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# Resolute choice in sequential decision problems with multiple priors



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Hélène Fargier, Gildas Jeantet et Olivier Spanjaard  
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# Sequential decision-making under uncertainty

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- Consequences of actions are dependent on states of the world
- Applications : medical diagnosis, troubleshooting under uncertainty, poker-playing program, etc.
- Graphical models :
  - decision trees (Raiffa, 1968)
  - influence diagrams (Shachter, 1986)
  - MDPs (Dean *et al.*, 1993; Kaelbling *et al.*, 1999)
- Sometimes hard to elicit sharp probabilities (several experts, missing data)

Need for models and algorithms  
for dealing with imprecise probabilities

# Expected utility model

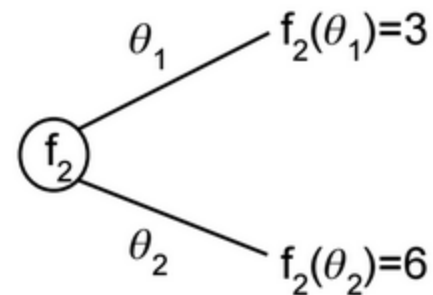
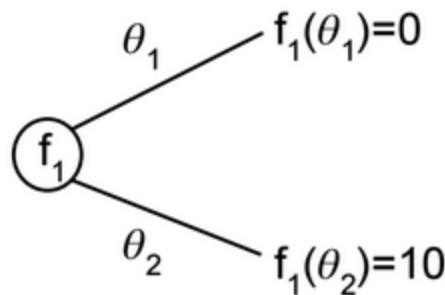
Given an act  $f : \Theta \rightarrow X$

where  $\Theta$  is the set of states of the world

$X$  is the set of consequences

and  $u:R \rightarrow R$  a nondecreasing function:

$$EU_{P,u}(f) = \sum_{\theta} P(\theta) \cdot u(f(\theta))$$



If  $u(x) = \sqrt{x}$  then:

$$EU(f_1) = \frac{1}{2} \cdot u(0) + \frac{1}{2} \cdot u(10) \approx 1.6 < 2.1 \approx \frac{1}{2} \cdot u(3) + \frac{1}{2} \cdot u(6) = EU(f_2)$$

$$f_2 > f_1$$

# Ambiguity: Ellsberg's example

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Ellsberg's urn:  $\frac{1}{3}$  of red balls,  $\frac{2}{3}$  of black or yellow balls.

Lottery	Red	Black	Yellow
$f_R$	1	0	0
$f_B$	0	1	0
$f_{RY}$	1	0	1
$f_{BY}$	0	1	1

Usually:  $f_R > f_B$  and  $f_{BY} > f_{RY}$

There exists no probability  $P$  and utility function  $u$  such that:

$$EU_{P,u}(f_R) > EU_{P,u}(f_B) \text{ and } EU_{P,u}(f_{BY}) > EU_{P,u}(f_{RY})$$

# Min expected utility model

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## Multiple priors

The underlying probability measure  $P$  could be any probability in the set:

$$\mathcal{P} = \{ P : P(\text{Red})=1/3, P(\text{Black or Yellow})=2/3 \}$$

## Min expected utility (Gilboa & Schmeidler, 1989)

Most DM do use the EU model, but on the basis of the whole *set* of priors. They maximize the min, over  $\mathcal{P}$ , of the possible values of EU:

$$\underline{EU}_{\mathcal{P},u}(f) = \min_{P \in \mathcal{P}} EU_{P,u}(f)$$

# Back to Ellsberg's example

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Lottery	Red	Black	Yellow
$f_R$	1	0	0
$f_B$	0	1	0
$f_{RY}$	1	0	1
$f_{BY}$	0	1	1

$$\underline{EU}_{\mathcal{P},u}(f_R) = \frac{1}{3}$$

$$\underline{EU}_{\mathcal{P},u}(f_{BY}) = 0$$

$$\underline{EU}_{\mathcal{P},u}(f_B) = \frac{1}{3}$$

$$\underline{EU}_{\mathcal{P},u}(f_{RY}) = \frac{2}{3}$$

# A sequential game with ambiguity

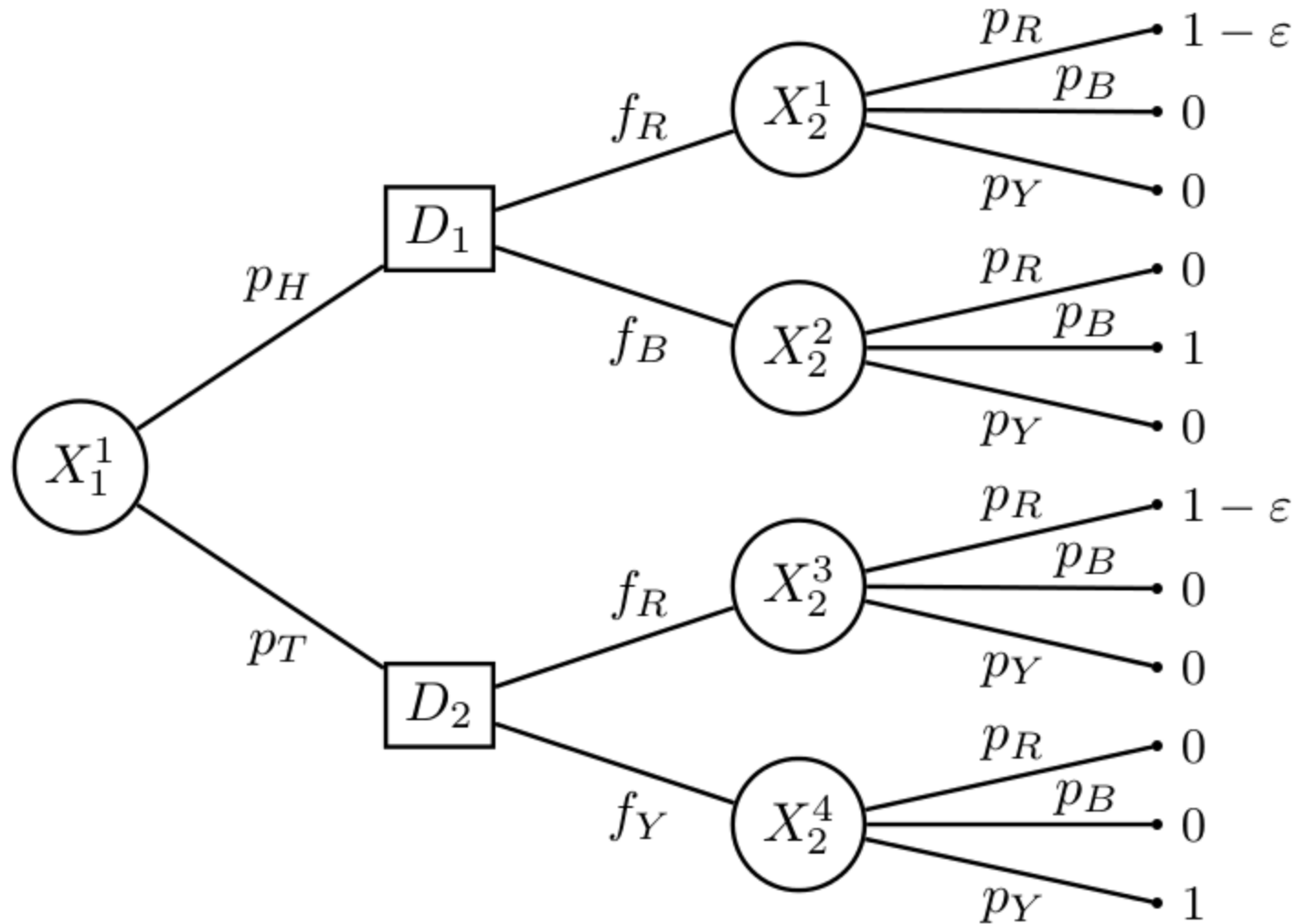
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Consider the following game:

1. toss a coin;
2. a ball is drawn from an Ellsberg's urn ( $\frac{1}{3}$  of red balls,  $\frac{2}{3}$  of black or yellow balls):
  - a. if the coin comes up heads, then bet on red or black
  - b. if the coin comes up tails, then bet on red or yellow
3. if the guess is wrong, then win 0, otherwise win  $1-\varepsilon$  if red, 1 if another color.



# Decision tree with ambiguity





# Related works

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Two research directions:

- assume **dynamic feasibility** [Kikuti et al., 2011] (seeking a strategy returned by rolling back the decision tree): strategy followed by **consequentialist** decision maker, i. e. a DM whose present decision does not depend on the past nor on what she planned to do when making her first decision.

Pros: appealing from an algorithmic viewpoint

Cons: it may return a **dominated** strategy [Hammond, 1988]

- follow a **resolute choice** approach [McClennen, 1990]: commit to an initial strategy and never deviate later

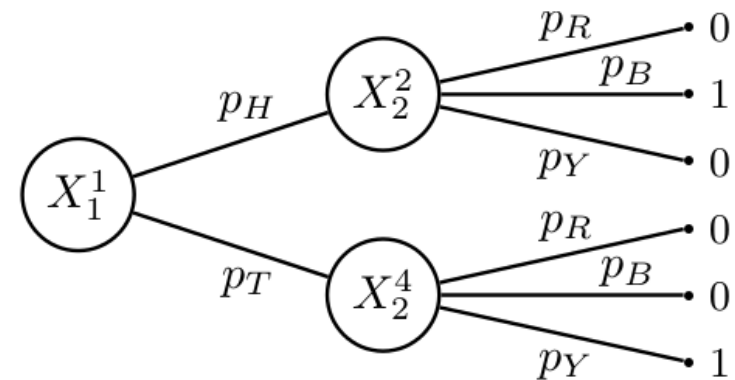
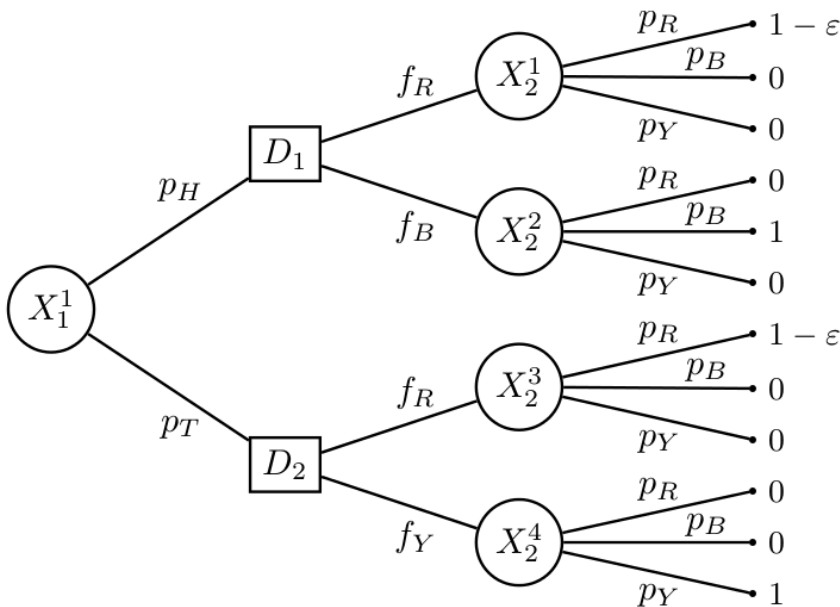
Huntley and Troffaes [2008] proposed a generic method.

# Evaluating a strategy

Evaluating strategy

$$(D_1 = f_B, D_2 = f_Y)$$

amounts to evaluate  
compound lottery:

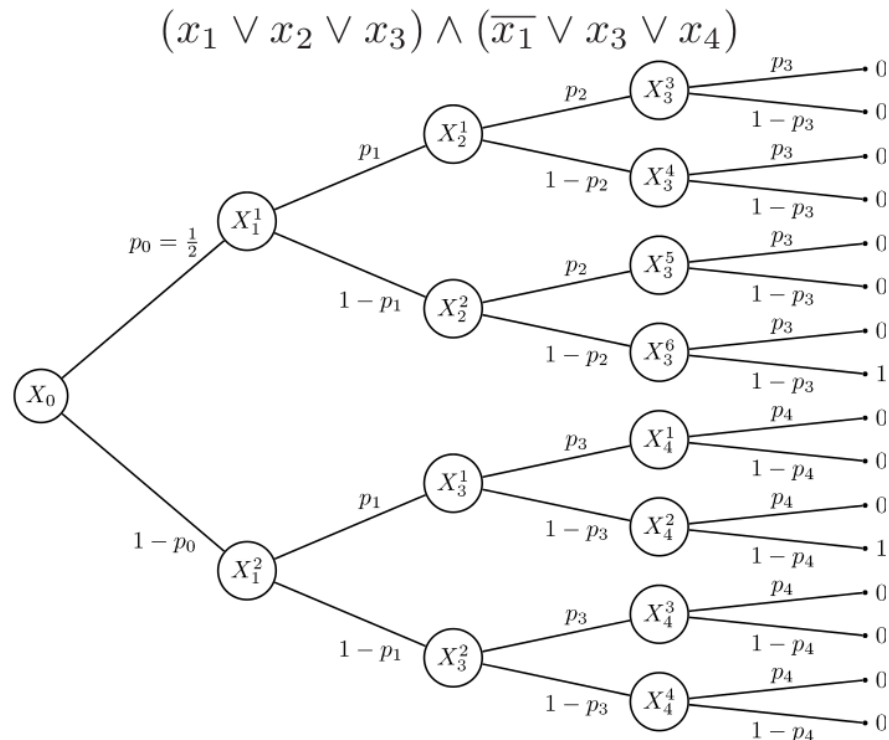


with  $p_H = 1/2$ ,  $p_T = 1/2$ ,  
 $p_R = 1/3$  and  $p_B + p_Y = 2/3$ .

# Evaluating a strategy

**Proposition.** Evaluating a strategy according to its min expected utility is an NP-hard problem, even if all non-degenerated probability intervals are  $[0, 1]$ .

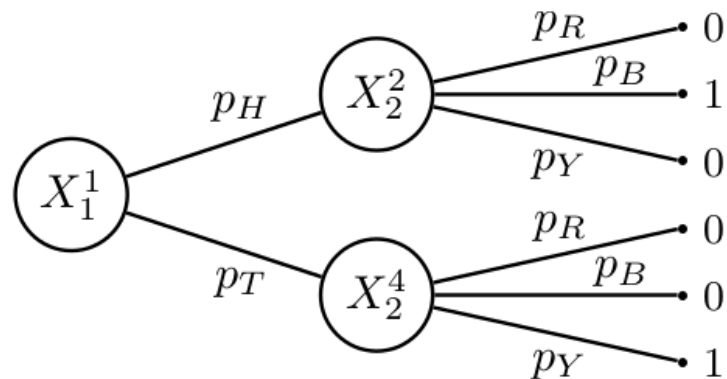
*Proof.* Reduction  
from 3-SAT:



The 3-SAT formula is satisfiable iff min expected utility = 0.

# Evaluating a strategy

The evaluation of a compound lottery can be done via a **mathematical programming formulation**, with one variable for each instantiation of  $X = \langle X_1, \dots, X_n \rangle$ :

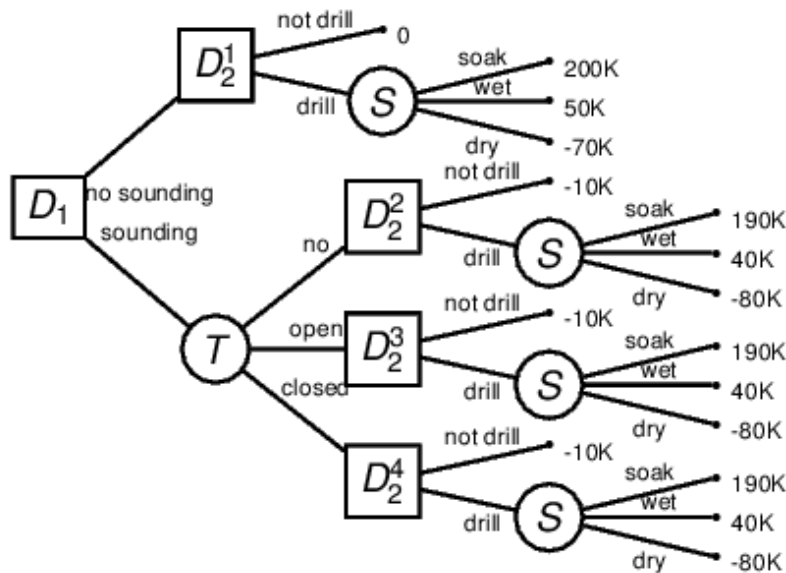


$$\min_{P \in \mathcal{P}} P(X_1 = H, X_2 = B) + P(X_1 = T, X_2 = Y)$$

where  $\mathcal{P}$  denotes the set of possible probability measures over the considered decision tree.

# Characterizing set $\mathcal{P}$ : main difficulty

## Oil wildcatter problem



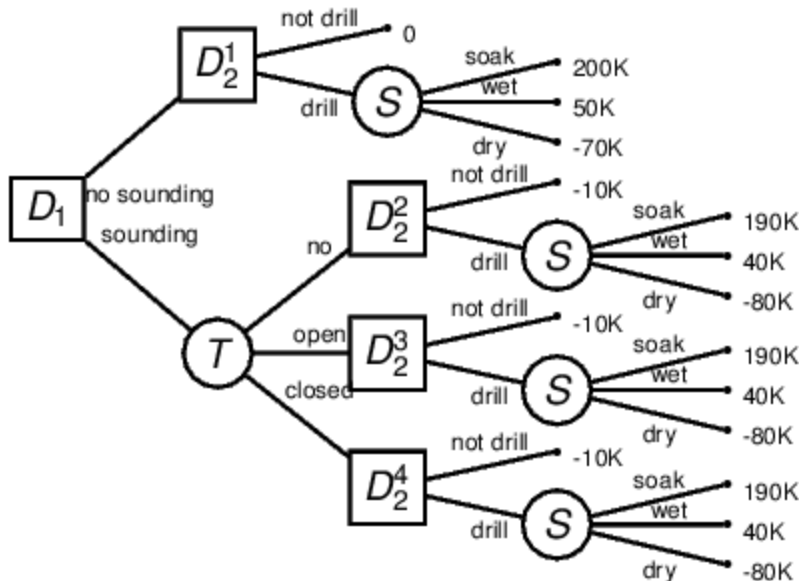
$P(S T)$	dry	wet	soak
no	[0.500,0.666]	[0.222,0.272]	[0.125,0.181]
open	[0.222,0.333]	[0.363,0.444]	[0.250,0.363]
closed	[0.111,0.166]	[0.333,0.363]	[0.454,0.625]

$T$	no	open	closed
$P(T)$	[0.181,0.222]	[0.333,0.363]	[0.444,0.454]

$S$	dry	wet	soak
$P(S)$	[0.214,0.344]	[0.309,0.386]	[0.307,0.456]

# Characterizing set $\mathcal{P}$ : main difficulty

## Oil wildcatter problem



$P(S T)$	dry	wet	soak
no	0.55	[0.222,0.272]	[0.125,0.181]
open	0.33	[0.363,0.444]	[0.250,0.363]
closed	0.12	[0.333,0.363]	[0.454,0.625]

$T$	no	open	closed
$P(T)$	0.20	0.35	0.45

$S$	dry	wet	soak
$P(S)$	0.22	[0.309,0.386]	[0.307,0.456]

The **total probability theorem** does not hold:

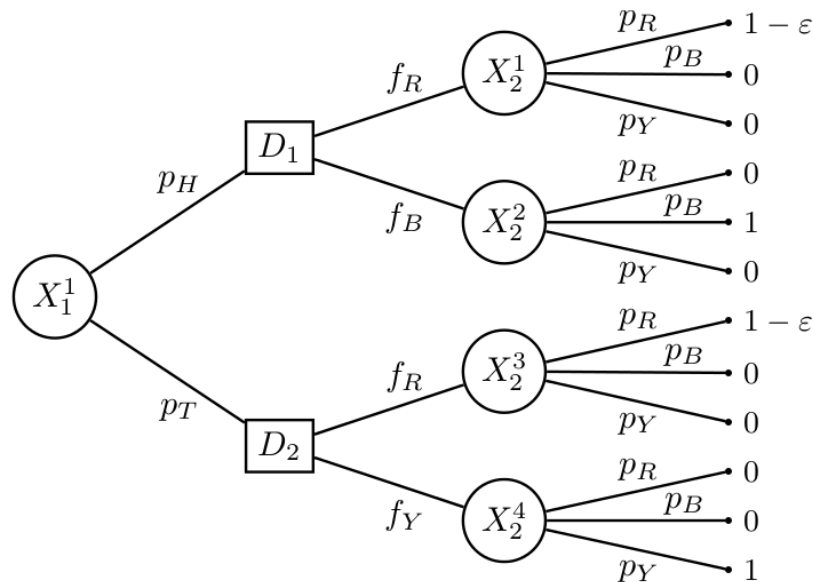
$$P(S = \text{dry} | T = \text{no})P(T = \text{no}) + P(S = \text{dry} | T = \text{open})P(T = \text{open}) + P(S = \text{dry} | T = \text{closed})P(T = \text{closed}) = 0.2795 \neq 0.22 = P(S = \text{dry})$$

# Selecting a strategy

The optimality principle does not hold:

In  $D_1$ :  $EU(f_R) = (1-\varepsilon)/3 > 0 = EU(f_B) \Rightarrow$  the DM prefers  $f_R$

In  $D_2$ :  $EU(f_R) = (1-\varepsilon)/3 > 0 = EU(f_Y) \Rightarrow$  the DM prefers  $f_R$



Strategy returned by rolling back:  $(D_1=f_R, D_2=f_R)$

Min expected utility of  $(D_1=f_R, D_2=f_R)$ :  $(1-\varepsilon)/3$

Min expected utility of  $(D_1=f_B, D_2=f_Y)$ :  $1/3$

# Selecting: separable case

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**Separable decision tree.** For each chance node  $X_i^j$ , we denote by  $\mathcal{P}_i^j$  the set of conditional probability distributions over  $X_i | \text{past}(X_i^j)$  that satisfies constraints  $\mathcal{C}_i^j$ . A decision tree  $\mathcal{T}$  is called *separable* (or *separately specified*, Kikuti *et al.*, 2011) if

$$\mathcal{P}_{\mathcal{T}} = \prod_{X_i^j \in \mathcal{N}_C} \mathcal{P}_i^j.$$

**Example:** sequential variant of Ellsberg's urn with two distinct Ellsberg's urns.

The optimal strategy can be computed by **rolling back the decision tree**. It involves the solution of **a (small) linear program** at each chance node, where the variables are the conditional probabilities.



# Selecting: non-separable case

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**Dominance relation.** A strategy  $s$  **dominates**  $s'$  if:

$$\forall P \in \mathcal{P}, EU_{P,u}(s) \leq EU_{P,u}(s').$$

**Dominance test:** **mathematical programming.**

$$\text{If } s \text{ dominates } s', \text{ then } \underline{EU}_{\mathcal{P},u}(s) \leq \underline{EU}_{\mathcal{P},u}(s').$$

## Two-phases approach:

1. Compute the set ND of non-dominated strategies by rolling back the decision tree [Huntley & Troffaes, 2008]
2. Determine an optimal strategy in ND

# Numerical tests

*Separable decision trees (times in sec.)*

$h \setminus d$	3		4	
	# nodes	time	# nodes	time
8	2073	< 1	5851	< 1
10	12441	< 1	46811	< 1
12	74639	1.2	374491	5.7
14	447897	7.8	2995931	65.5
16	2687385	57.3	X	X
18	X	X	X	X

$h$ : depth of the decision tree;  
 $d$ : outdegree of chance nodes.

*Non-separable decision trees (times in sec.)*

$h$	8		10	
	$n \setminus w$	0.05	0.1	0.05
7	< 1	< 1	22.0	23.0
8	1.4	2.0	51.6	58.0
9	2.2	2.4	114.9	142.3
10	4.3	4.6	253.6	328.1
11	7.4	7.7	590.7	X
12	14.3	17.8	X	X
ND	5	8	29	32

$n$ : number of random variables;  $w$ : imprecision degree;  
 $ND$ : average size of the non-dominated set.

*Algorithms implemented in C++.*

*CPLEX solved used to solve the mathematical programs.*

*Numerical tests performed on a Pentium IV 2.13Ghz CPU computer, 3GB RAM*

# Research directions

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- Use **credal networks** to define set  $\mathcal{P}$ .
- Extend to **influence diagrams** with imprecise probabilities
- Resolute choice **with selves** [Jaffray & Nielsen, 2006]:

Consider each decision node as a **self** and search for a compromise between the selves

**More specifically:** define a regret for each self, and compute a strategy that optimizes an aggregation of the regrets.

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Thank you

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