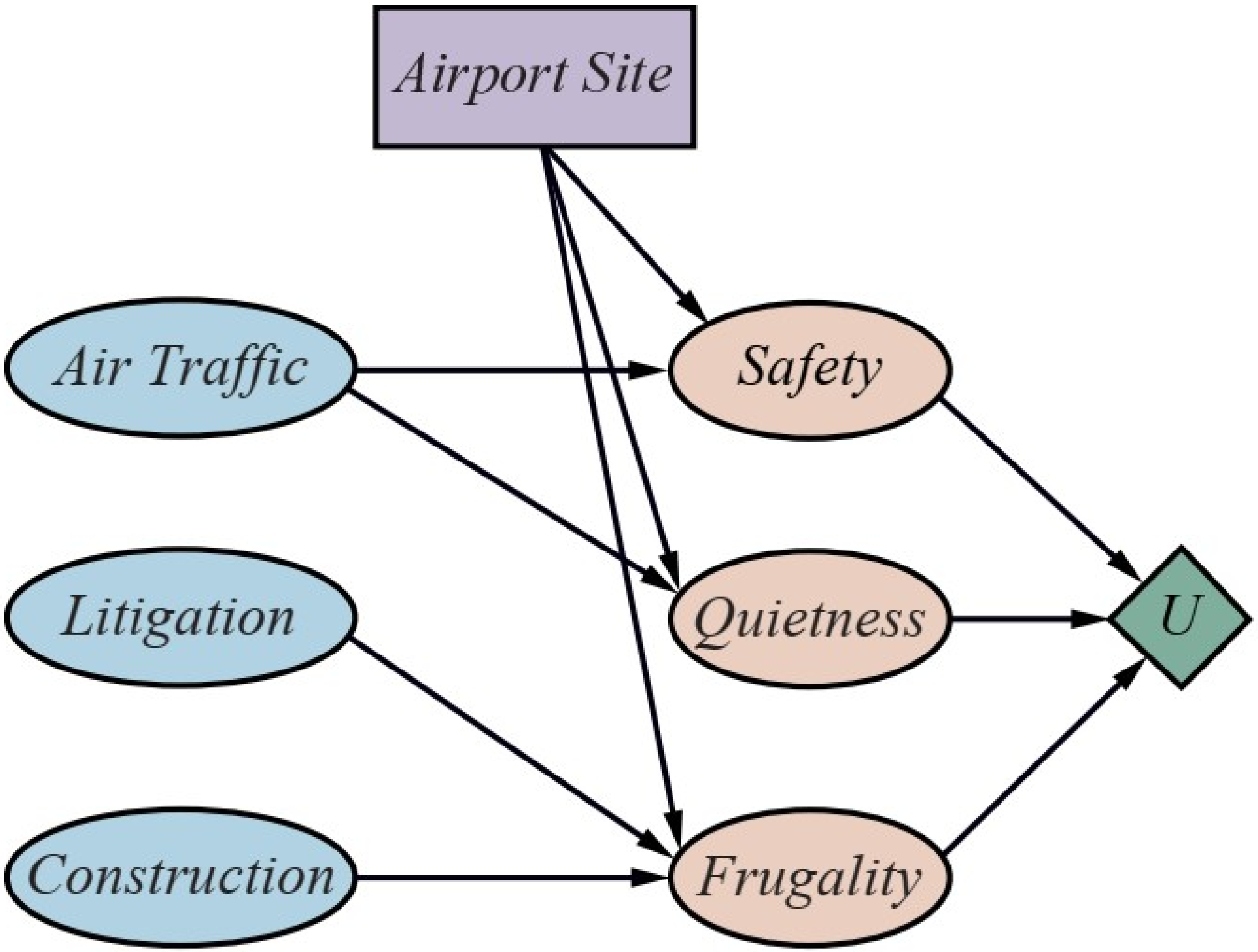
- **decision nodes:**



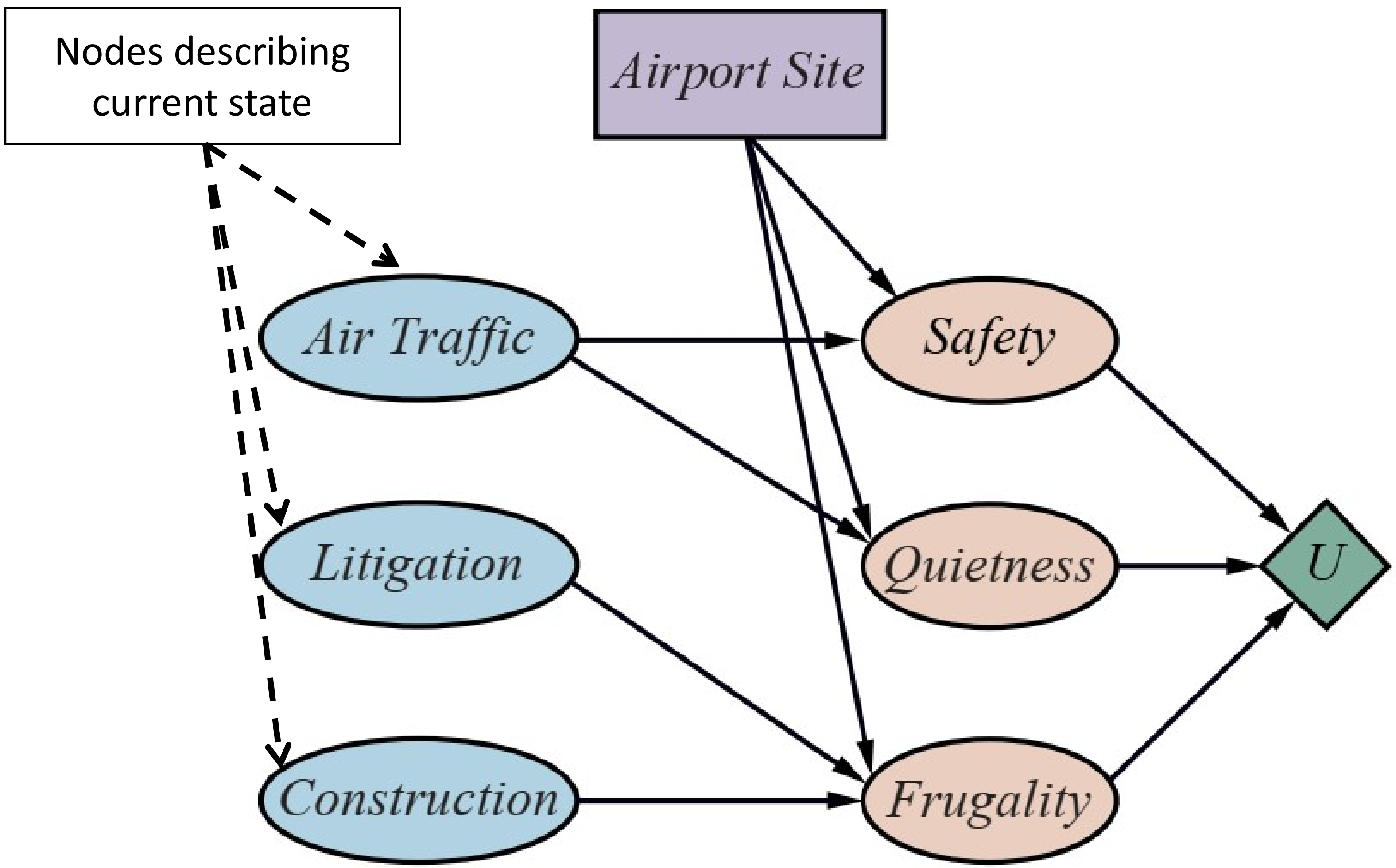
- **utility (or value) nodes**



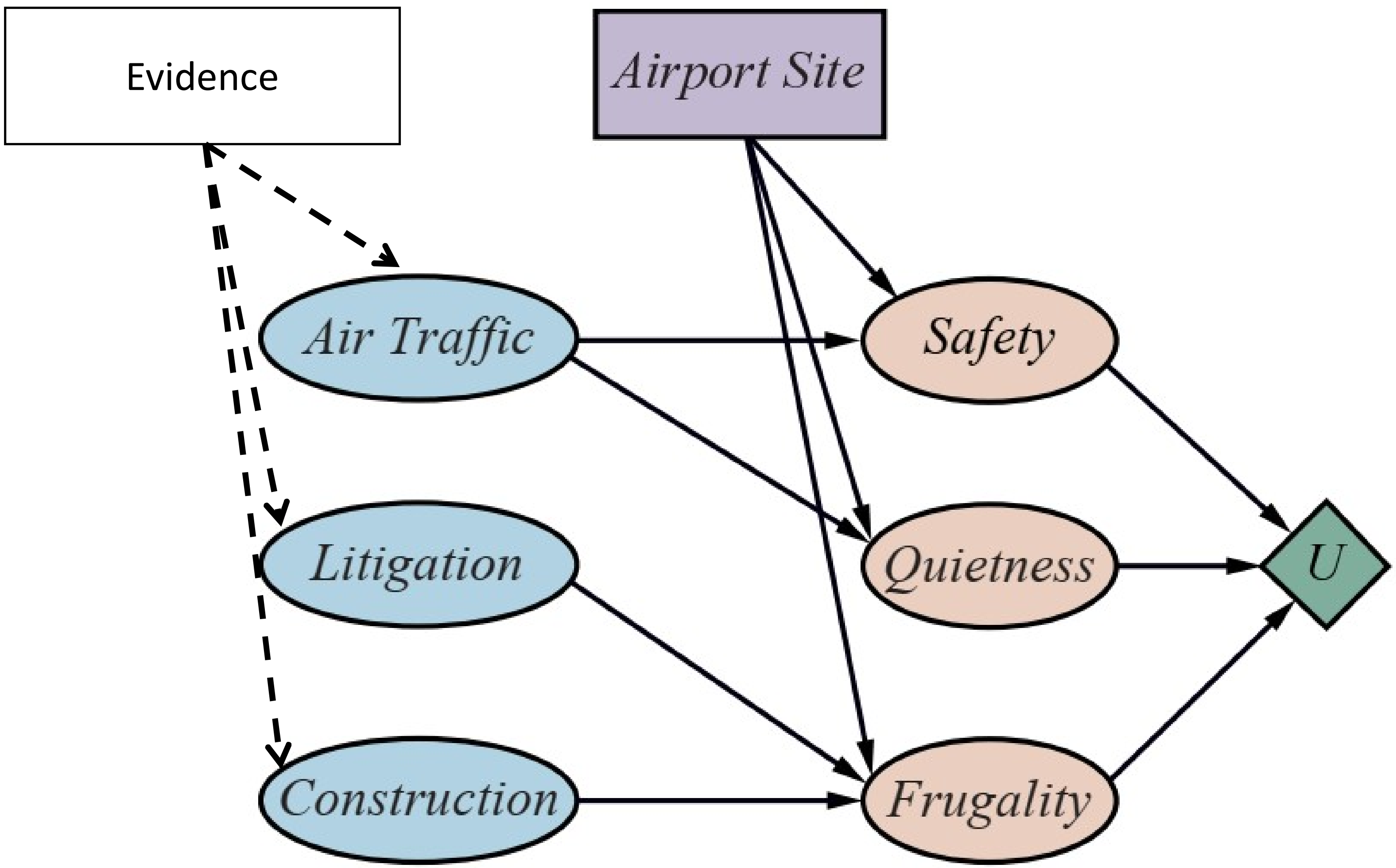
Decision Network: Example



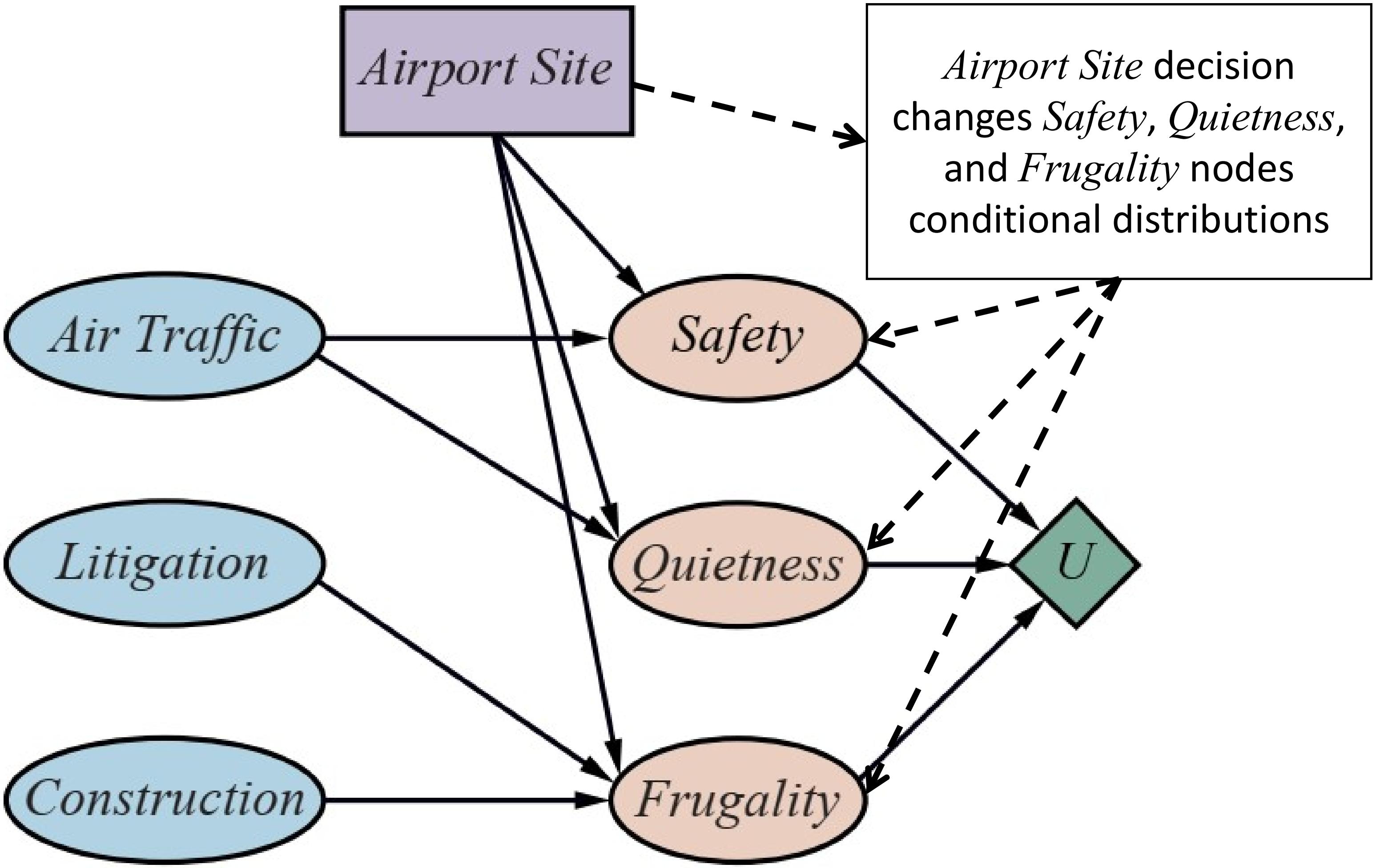
Decision Network: Example



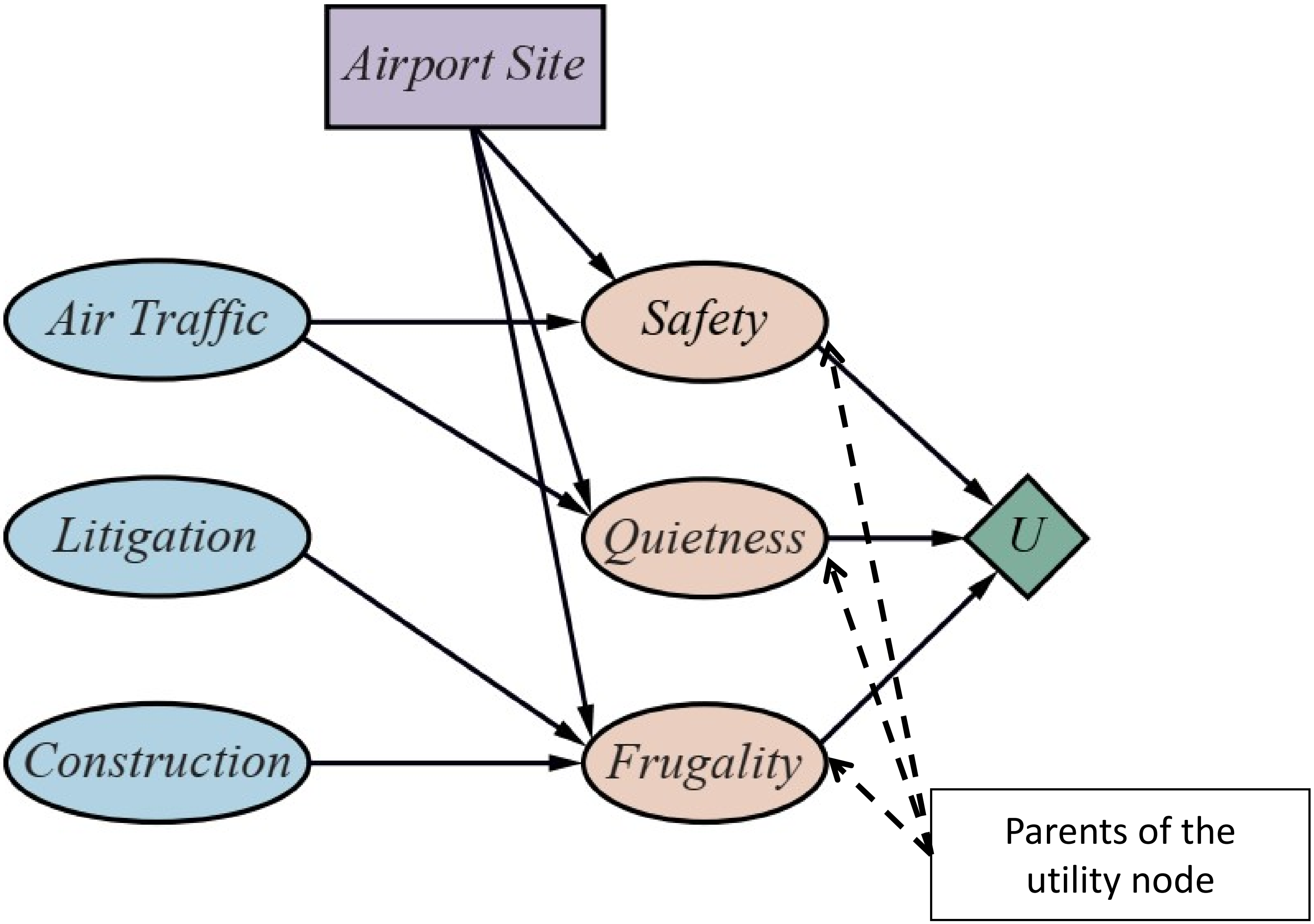
Decision Network: Example



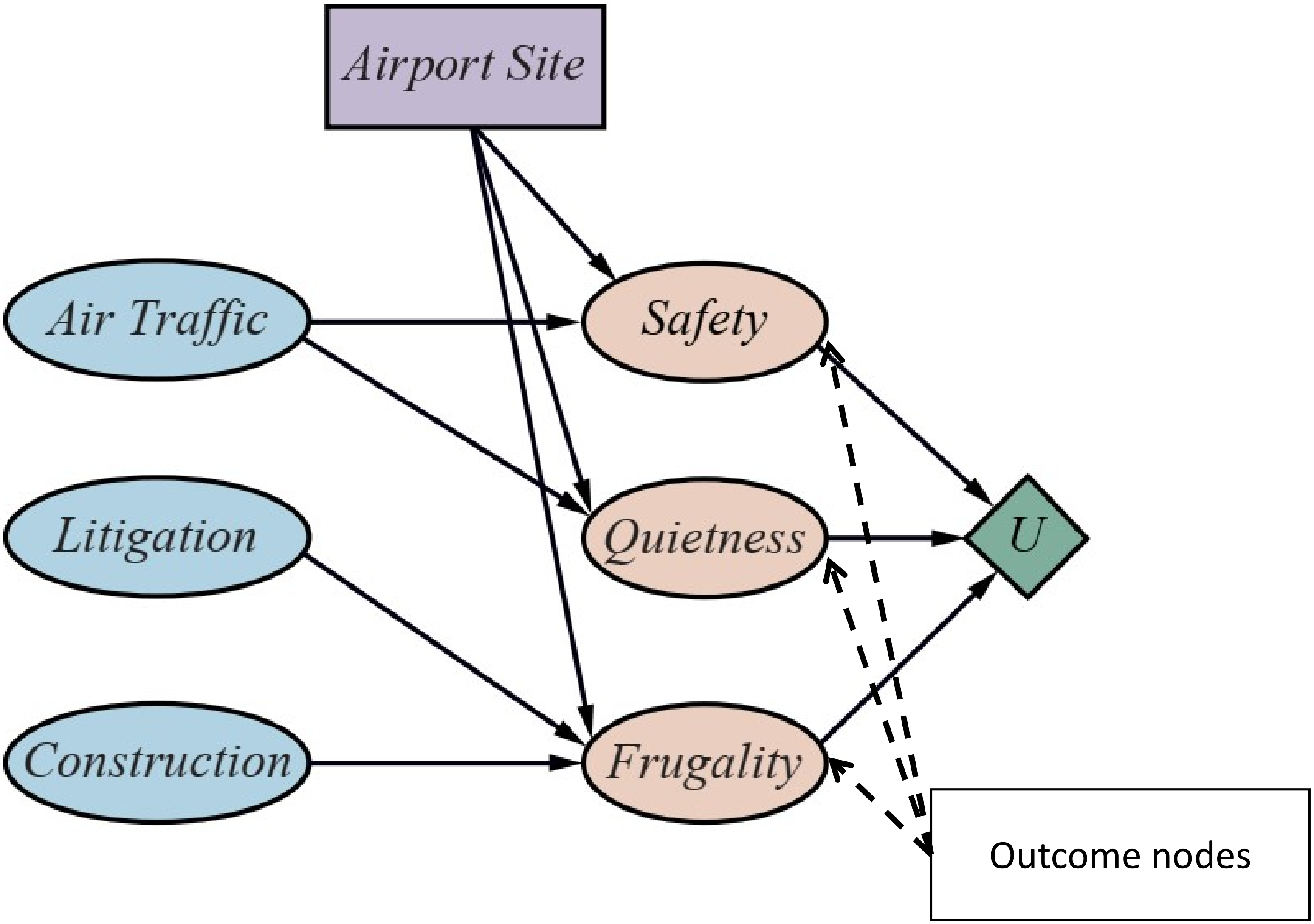
Decision Network: Example



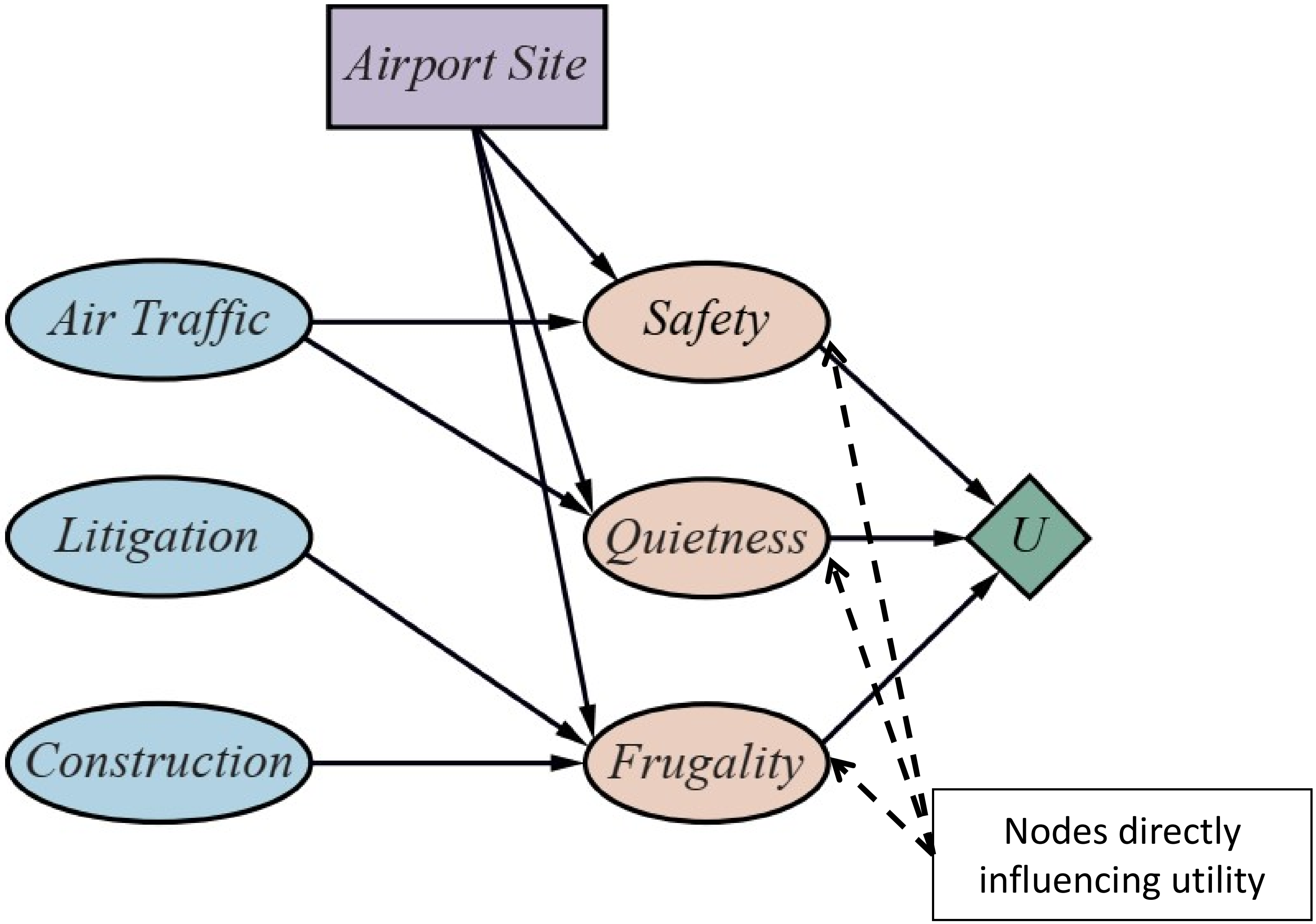
Decision Network: Example



Decision Network: Example



Decision Network: Example

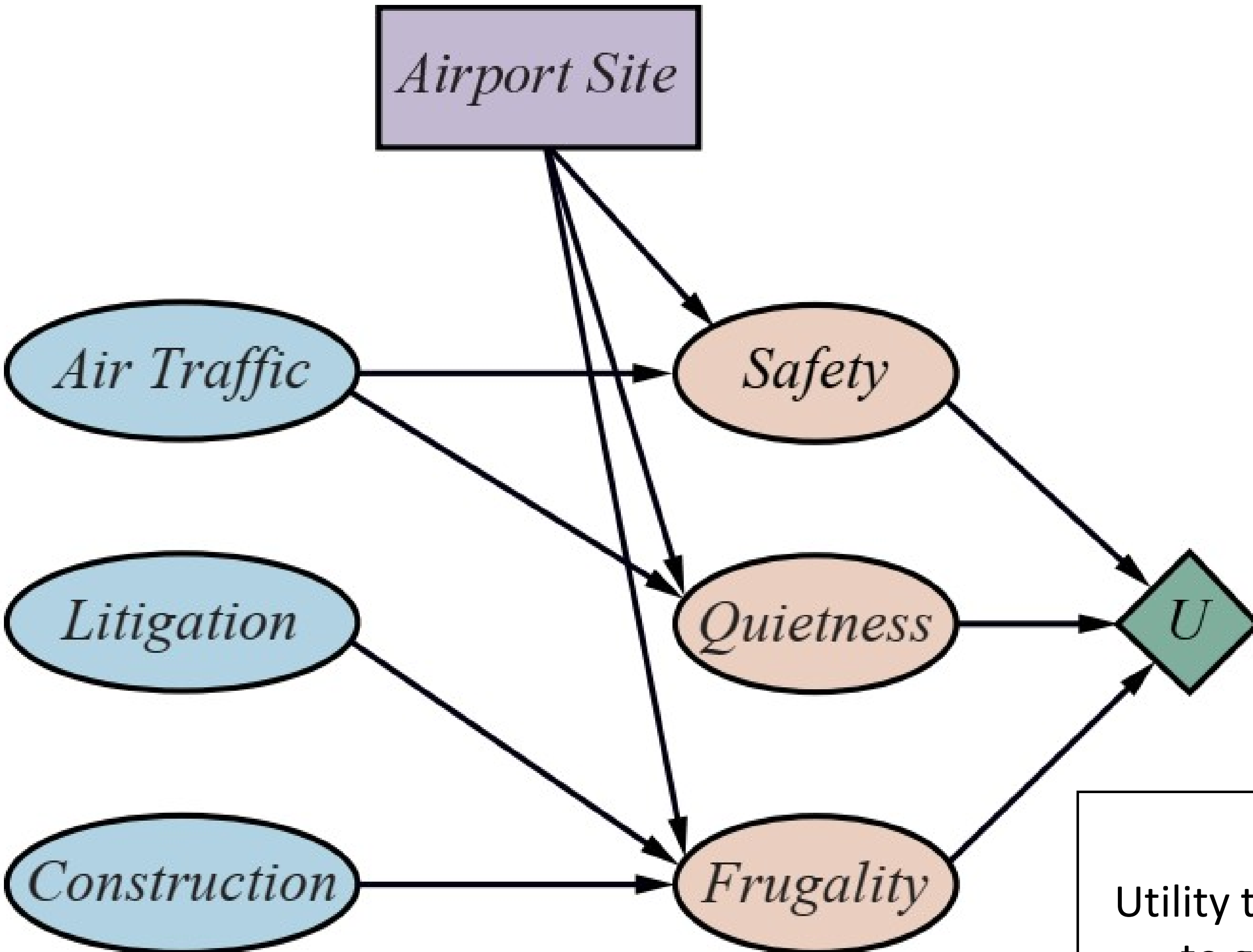


Decision Network: Evaluation

The algorithm for decision network evaluation is as follows:

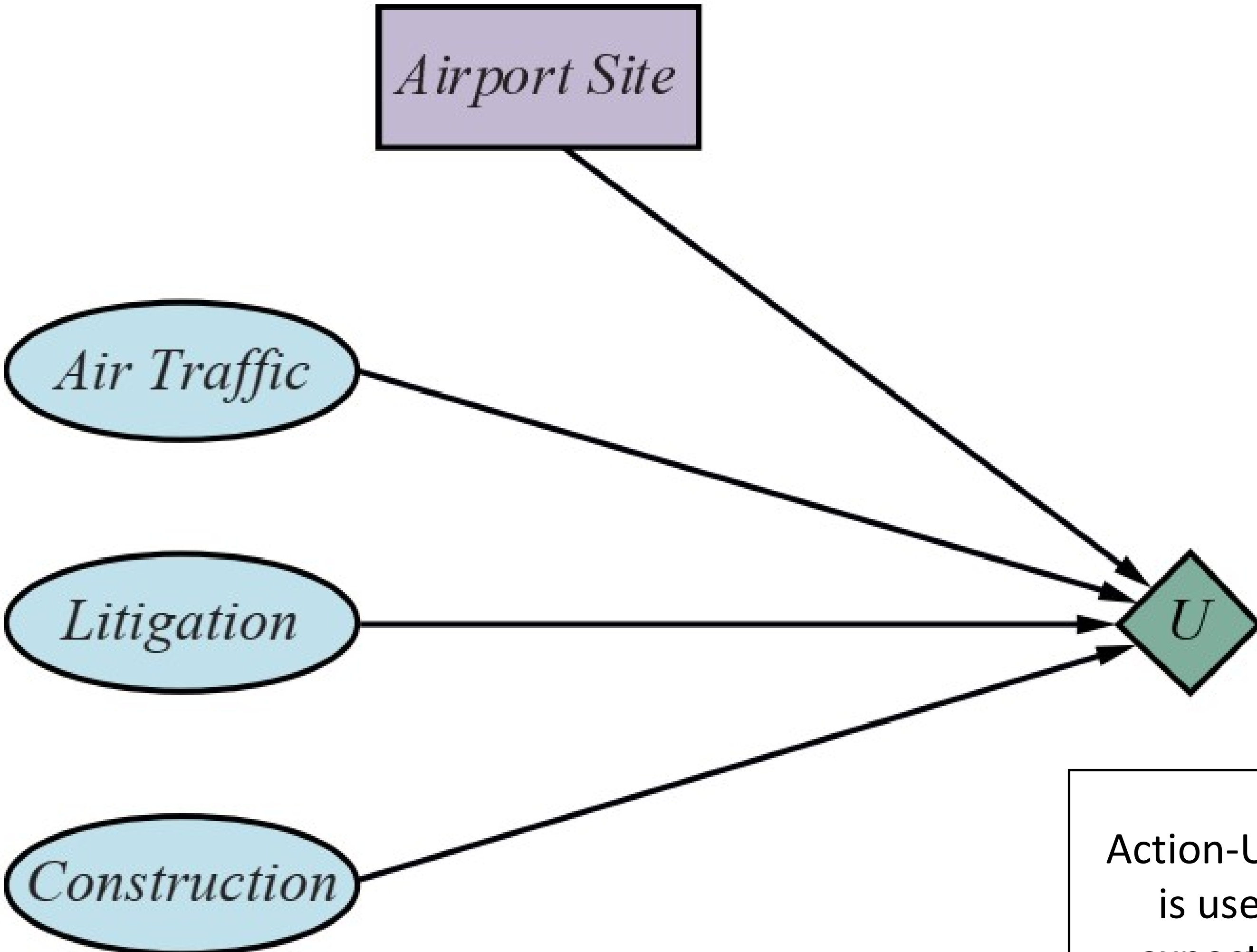
1. Set the evidence variables for the current state
2. For each possible value a of decision node:
   a. Set the decision node to that value
   b. Calculate the posterior probabilities for the parent nodes of the utility node
   c. Calculate the utility for the action / value a
3. Return the action with highest utility

Decision Network: Example



Utility table is used to get utility

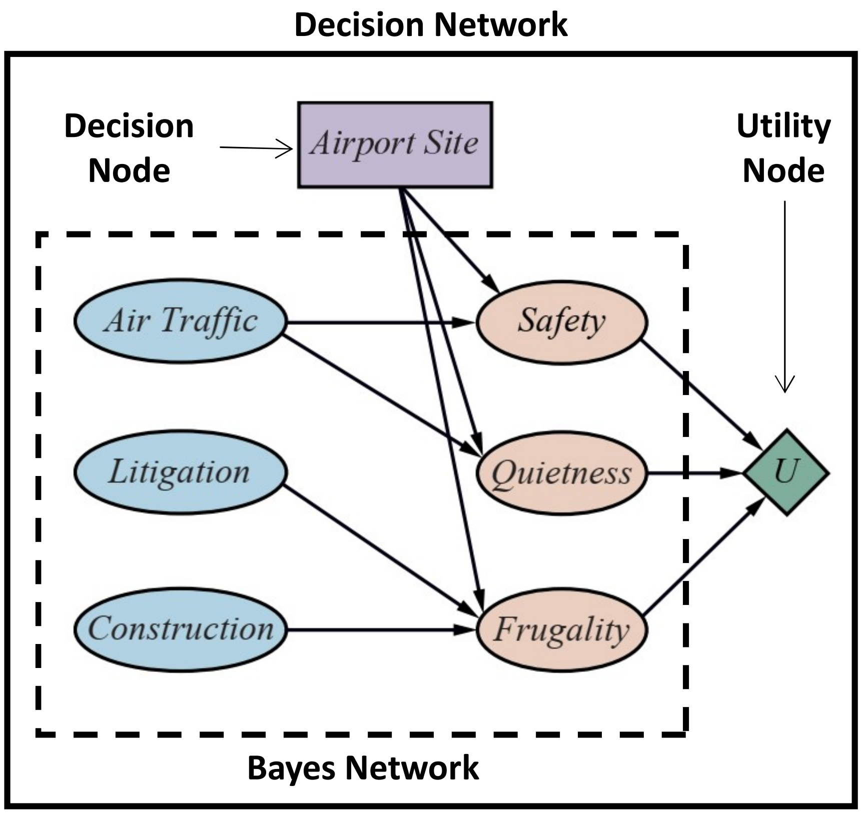
Decision Network: Simplified Form



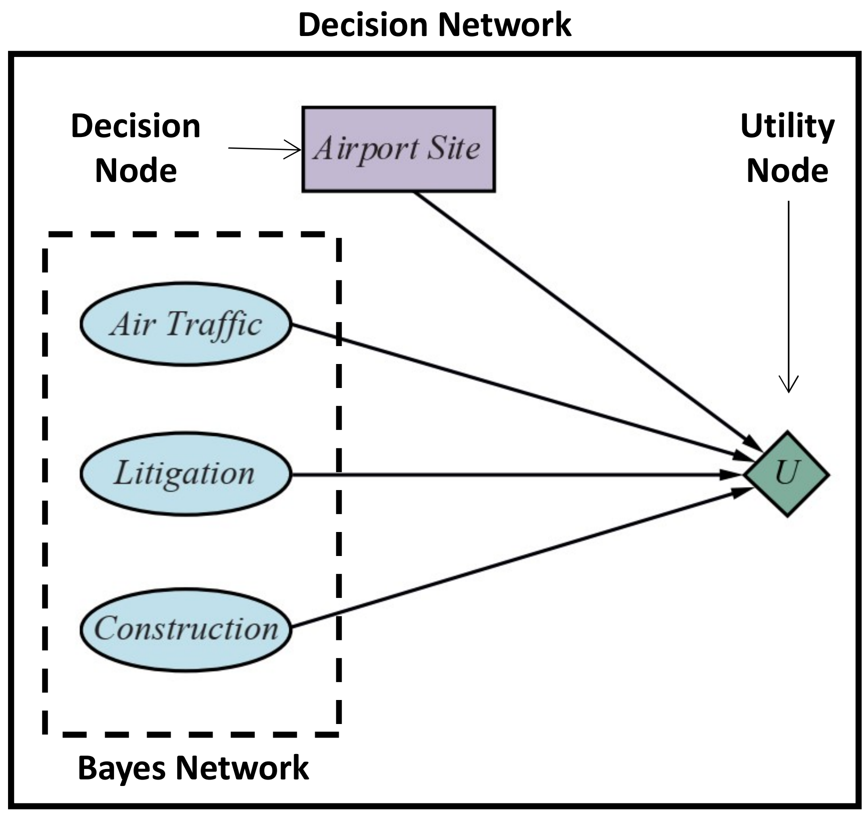
Action-Utility table is used to get expected utility

(Single-Stage) Decision Networks

General Structure

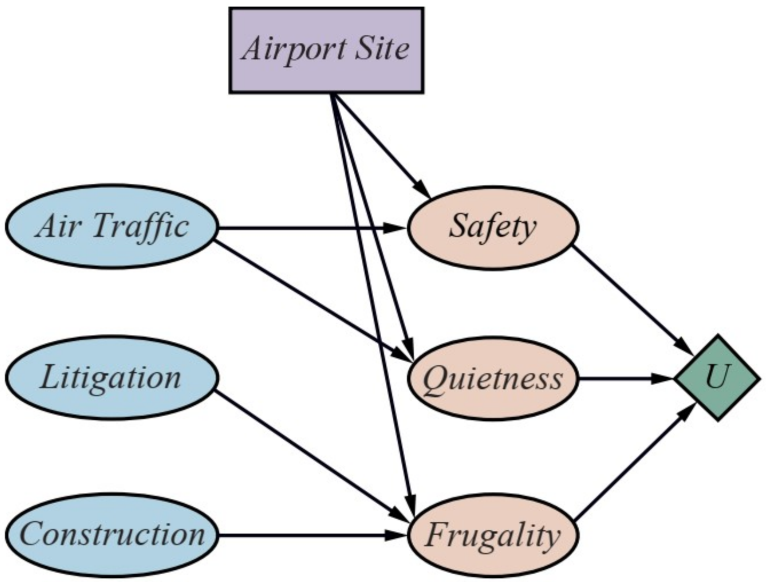


Simplified Structure



(Single-Stage) Decision Networks

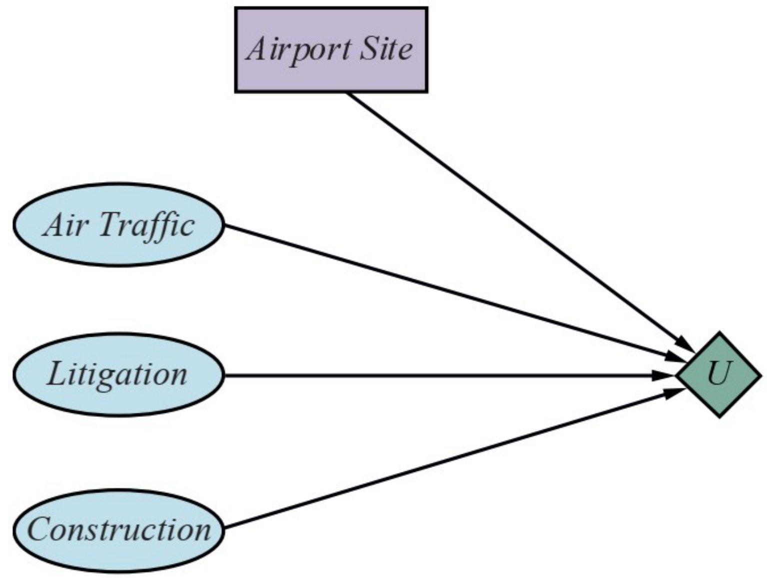
General Structure



Utility Table

S	low	low	low	low	high	high	high	high
Q	low	low	high	high	low	low	high	high
F	low	high	low	high	low	high	low	high
U	10	20	5	50	70	150	100	200

Simplified Structure



Action-Utility Table (not all columns shown)

AT	low	low	low	---	---	high	high	high
L	low	low	high	---	---	low	high	high
C	low	high	low	---	---	high	low	high
AS	A	A	A	---	---	B	B	B
U	10	20	5	---	---	150	100	200

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Agent's Decisions

Recall that agent ACTIONS change the state:

- **if we are in state** s
- **action** a **is expected to**
- **lead to another state** s' **(outcome)**

Given uncertainty about the current state s **and action outcome** s' **we need to define the following:**

- **probability (belief) of being in state** s**:** $P(s)$
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Now:

$$P(s' \mid s, a) = P(\textsc{Result}(a) = s') = \sum_s P(s) * P(s' \mid s, a)$$

Expected Action Utility

The expected utility of an action a given the evidence is the average utility value of all possible outcomes s' of action a, weighted by their probability (belief) of occurence:

$$EU(a) = \sum_{s'} \sum_{s} P(s) * P(s' \mid s, a) * U(s') = \sum_{s'} P(Result(a) = s') * U(s')$$

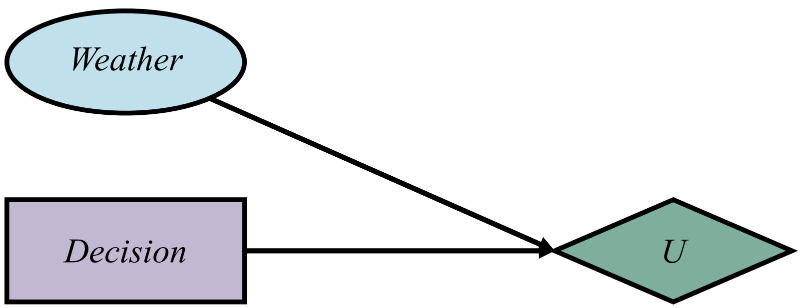
Rational agent should choose an action that maximizes the expected utility:

$$\text{chosen action} = \underset{a}{\text{argmax}}\ EU(a)$$

Decision Networks: Example

Decision: take umbrella

P(W=rain)	P(W=sun)
0.30	0.70



D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

Decision: leave umbrella

P(W=rain)	P(W=sun)
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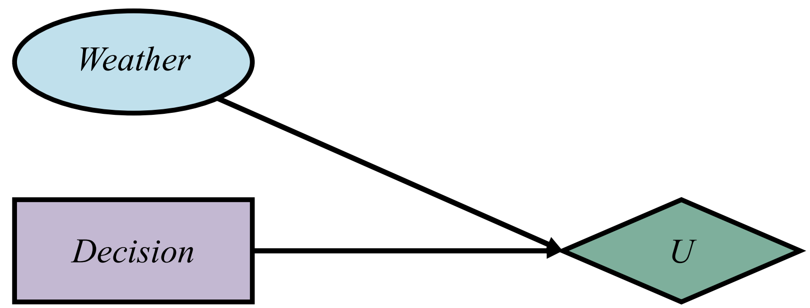

D	W	U
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Decision Networks: Example

Decision: take umbrella

$$EU(a) = \sum_{s'} P(Result(a) = s') * U(s')$$

P(W=rain)	P(W=sun)
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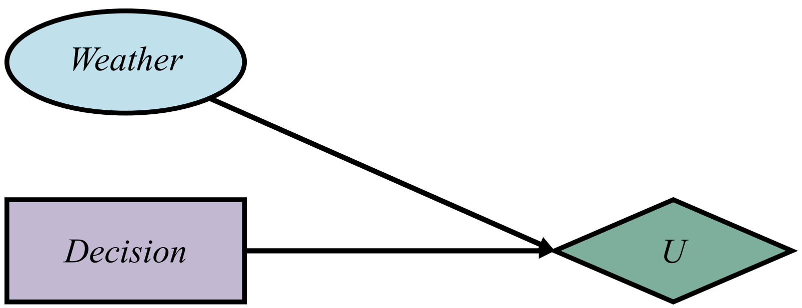

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

$$EU(take) = ???$$

Decision: leave umbrella

$$EU(a) = \sum_{s'} P(Result(a) = s') * U(s')$$

P(W=rain)	P(W=sun)
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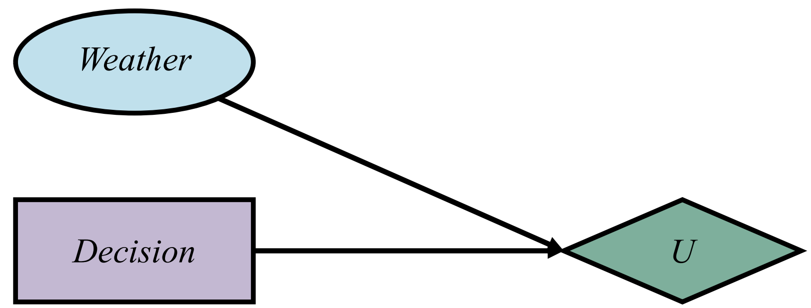

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Decision Networks: Example

Decision: take umbrella

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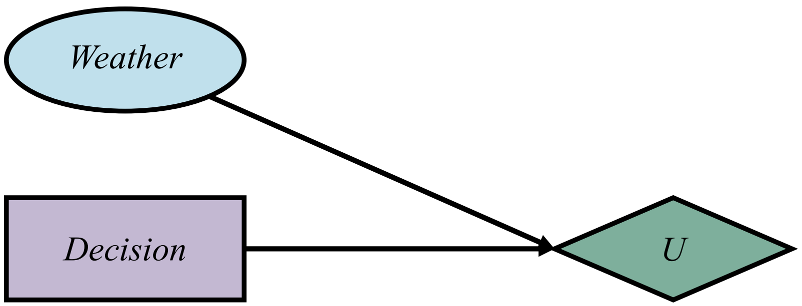


S_1': D = take, W = sun
S_2': D = take, W = rain
EU(take) =
P(Result(take) = S_1')*U(S_1') +
P(Result(take) = S_2')*U(S_2') =
0.70 * 20 + 0.30 * 70 = 35

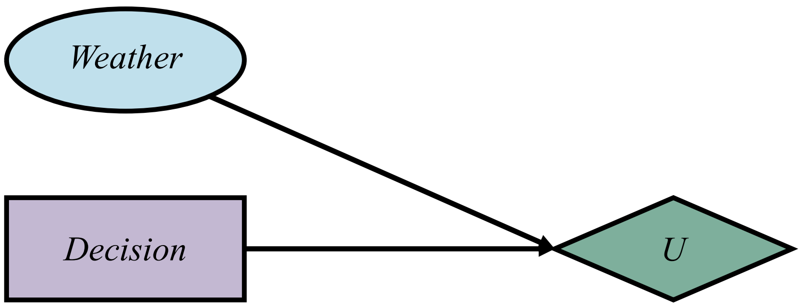
D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

$$EU(take) = 35$$

Decision: leave umbrella

$$EU(a) = \sum_{s'} P(Result(a) = s') * U(s')$$

P(W=rain)	P(W=sun)
0.30	0.70



S_3': D = leave, W = sun
S_4': D = leave, W = rain
EU(leave) =
P(Result(leave) = S_3')*U(S_3') +
P(Result(leave) = S_4')*U(S_4') =
0.70 * 100 + 0.30 * 0 = 70

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

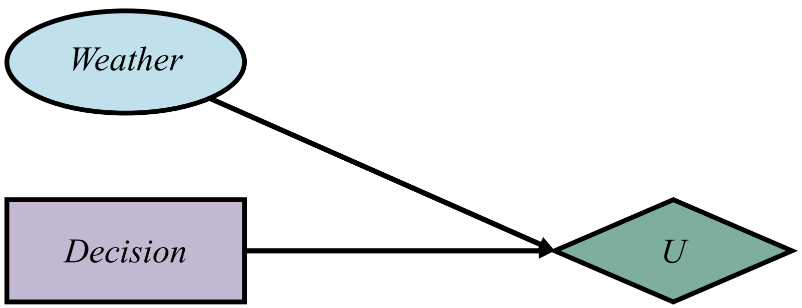
$$EU(leave) = 70$$

Decision Networks: Example

Which action to choose: take or leave Umbrella?

$EU(a) = \sum_{s'} P(Result(a) = s') * U(s')$

P(W=rain)	P(W=sun)
0.30	0.70

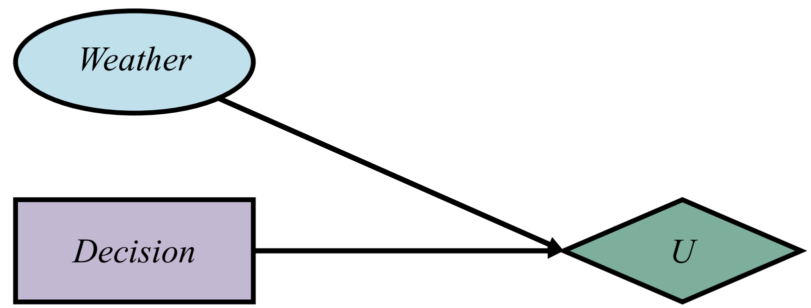


S_1': D = take, W = sun
S_2': D = take, W = rain
EU(take) =
P(Result(take) = S_1')*U(S_1') +
P(Result(take) = S_2')*U(S_2') =
0.70 * 20 + 0.30 * 70 = 35

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

$EU(a) = \sum_{s'} P(Result(a) = s') * U(s')$

P(W=rain)	P(W=sun)
0.30	0.70



S_3': D = leave, W = sun
S_4': D = leave, W = rain
EU(leave) =
P(Result(leave) = S_3')*U(S_3') +
P(Result(leave) = S_4') U(S_4') =
0.70 * 100 + 0.30 * 0 = 70

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

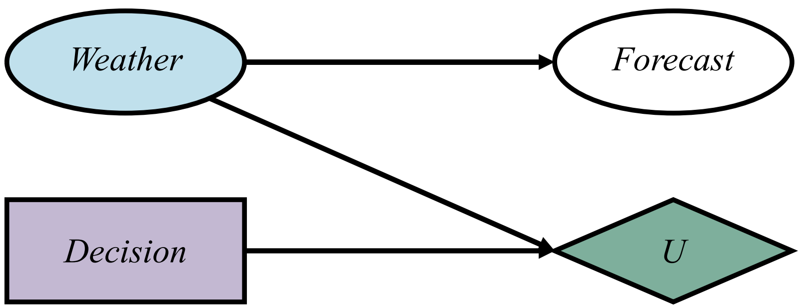
$$\text{action} = \underset{a}{\text{argmax}}\ EU(a) \mid \max(EU(take), \underline{\mathbf{EU(leave)}}) = \max(35, \mathbf{70}) \rightarrow \mathbf{leave}$$

Decision Networks: Example

Decision: take umbrella

P(W=rain)	P(W=sun)
0.30	0.70

P(F=sun)	P(F=rain)
0.59	0.41



D	W	U
leave	sun	100
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take	sun	20
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Decision: leave umbrella

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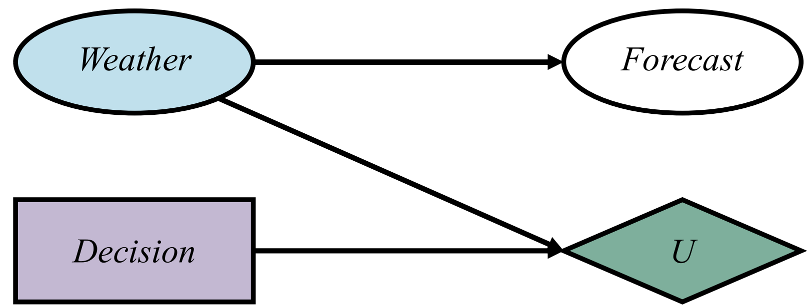


D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

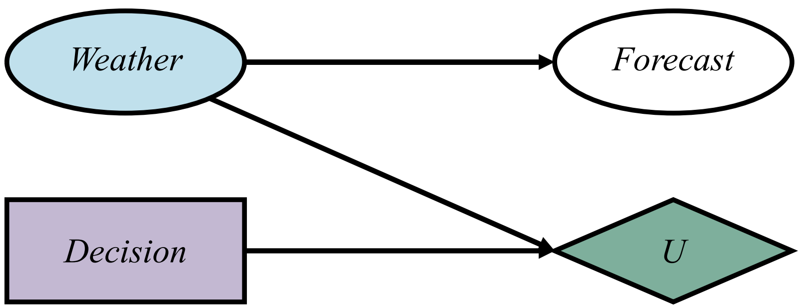
Decision Networks: Example

Decision: take umbrella given e

$$\mathrm{EU}(a \mid e) = \sum_{s'} \mathrm{P}(Result(a) = s' \mid e) * \mathrm{U}(s')$$

P(rain | F)	P(sun | F)
???	???

P(F=sun)	P(F=rain)
0.59	0.41



D	W	U
leave	sun	100
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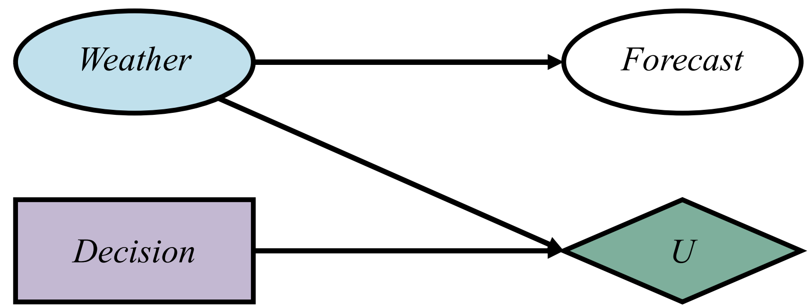
Decision: leave umbrella given e

$$\mathrm{EU}(a \mid e) = \sum_{s'} \mathrm{P}(Result(a) = s' \mid e) * \mathrm{U}(s')$$

P(rain | F)	P(sun | F)
???	???

P(F=sun)	P(F=rain)
0.59	0.41



D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

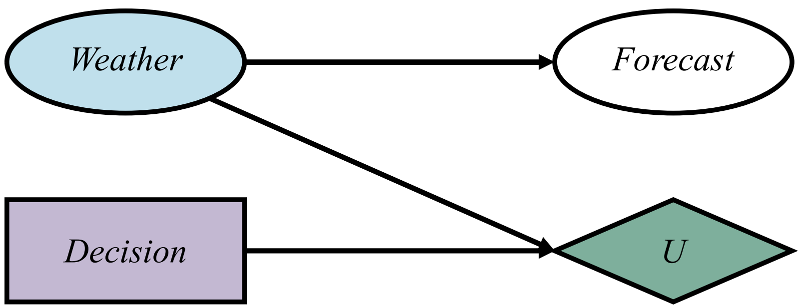
Decision Networks: Example

Decision: take umbrella given e

$$EU(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$$

P(W=rain)	P(W=sun)
0.30	0.70

P(F=sun)	P(F=rain)
0.59	0.41



D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

Conditional probabilities

Assume that we are given:

F	W	P(F|W)
sun	sun	0.80
rain	sun	0.20
sun	rain	0.10
rain	rain	0.90

By Bayes' Theorem:

$$P(W = sun \mid F = sun) = \frac{P(F = sun \mid W = sun) * P(W = sun)}{P(F = sun)} = \frac{0.80 * 0.70}{0.59} = 0.95$$

$$P(W = sun \mid F = rain) = \frac{P(F = rain \mid W = sun) * P(W = sun)}{P(F = rain)} = \frac{0.20 * 0.70}{0.41} = 0.34$$

$$P(W = rain \mid F = sun) = \frac{P(F = sun \mid W = rain) * P(W = rain)}{P(F = sun)} = \frac{0.10 * 0.30}{0.59} = 0.05$$

$$P(W = rain \mid F = rain) = \frac{P(F = rain \mid W = rain) * P(W = rain)}{P(F = rain)} = \frac{0.90 * 0.30}{0.41} = 0.66$$

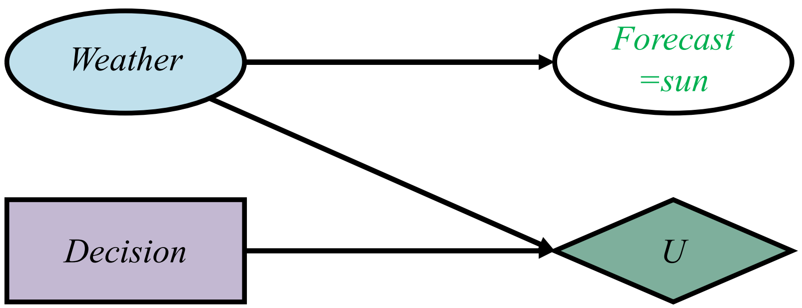
Decision Networks: Example

Decision: take umbrella given sun

$EU(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$

P(rain | F)	P(sun | F)
0.05	0.95

P(F=sun)	P(F=rain)
0.59	0.41



D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

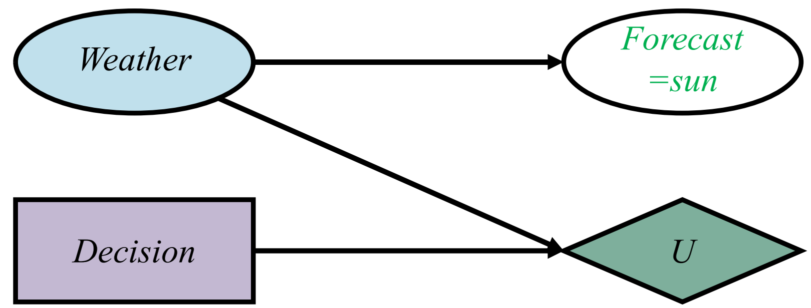
EU(take given sun forecast) = ? ? ?

Decision: leave umbrella given sun

$EU(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$

P(rain | F)	P(sun | F)
0.05	0.95

P(F=sun)	P(F=rain)
0.59	0.41



D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

EU(leave given sun forecast) = ? ? ?

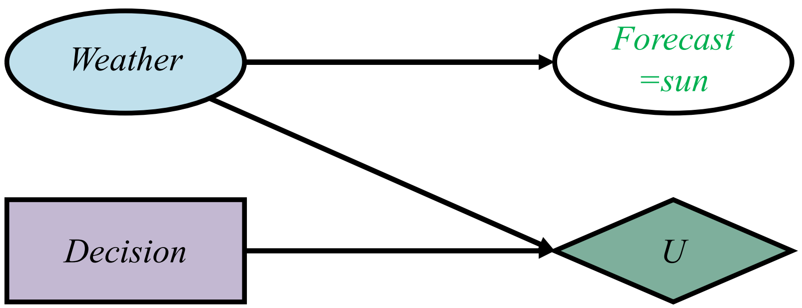
Decision Networks: Example

Decision: take umbrella given sun

$$EU(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$$

P(rain | F)	P(sun | F)
0.05	0.95

P(F=sun)	P(F=rain)
0.59	0.41



S_1': D = take, W = sun
S_2': D = take, W = rain
EU(take) =
P(Result(take)=S_1'|e)*U(S_1') +
P(Result(take)=S_2'|e)*U(S_2') =
0.95 * 20 + 0.05 * 70 = 22.5

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

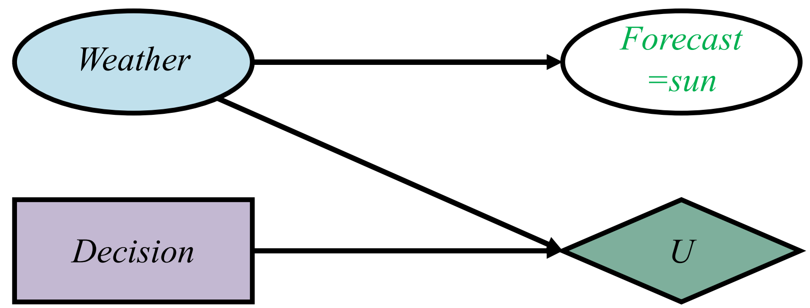
EU(take given sun forecast) = 22.5

Decision: leave umbrella given sun

$$EU(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$$

P(rain | F)	P(sun | F)
0.05	0.95

P(F=sun)	P(F=rain)
0.59	0.41



S_3': D = leave, W = sun
S_4': D = leave, W = rain
EU(leave) =
P(Result(leave)=S_3'|e)*U(S_3') +
P(Result(leave)=S_4'|e)*U(S_4') =
0.95 * 100 + 0.05 * 0 = 95

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

EU(leave given sun forecast) = 95

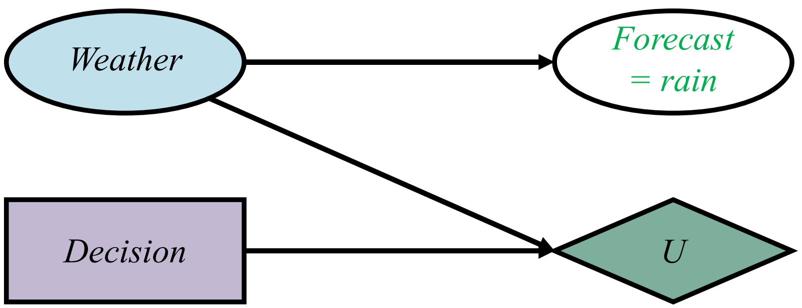
Decision Networks: Example

Decision: take umbrella given rain

$\mathrm{EU}(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$

P(rain | F)	P(sun | F)
0.66	0.34

P(F=sun)	P(F=rain)
0.59	**0.41**



D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

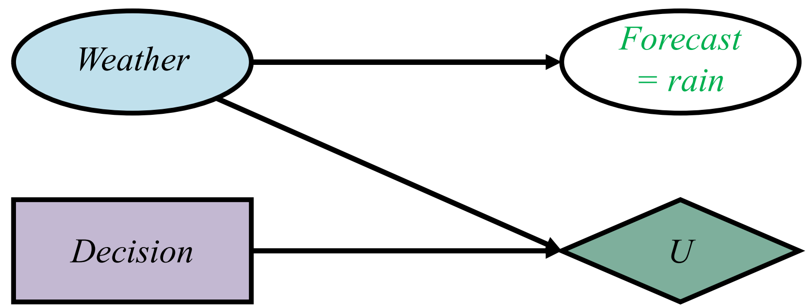
EU(take given rain forecast) = ? ? ?

Decision: leave umbrella given rain

$\mathrm{EU}(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$

P(rain | F)	P(sun | F)
0.66	0.34

P(F=sun)	P(F=rain)
0.59	**0.41**



D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

EU(leave given rain forecast) = ? ? ?

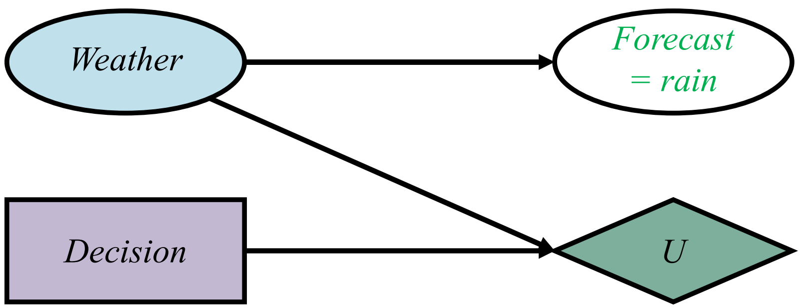
Decision Networks: Example

Decision: take umbrella given rain

$EU(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$

P(rain | F)	P(sun | F)
0.66	0.34

P(F=sun)	P(F=rain)
0.59	**0.41**



S_1': D = take, W = sun
S_2': D = take, W = rain
EU(take) =
P(Result(take)=S_1'|e)*U(S_1') +
P(Result(take)=S_2'|e)*U(S_2') =
0.34 * 20 + 0.66 * 70 = 53

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

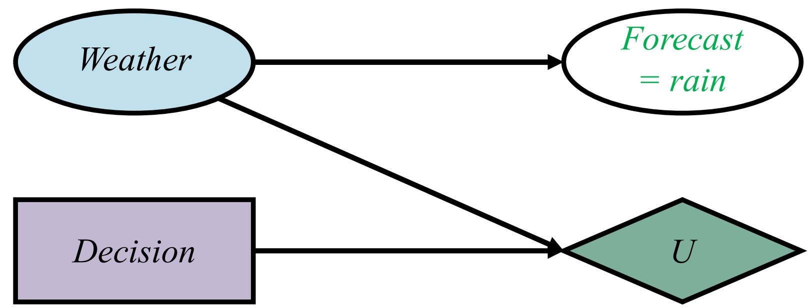
EU(take given rain forecast) = 53

Decision: leave umbrella given rain

$EU(a \mid e) = \sum_{s'} P(Result(a) = s' \mid e) * U(s')$

P(rain | F)	P(sun | F)
0.66	0.34

P(F=sun)	P(F=rain)
0.59	**0.41**



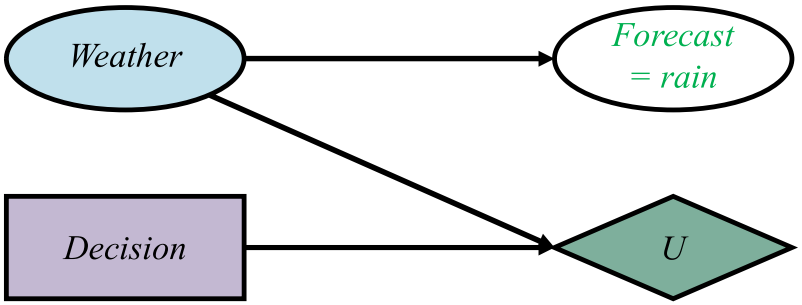
S_3': D = leave, W = sun
S_4': D = leave, W = rain
EU(leave) =
P(Result(leave)=S_3'|e)*U(S_3') +
P(Result(leave)=S_4'|e)*U(S_4') =
0.34 * 100 + 0.66 * 0 = 34

D	W	U
leave	sun	100
leave	rain	0
take	sun	20
take	rain	70

EU(leave given rain forecast) = 34

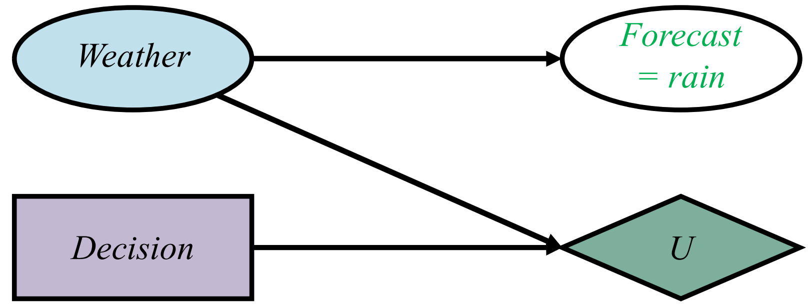
Decision Networks: Example

Decision: take umbrella given rain



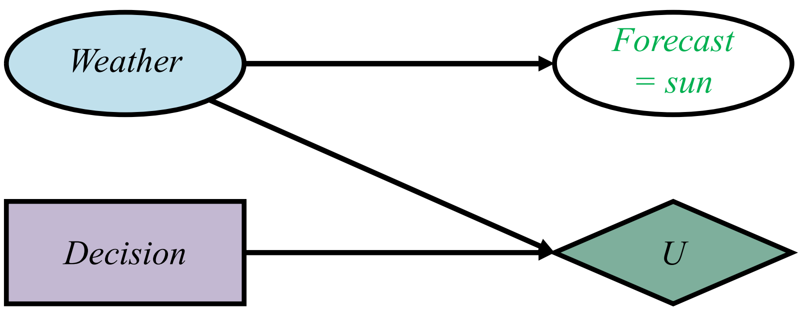
EU(take given rain forecast) = 53

Decision: leave umbrella given rain



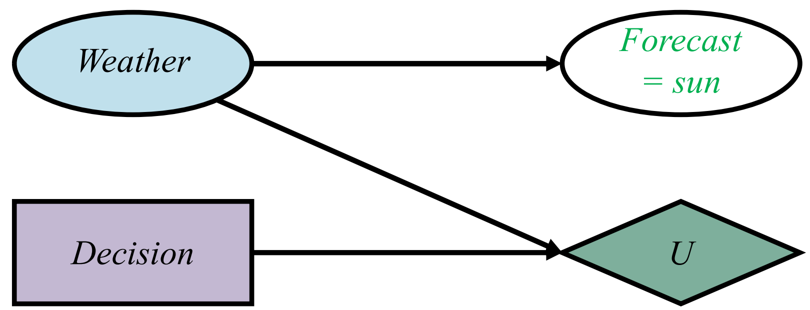
EU(leave given rain forecast) = 34

Decision: take umbrella given sun



EU(take given sun forecast) = 22.5

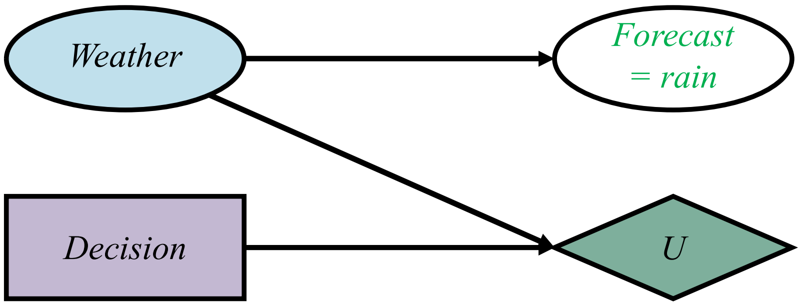
Decision: leave umbrella given sun



EU(leave given sun forecast) = 95

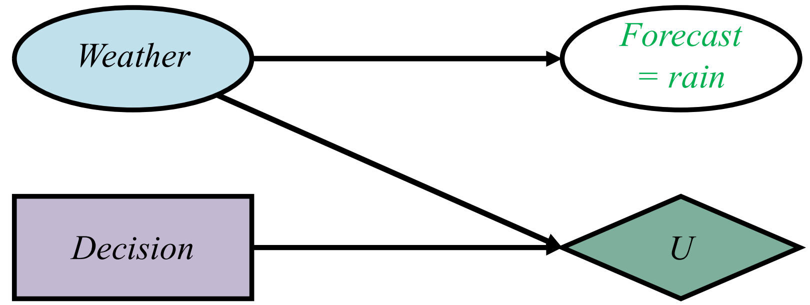
Decision Networks: Example

Decision:take umbrella given rain



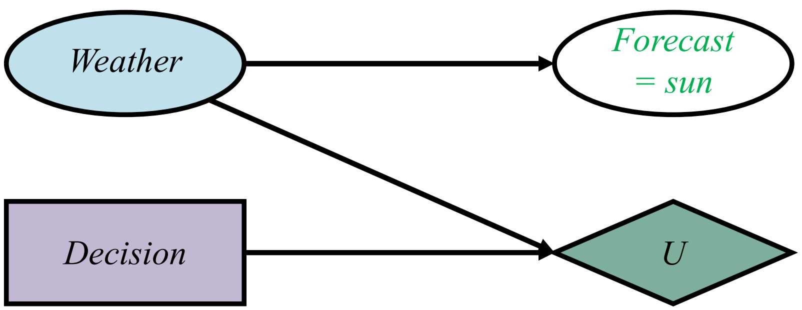
EU(take given rain forecast) = 53

Decision:leave umbrella given rain



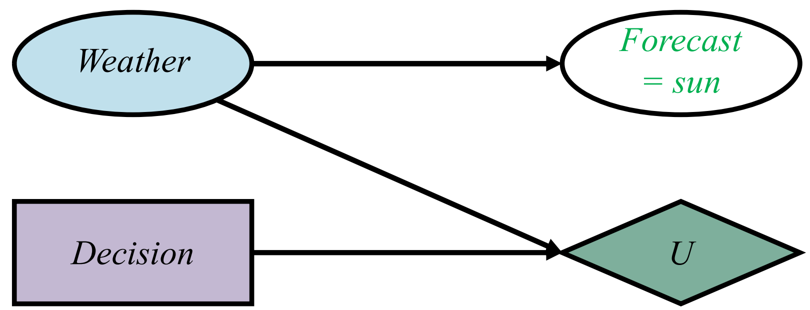
EU(leave given rain forecast) = 34

Decision:take umbrella given sun



EU(take given sun forecast) = 22.5

Decision:leave umbrella given sun



EU(leave given sun forecast) = 95

Value of Perfect Information

The value/utility of best action α without additional evidence (information) is :

$$\mathrm{MEU}(\alpha) = \max_{a} \sum_{s'} \mathrm{P}(Result(a) = s') * \mathrm{U}(s')$$

If we include new evidence/information ($\mathrm{E_j} = \mathrm{e_j}$) given by some variable Ej, value/utility of best action α becomes:

$$\mathrm{MEU}(a_{e_j} \mid e_j) = \max_{a} \sum_{s'} \mathrm{P}(Result(a) = s' \mid e_j) * \mathrm{U}(s')$$

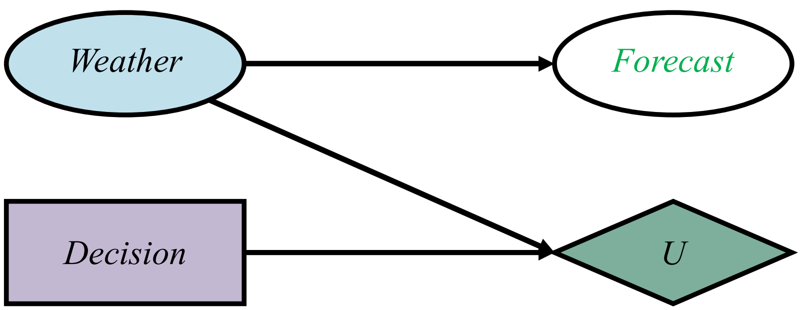
The value of additional evidence/information from Ej is:

$$\mathrm{VPI}(E_j) = \left(\sum_{e_j} \mathrm{P}(E_j = e_j) * \mathrm{MEU}(a_{e_j} \mid E_j = e_j)\right) - MEU(a)$$

using our current beliefs about the world.

Decision Network: Example

Decision network



The value of best action α without additional evidence

$$\text{MEU}(\alpha) = \text{MEU}(\text{leave}) = 70$$

With evidence information ($E_j = e_j$) given by Forecast:

$$\text{MEU}(a_{e_1} \mid e_1) = \text{MEU}(\text{take} \mid F = rain) = 53$$

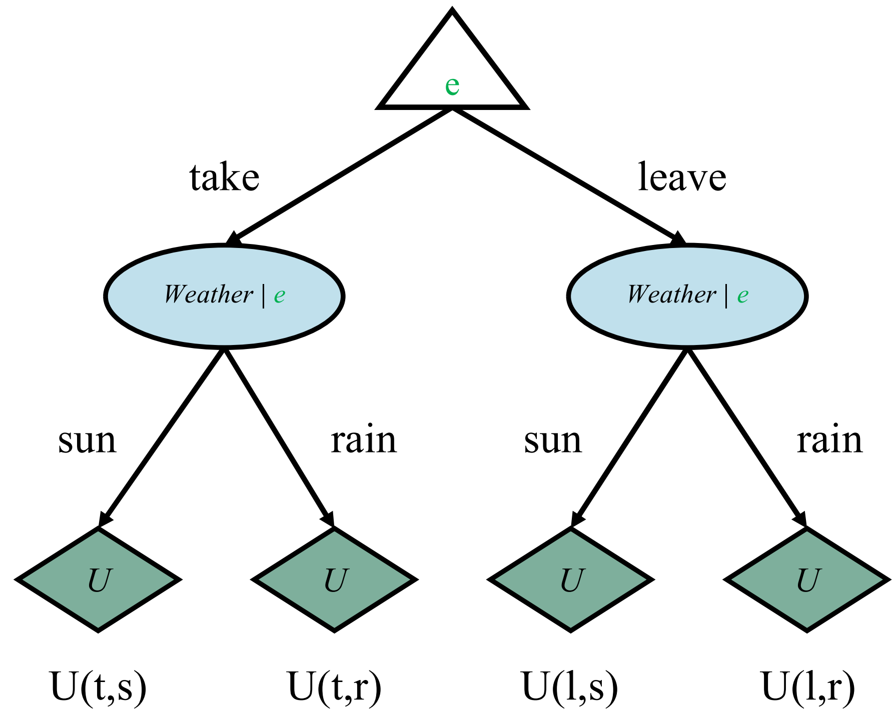
$$\text{MEU}(a_{e_2} \mid e_2) = \text{MEU}(\text{leave} \mid F = sun) = 95$$

The value of additional evidence / information from F is:

$$\text{VPI}(E_j) = \left(\sum_{e_j} \text{P}(E_j = e_j) * \text{MEU}(a_{e_j} \mid E_j = e_j)\right) - MEU(a)$$

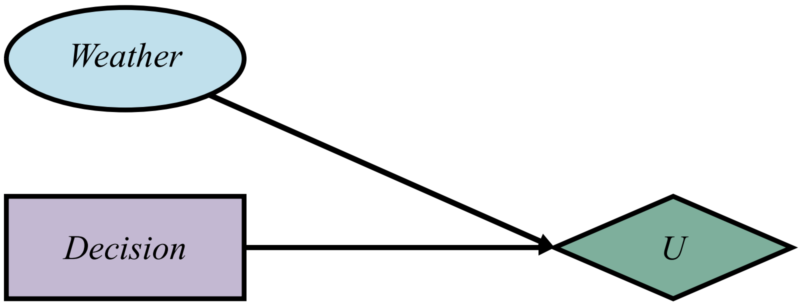
$$\text{VPI}(F) = (\text{P}(F = rain) * \text{MEU}(take \mid F = rain) + \text{P}(F = sun) * \text{MEU}(\text{leave} \mid F = sun)) - MEU(leave) = (0.41 * 53 + 0.59 * 95) - 70 = 7.78$$

Outcome tree



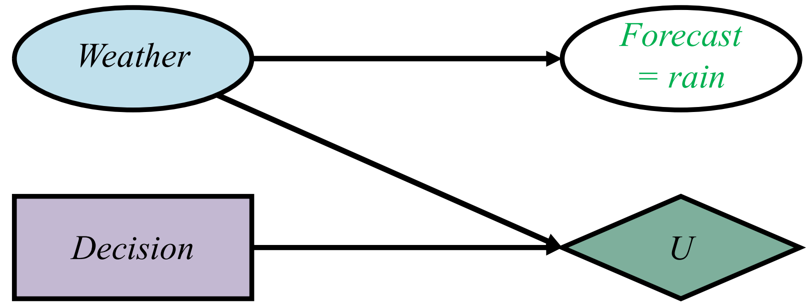
Decision Networks: Example

Decision: leave umbrella



$\mathrm{EU}(\mathrm{leave}) = 70$

Decision: take umbrella given rain



$\mathrm{EU}(\mathrm{take\ given\ rain\ forecast}) = 53$

The value of best action α without additional evidence

$$\mathrm{MEU}(\alpha) = \mathrm{MEU}(\mathrm{leave}) = 70$$

With evidence information ($\mathrm{E_j} = \mathrm{e_j}$) given by Forecast:

$$\mathrm{MEU}(a_{e_1} \mid e_1) = \mathrm{MEU}(\mathrm{take} \mid F = rain) = 53$$

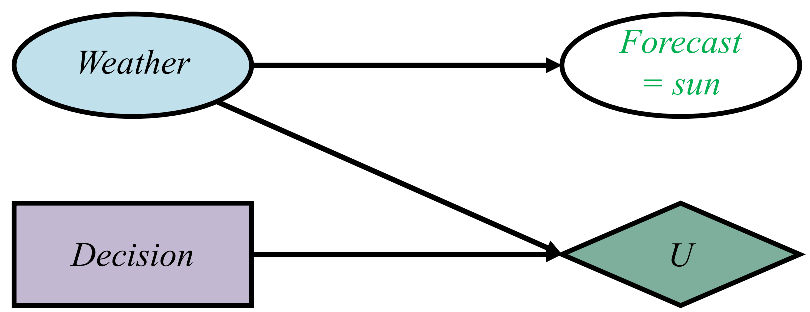
$$\mathrm{MEU}(a_{e_2} \mid e_2) = \mathrm{MEU}(\mathrm{leave} \mid F = sun) = 95$$

The value of additional evidence / information from F is:

$$\mathrm{VPI}(E_j) = \left(\sum_{e_j} \mathrm{P}(E_j = e_j) * \mathrm{MEU}(a_{e_j} \mid E_j = e_j)\right) - MEU(a)$$

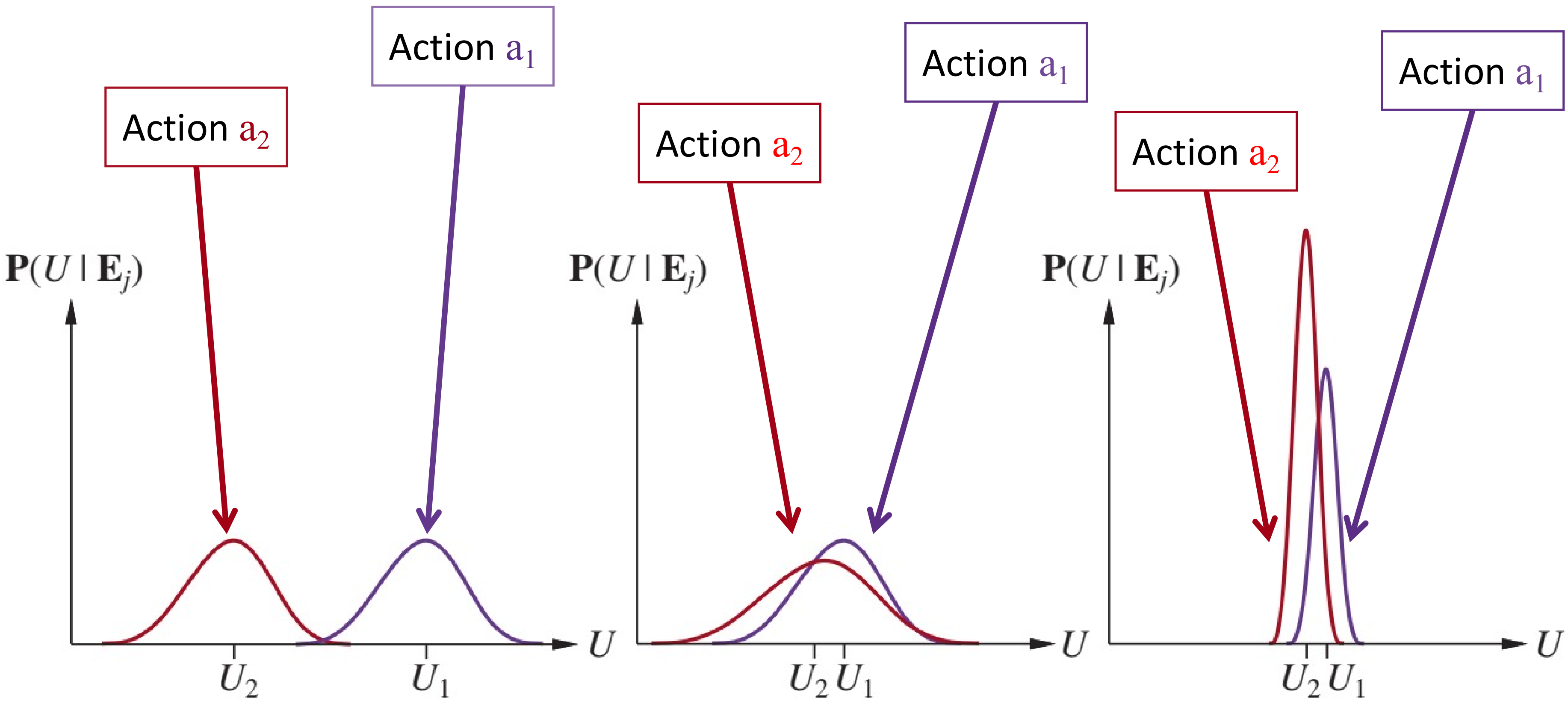
$$\mathrm{VPI}(F) = (\mathrm{P}(F = rain) * \mathrm{MEU}(take \mid F = rain) + \mathrm{P}(F = sun) * \mathrm{MEU}(\mathrm{leave} \mid F = sun)) - MEU(leave) = (0.41 * 53 + 0.59 * 95) - 70 = 7.78$$

Decision: leave umbrella given sun



$\mathrm{EU}(\mathrm{leave\ given\ sun\ forecast}) = 95$

Utility & Value of Perfect Information



New information will not help here.

New information may help a lot here.

New information may help a bit here.

VPI Properties

Given a decision network with possible observations $\mathrm{E_j}$ (sources of new information / evidence):

- **The expected value of information is nonnegative:**

$$\forall_{\mathrm{j}}\, \mathrm{VPI}(E_j) \geq 0$$

- **VPI is not additive:**

$$\mathrm{VPI}(E_j, E_k) \neq \mathrm{VPI}(E_j) + \mathrm{VPI}(E_k)$$

- **VPI is order-independent:**

$$\mathrm{VPI}(E_j,\ E_k) = VPI(E_j) + VPI(\ E_k \mid E_j) = VPI(E_k) + VPI(\ E_j \mid E_k) = VPI(E_k\ ,\ E_j)$$

Information Gathering Agent

function INFORMATION-GATHERING-AGENT(*percept*) **returns** an *action*
  persistent: D, a decision network

  integrate *percept* into D
  $j \leftarrow$ the value that maximizes $VPI(E_j)\ /\ C(E_j)$
  if $VPI(E_j)\ >\ C(E_j)$
    then return $Request(E_j)$
  else return the best action from D