The uncertainty of risk
The risk of uncertainty

Enrico Zio

Risk & Uncertainty

The (uncertain) flow of the presentation

PART I: The uncertainty of risk

- Problem Setting: RISK, QRA, PRA
- Uncertainty: types and sources
- Worries
- Frameworks of uncertainty/information/knowledge representation

PART II: The risk of uncertainty

- Decision maker dreams and nightmares

The (risky) flow of the presentation

PART III: “Things I know”

- “Faithful” representation of information and introduction of knowledge

PART IV: Jingles

- Conclusions
- Advertisement
- Acknowledgments

PART I:
The uncertainty of risk

Risk and Quantitative Risk Analysis (QRA)

RISK = (*A*, *C*, *L*(*U*))

1. What undesired conditions may occur? ➡ **Accident, *A***

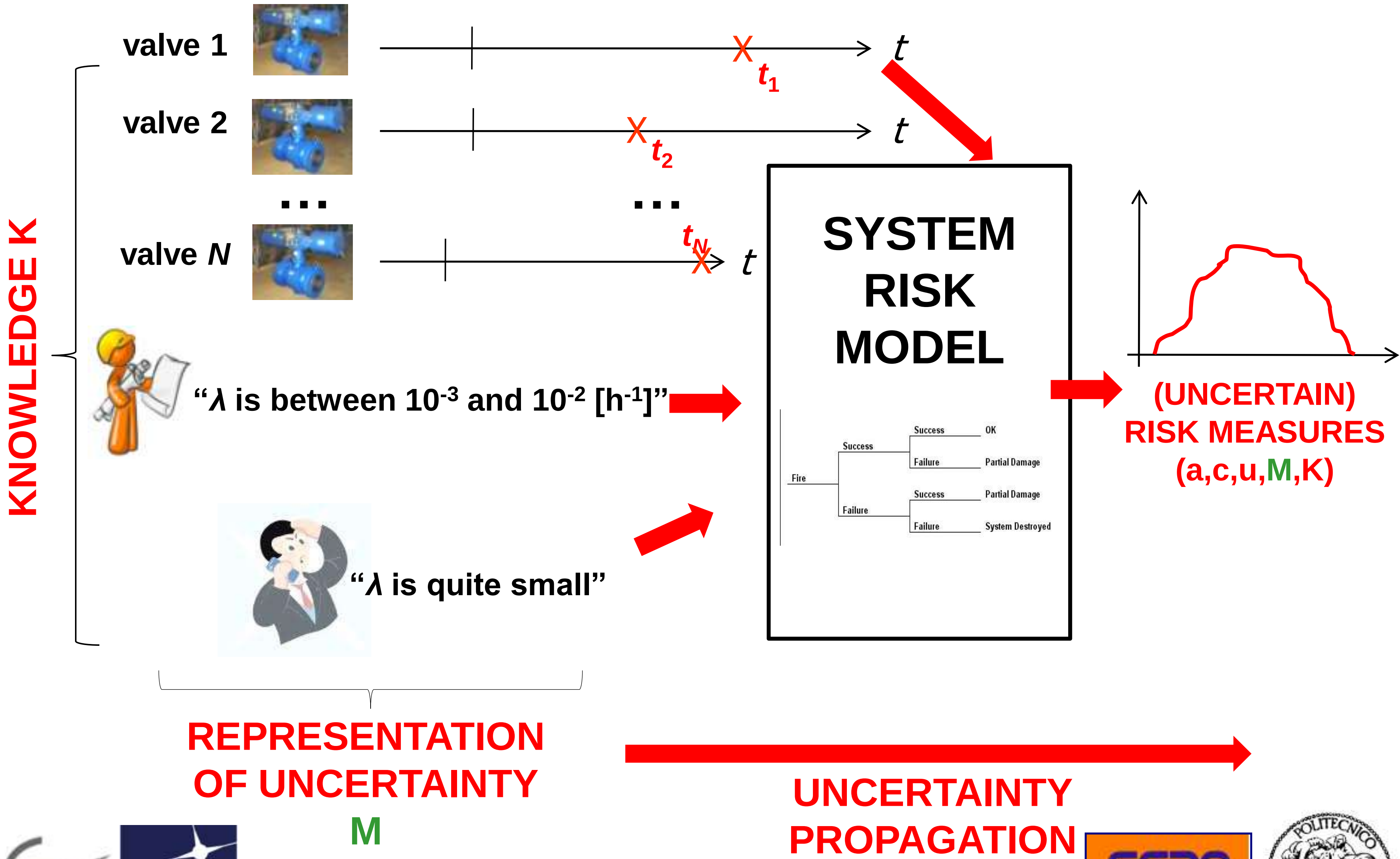
2. What damage do they cause? ➡ **Consequence, *C***

3. What is the likelihood (uncertainty) of occurrence? ➡ **Likelihood, L(*U*)**

Quantitative Risk Analysis Model

risk =(*a*, *c*, l(*u*), *K*)

Quantitative Risk Analysis



Probabilistic Risk Analysis

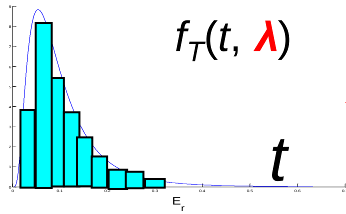
KNOWLEDGE K

valve 1

valve 2

...

valve N

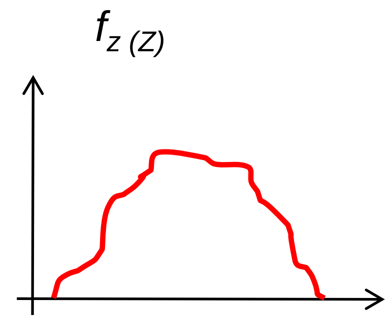


"λ is UNIFORM between 10^{-3} and 10^{-2} [h^{-1}]"

"λ is less than 10^{-2} [h^{-1}] with probability 0.9"

SYSTEM RISK MODEL

Fire	Success	Success	OK
		Failure	Partial Damage
	Failure	Success	Partial Damage
		Failure	System Destroyed



(PROBABILISTIC) RISK MEASURES

(a,c,u,P,K)

PROBABILISTIC REPRESENTATION OF UNCERTAINTY (M=P)

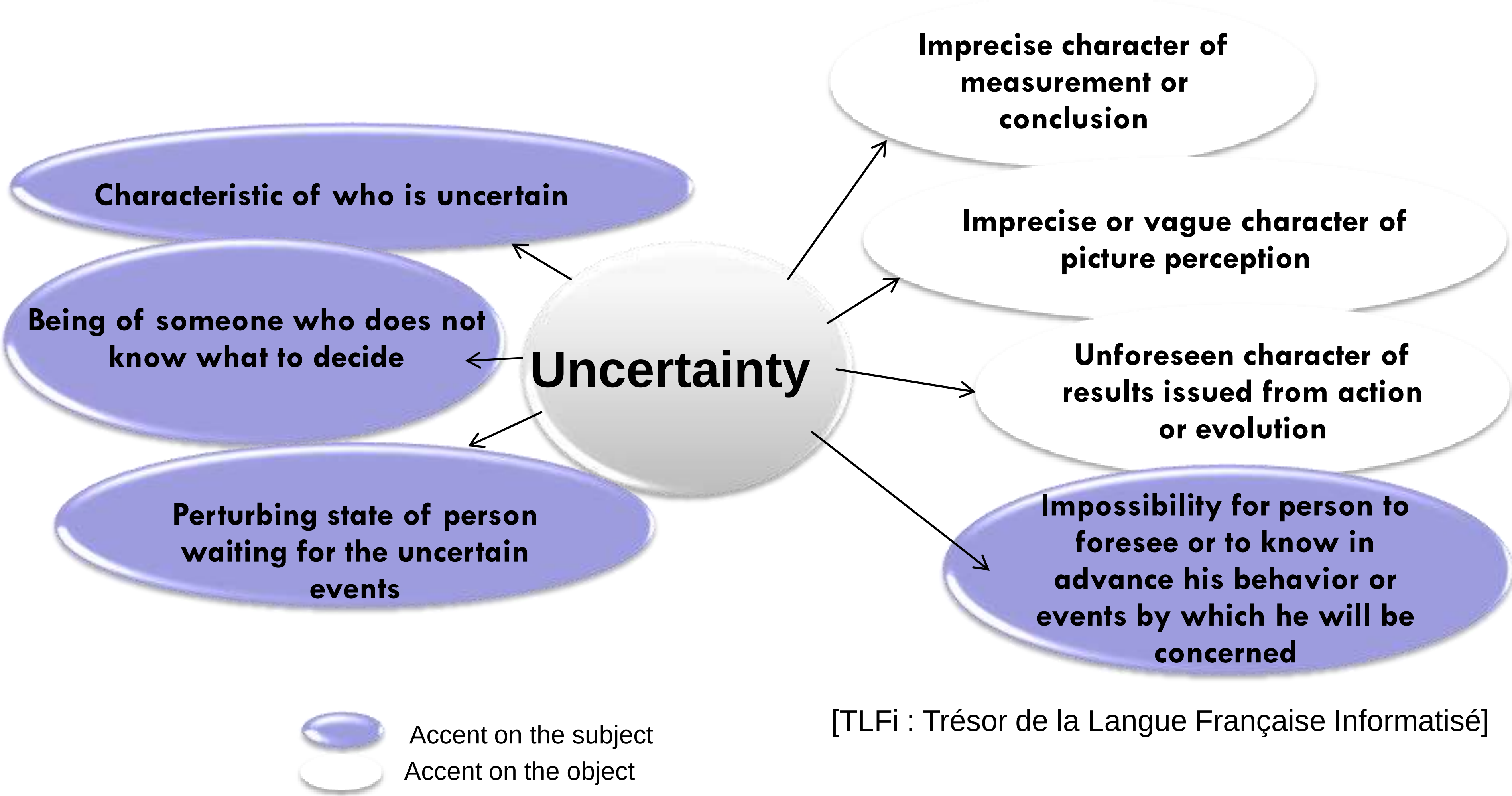
UNCERTAINTY PROPAGATION

Uncertainty

Uncertainty is not in the things but in our head: uncertainty is lack of knowledge

J. Bernoulli

Uncertainty (in the dictionary)



[TLFi : Trésor de la Langue Française Informatisé]

Adapted from S. Farnoud and S. Tillement, IFIS Toulouse 2010

Uncertainty (in the epistemology)

Uncertainty

from latin *certitudo*

From latin *certus*

From the latin verb *cernere*
« discern, decide »

from latin *cerno* : from common indo-european *(s)ker* : cut, which pairs it with the ancient greek *krino* : shear

Adapted from S. Farnoud and S. Tillement, IFIS Toulouse 2010

Uncertainty (in the history)

2000

De Finetti, Knight, Zadeh, …

Modern era

Laplace, Carnap, Shackle, Gödel

Renaissance

Descartes, Pascal, Kant

1500

Middle Ages

Incoherence of philosophies of Ghazali, necessity to prove the validity of reason, independent from reason.

500

- Socrate, Platon, Carnéade
- Sophism
- Skepticism
- 500 before J.C. Empédocle d'Agrigente (father of **rhetoric**), Gorgias
- **Mathematics** were used to create confidence [Philippe De Wilde 2010].
- **Logic** provides reasoning rules to reduce uncertainty.
- **Religion** provides a narrative to create confidence [Philippe De Wilde 2010].
- **Mythe** was the first attempt to reduce uncertainty [Gérald Bronner 1997].

0

Antiquity

- 500

-1000

Prehistory

- The development of Homo sapiens in an uncertain environment: predator, war …. Chimpanzees still live in this environment [Philippe De Wilde 2010].
- Evolution has selected the anatomy of the brain that is optimized to some degree to cope with uncertainty[Philippe De Wilde 2010].

-3000

Adapted from S. Farnoud and S. Tillement, IFIS Toulouse 2010

Uncertainty in QRA

aleatory uncertainty

» irreducible uncertainty
» property of the system
» random fluctuations / variability/ stochasticity

epistemic uncertainty

» reducible uncertainty
» property of the analyst
» incomplete knowledge

Adapted from G. Apostolakis, Workshop LA 2010 and M. Beer, Seminar Paris 2012

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Uncertainty in QRA

<u>aleatory uncertainty</u>

» irreducible uncertainty
» property of the system
» random fluctuations / variability/ stochasticity

<u>epistemic uncertainty</u>

» reducible uncertainty
» property of the analyst
» lack of knowledge or perception

Adapted from G. Apostolakis, Workshop LA 2010 and M. Beer, Seminar Paris 2012

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Uncertainty in QRA

- *Epistemic* uncertainties are further categorized as being due to
  - *parameter* values,
  - *model* assumptions, and
  - *incomplete* analyses
    - "*Known unknowns*" : initiating events, failure modes or mechanisms are known but not included in the model
    - "*Unknown unknowns*": phenomena or failure mechanisms are unknown

RISK = (*A*, *C*, *L*(*U*)) ≠ risk =(*a*, *c*, l(*u*), *K*)

Adapted from G. Apostolakis, Workshop LA 2010

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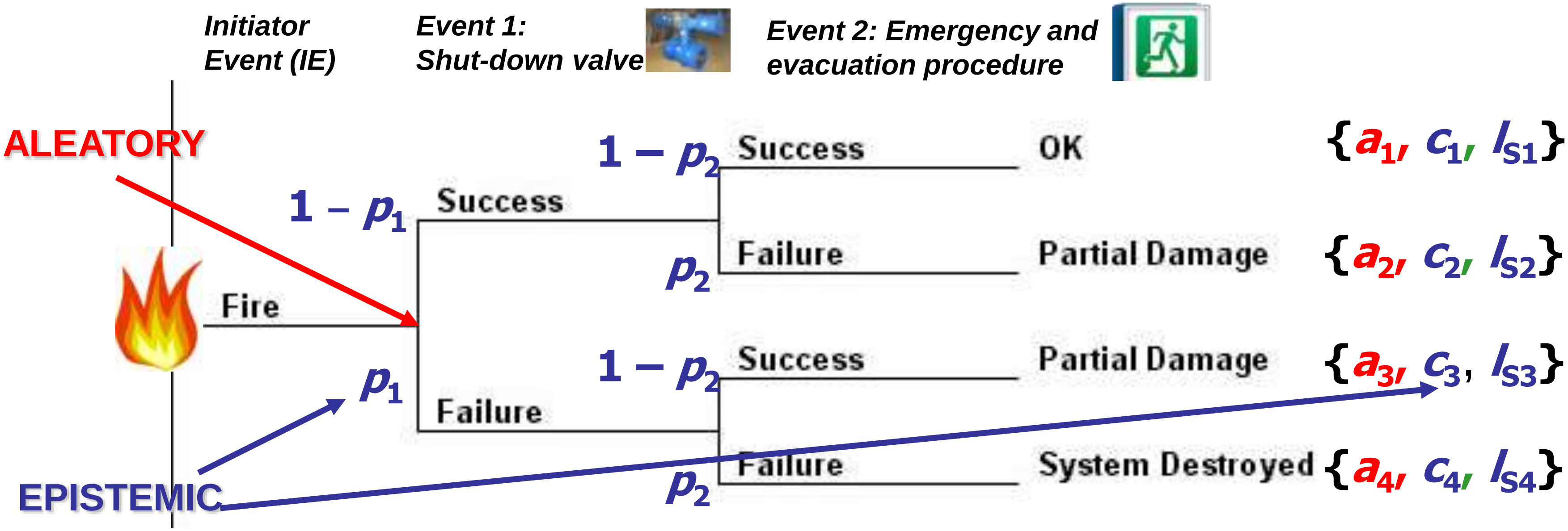
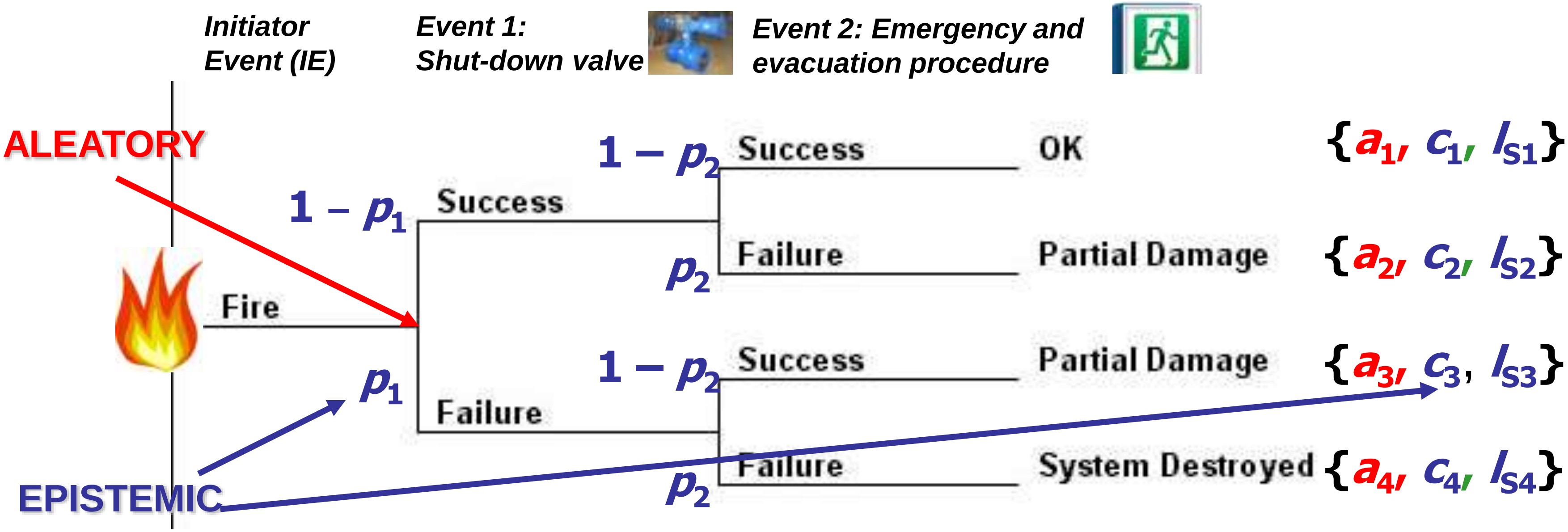
(aleatory and epistemic) Uncertainty in QRA



ALEATORY: **variability**, **randomness** (in **occurrence** of the **events** in the **scenarios)**

EPISTEMIC: **lack of knowledge/information (**on the **values** of the **parameters** of the **probability** and **consequence** models)

(aleatory and epistemic) Uncertainty in PRA



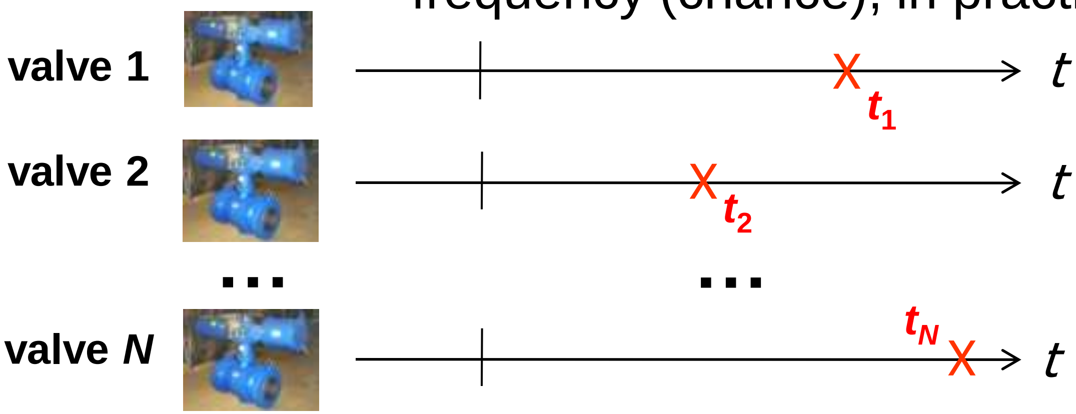
Probability used for representing both randomness and incomplete information/partial knowledge

Aleatory: STOCHASTIC MODELS

Epistemic: PROBABILITIES

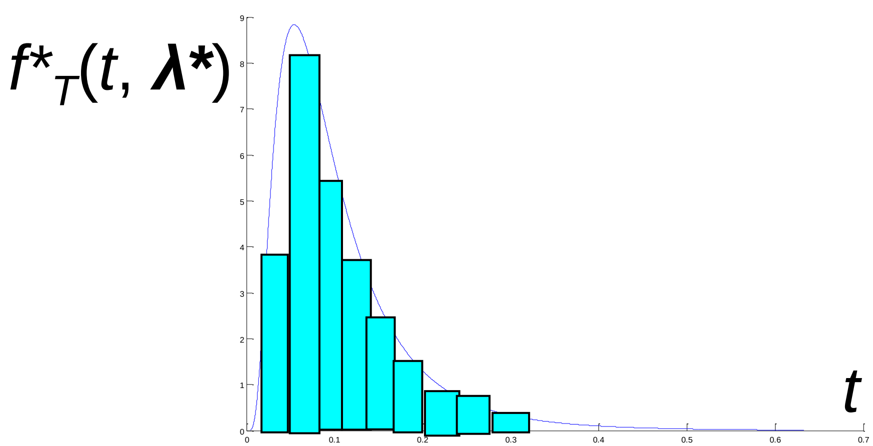
Probablistic representation of epistemic uncertainty in PRA

Sufficiently informative (statistical) **data**: P=limiting relative frequency (chance); in practice, estimated value P*



Hardware failure occurrence times:
Event 1 = failure of shut-down valve

Realizations of a random variable → Probability Density Function

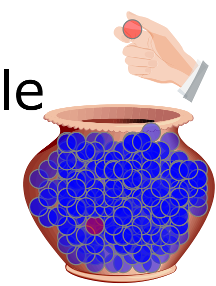


Probablistic representation of epistemic uncertainty in PRA

Scarce (possibly qualitative) **data**: P(A/K)=Subjective probability (knowledge-based probability)

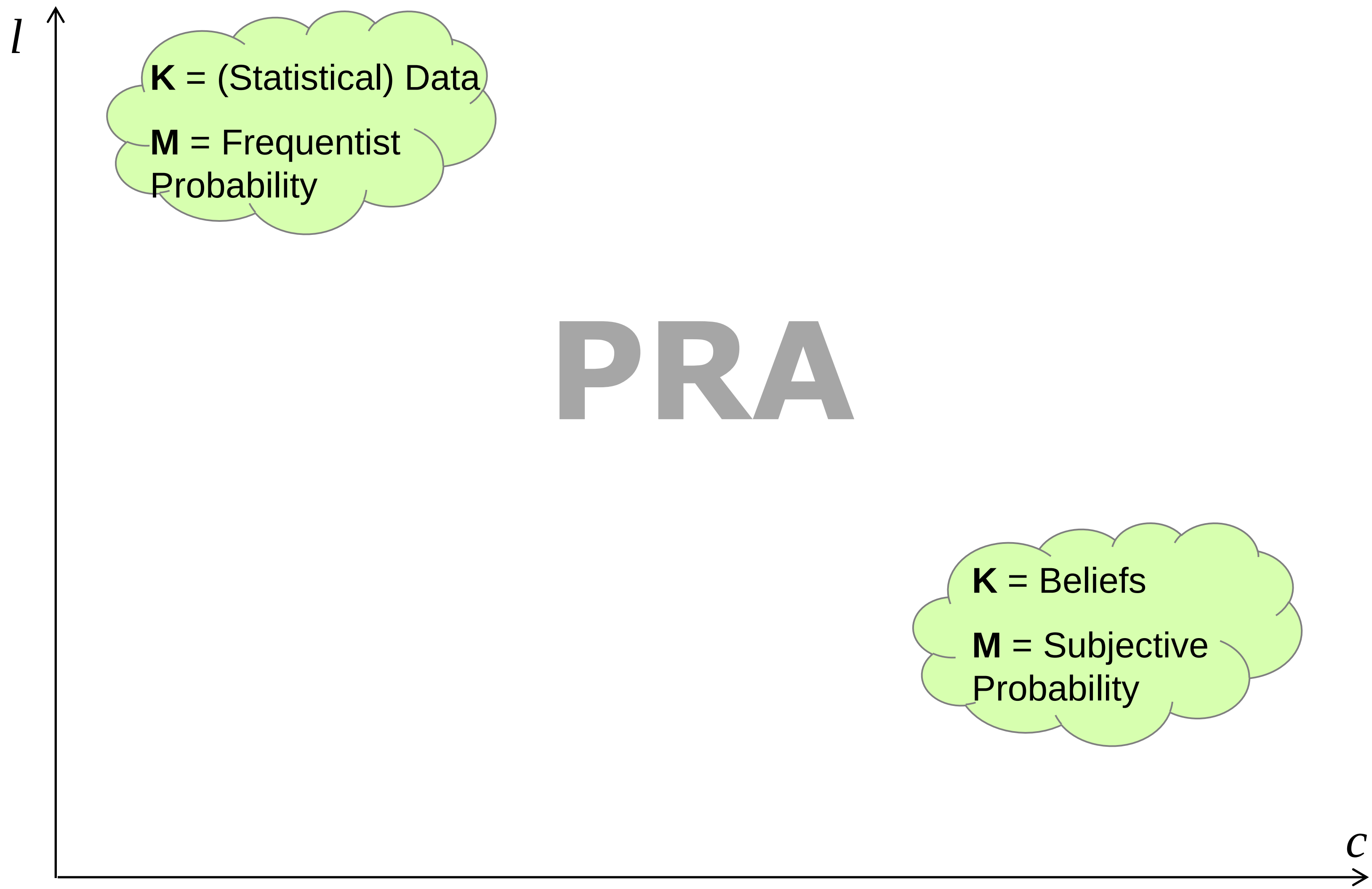
P(A/K)

- Betting interpretation:
  - The probability of the event A, P(A), equals the amount of money that the assigner would be willing to bet if he/she would receive a single unit of payment in the case that the event A were to occur, and nothing otherwise.
- Comparison with a standard
  - The assessor compares his/her uncertainty about the occurrence of the event A with e.g. drawing a favourable ball from an urn that contains P(A) · 100 % favourable balls (Lindley, 2000).



Adapted from T. Aven, Workshop LA 2010

Epistemic Uncertainty



Statement

PRA is a mature methodology.

Worries

Worries: known unknowns

In risk analysis assumptions are made that may be convenient but not really justified from the available information and knowledge:

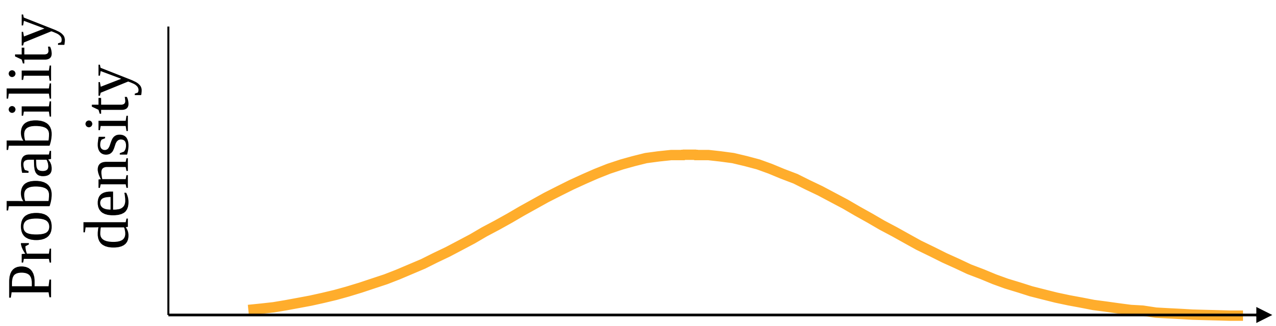
- Distributions are stationary (unchanging in time)
- Variables, experts are independent of one another
- Uniform distributions model “complete” uncertainty

Adapted from S. Ferson, Workshop LA 2010

Worries: known unknowns

Instability

Uniform + Uniform + Uniform + Uniform



The more (uncertain) inputs, the more certainty in the output…?

Adapted from S. Ferson, Workshop LA 2010

Frameworks of uncertainty/information/knowledge representation

Uncertainty representation

Tools for representing uncertainty

- **Probability distributions :**

+ good for expressing variability (aleatory)
- information/knowledge (data)-demanding
- difficult to justify when information/knowledge is incomplete (choice of a single distribution not satisfactory)

- **Sets (numerical intervals)**:

+ good for representing incomplete information/knowledge (epistemic)
- a very crude representation of uncertainty

Adapted from D. Dubois, Workshop LA 2010

Uncertainty representation

Representations that allow for both aspects of uncertainty

- ✓ Capable of distinguishing between (aleatory) uncertainty due to variability from (epistemic) uncertainty due to incomplete information/knowledge
- ✓ *More informative than the sets of pure interval (or classical) logic*
- ✓ *Less demanding than single probability distributions*
- ✓ *Explicitly allowing for missing information*

↓

Blend intervals and probability

Adapted from D. Dubois, Workshop LA 2010

Uncertainty representation

Blending intervals and probability

- ✓ Sets of probabilities: imprecise probability theory ($[P_*(A), P^*(A)]$)
- ✓ Random sets: Dempster-Shafer Theory ($[Bel(A), Pl(A)]$)
- ✓ Fuzzy sets: <u>numerical</u> possibility theory ($[\Pi(A, N(A)]$)

Instead of a single degree of probability, each event A has a degree of belief (certainty) and a degree of plausibility which "bound all probabilities"

Adapted from D. Dubois, Workshop LA 2010

Uncertainty representation

Practical ways for representing probability sets

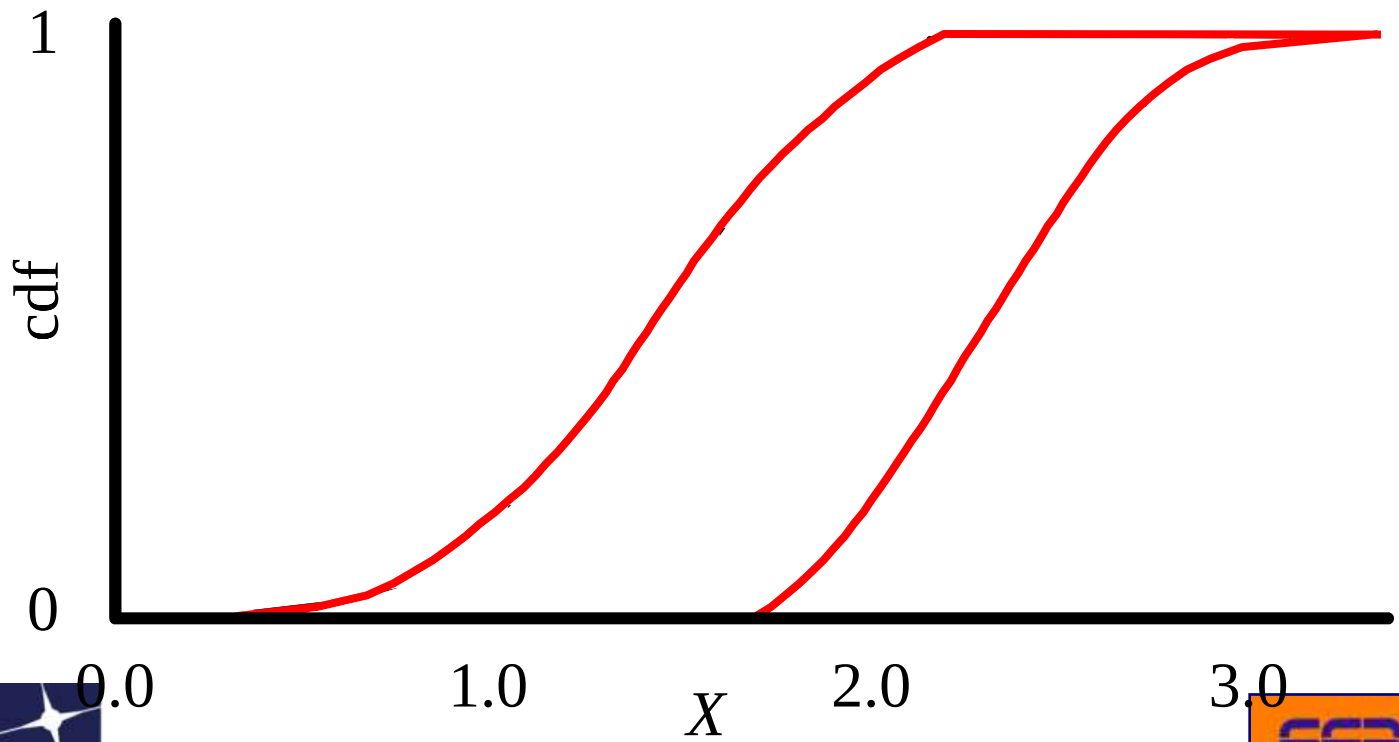
- Fuzzy (numerical) intervals (possibility theory)
- Probability intervals (bounding the probabilities of events)
- Probability boxes (pairs of pdfs or cdfs)

Adapted from D. Dubois, Workshop LA 2010

Uncertainty representation

Example: P-box

Interval bounds on a cdf



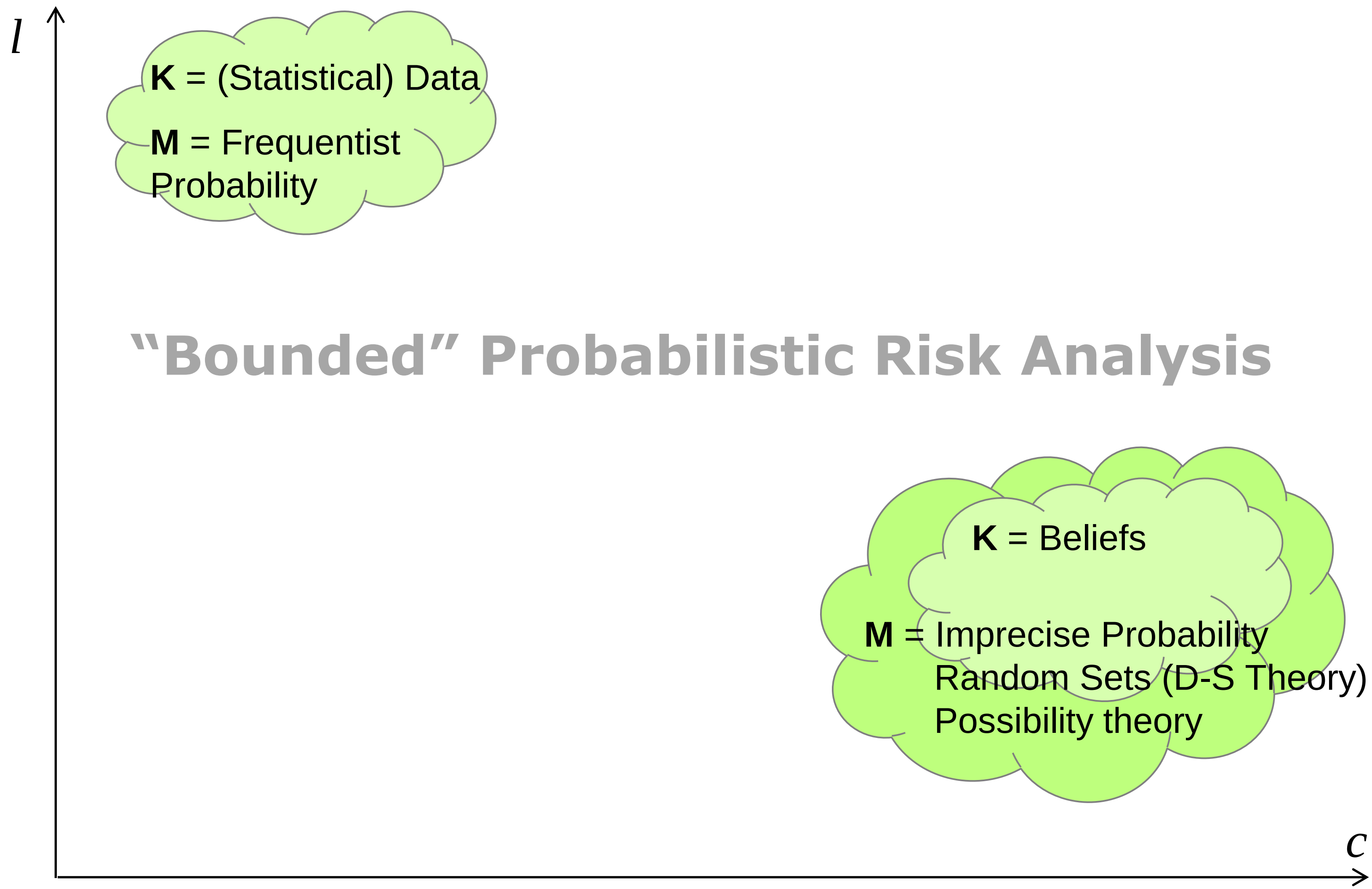
Adapted from S. Ferson, Workshop LA 2010

Probability Bounds: what they do

- Bridge qualitative information and quantitative data
- Distinguish aleatory and epistemic
- When data are abundant = probability theory
- When data are sparse = conservative and optimistic bounds

Adapted from S. Ferson, Workshop LA 2010

Epistemic Uncertainty



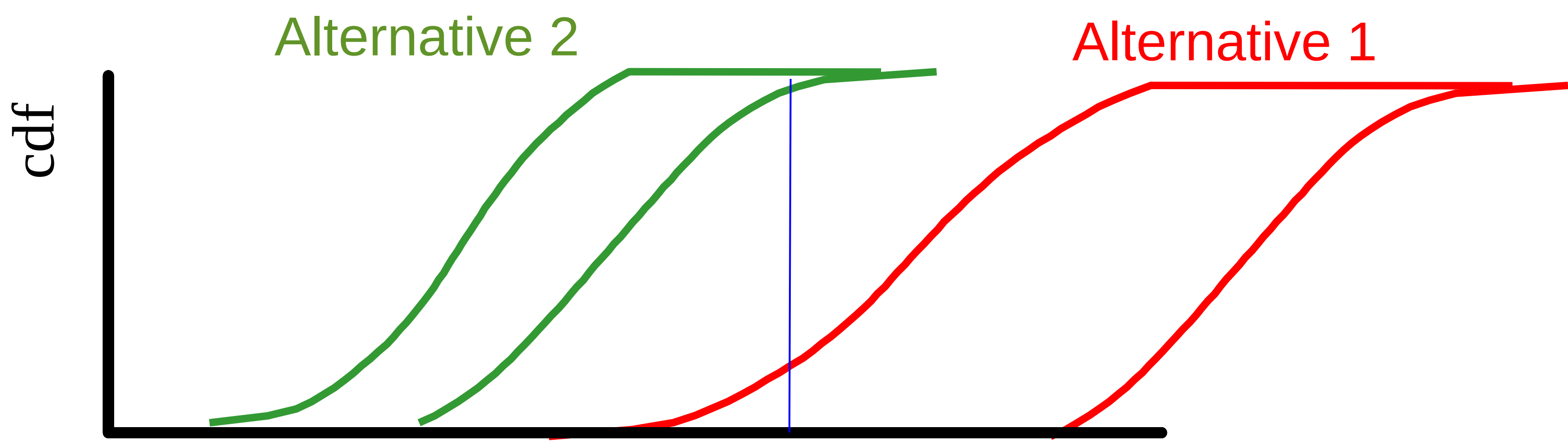
PART II:
The risk of uncertainty

Decision maker dreams…

Probability Bounds: how to use the results

- When uncertainty makes no difference

bounding gives confidence in the reliability of the decision



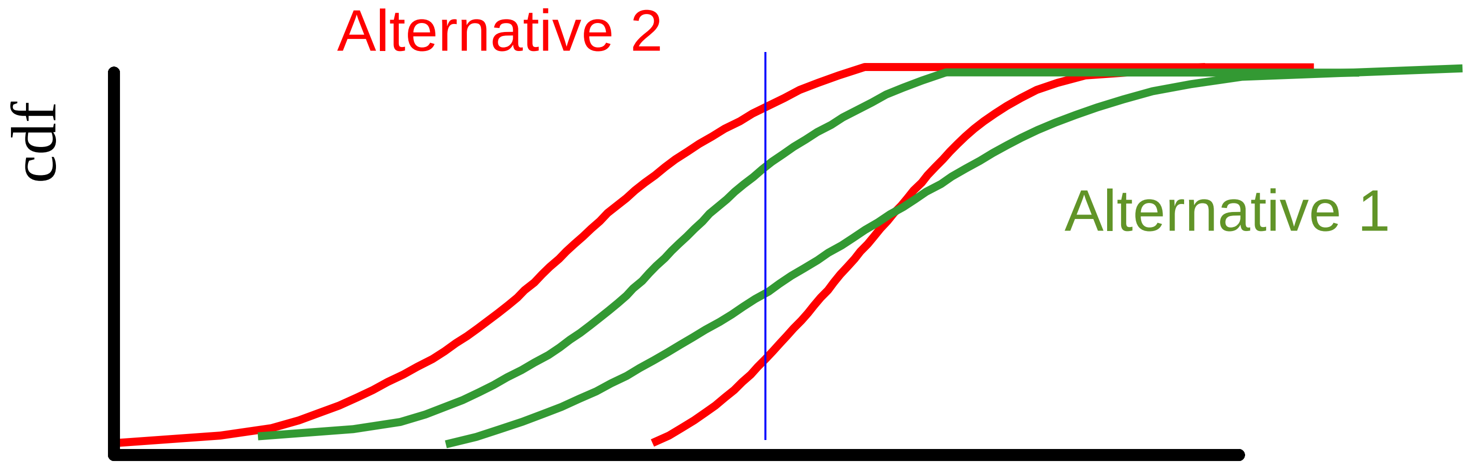
Adapted from S. Ferson, Workshop LA 2010

…and nightmares

Probability Bounds: how to use the results

- When uncertainty swamps the decision

identify issues to further investigate

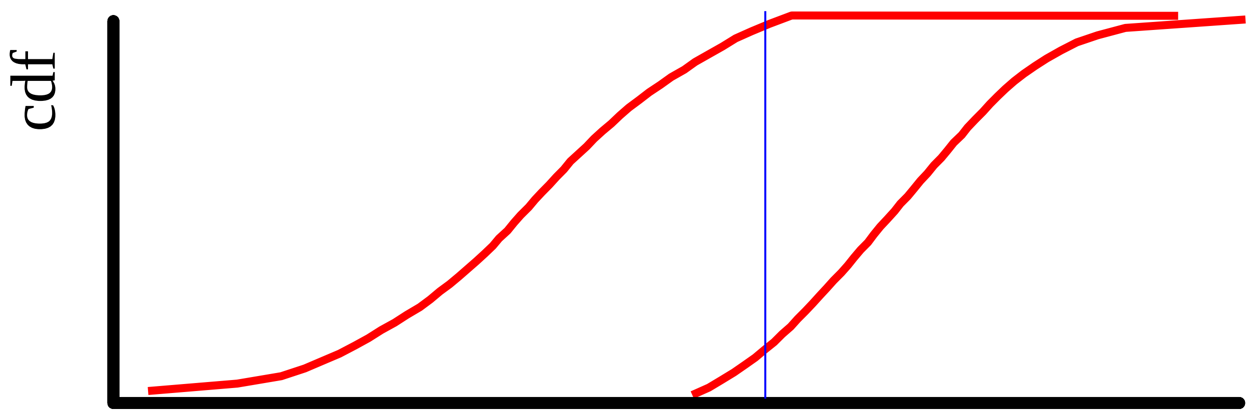


results should not mislead decisions

Adapted from S. Ferson, Workshop LA 2010

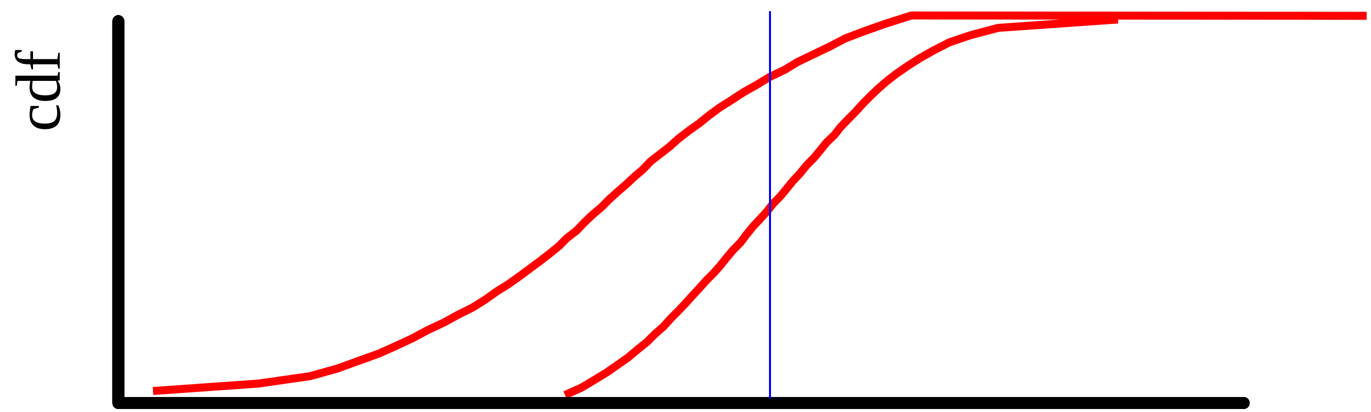
PART III:
"Things I Know"

Things I know: Information-based bounds



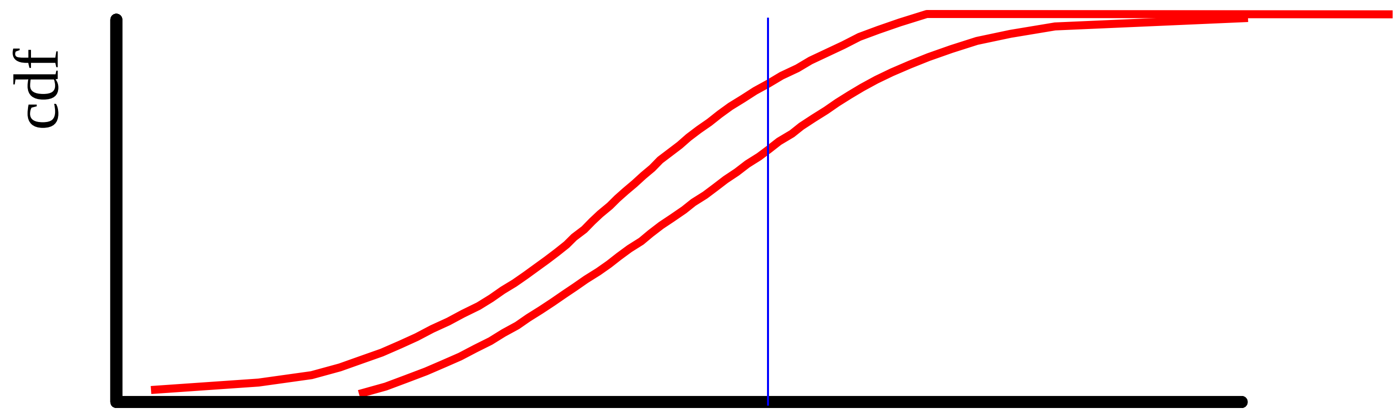
<u>Do not </u>add knowledge that is not included in the available information

Things I know: (expert) knowledge-based bounds



<u>Do</u> add expert knowledge
when reliable

Things I know: (expert) knowledge-based bounds



Do add expert knowledge
when reliable

PART IV:
Jingles

Concluding remarks

Intelligence can be measured by the amount of uncertainty which one can bear

I. Kant

Concluding remarks

Probability Bounds Framework

- Combines interval and probability methods: analyst can relax (towards interval analysis) or tighten (towards probability analysis) his/her assumptions, depending on what the information/knowledge justifies
- Allows distinguishing aleatory uncertainty (modeled by probabilty) from epistemic uncertainty (modeled by bounding interval analysis)

Adapted from S. Ferson, Workshop LA 2010

Concluding remarks

Theoretical issues

- Operational definitions of the quantities representing uncertainty (betting-like? standard comparison-like?), according to given behavioral rationality
- Dependence and independence (objective and epistemic) of information/knowledge
- Information and knowledge fusion
- Mathematical operations on the quantities representing uncertainty (e.g. Dempster rule of combination)

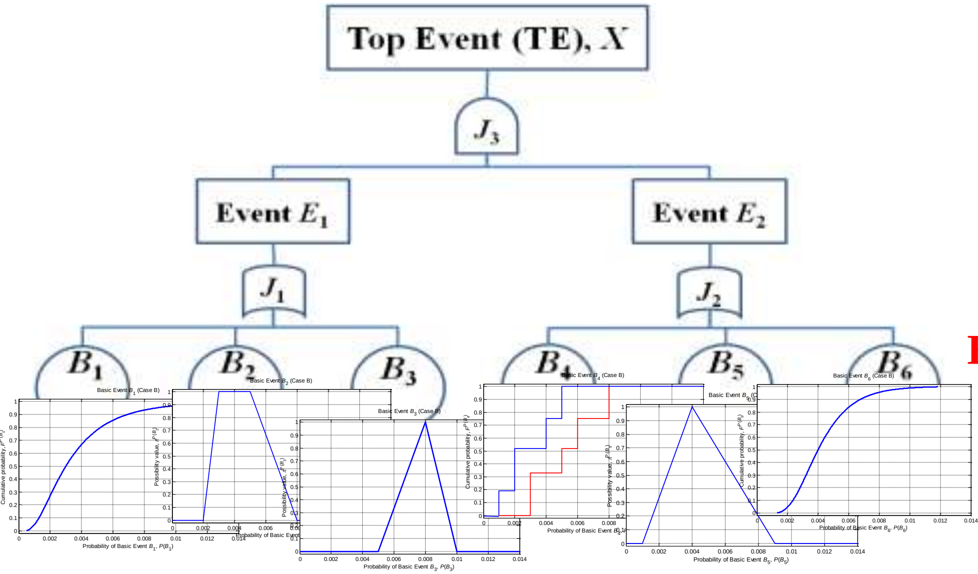
Adapted from D. Dubois, Workshop LA 2010

Concluding remarks

Practical issues

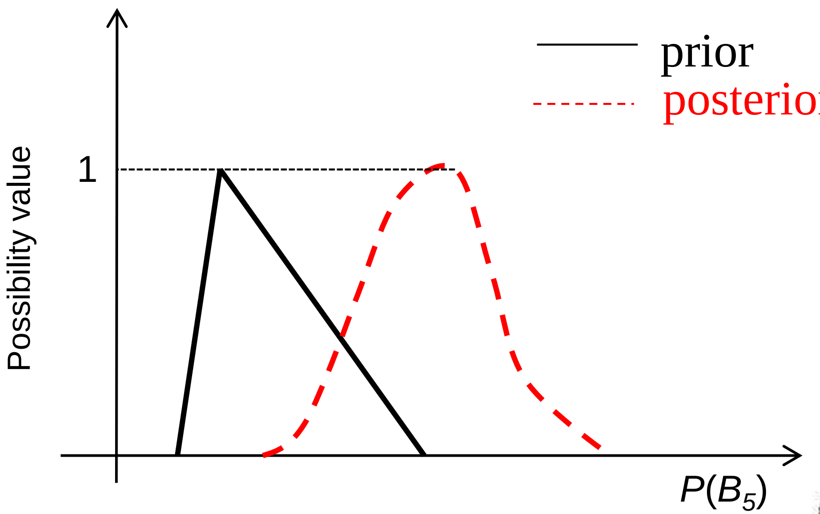
- Constructing bounding (imprecise) probabilities, from data (statistics with interval data), from experts (elicitation of upper/lower bounds for faithful representaton of incomplete information/knowledge)
- Uncertainty propagation (computational challenges of blending Monte Carlo simulation with interval mathematics)
- Representation of results with meaningful (for the DM) summary measures
- Updating with additional evidence
- Accounting for dependences in information sources, when fusing them

Updating…

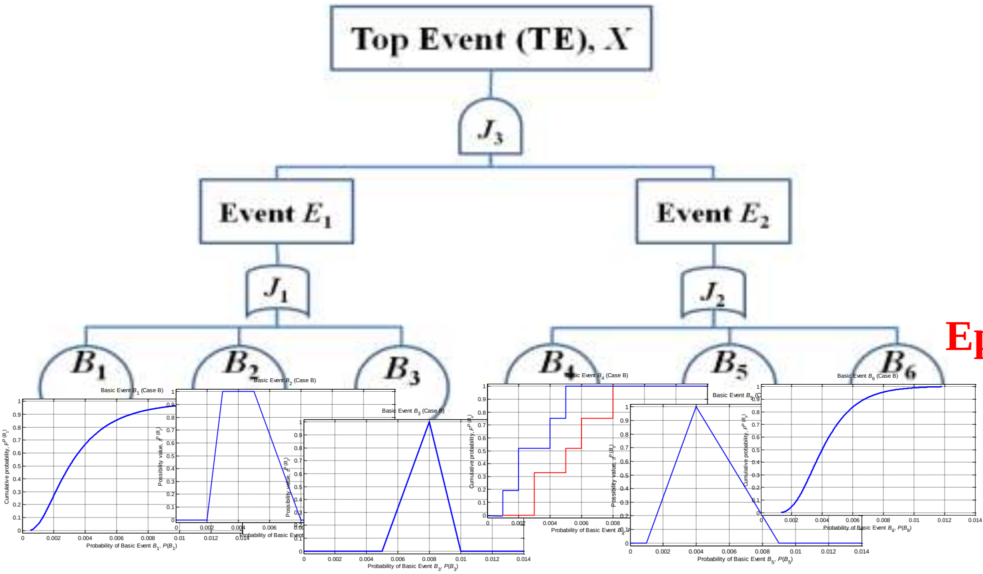


Epistemically-uncertain Basic Event (BE) probabilities

3 additional tests:
2 failures, 1 success

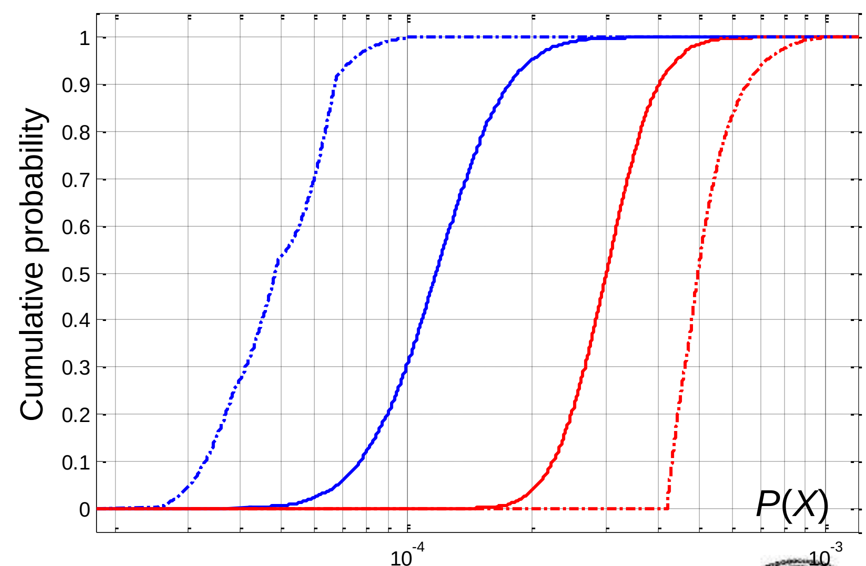


Dependences…

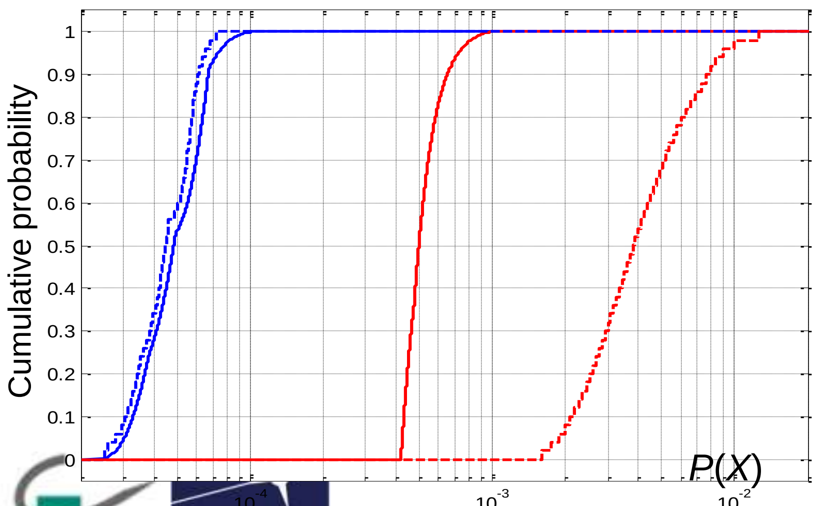


Epistemically-uncertain Basic Event (BE) probabilities

"*Epistemic*" dependence between BE *probabilities*



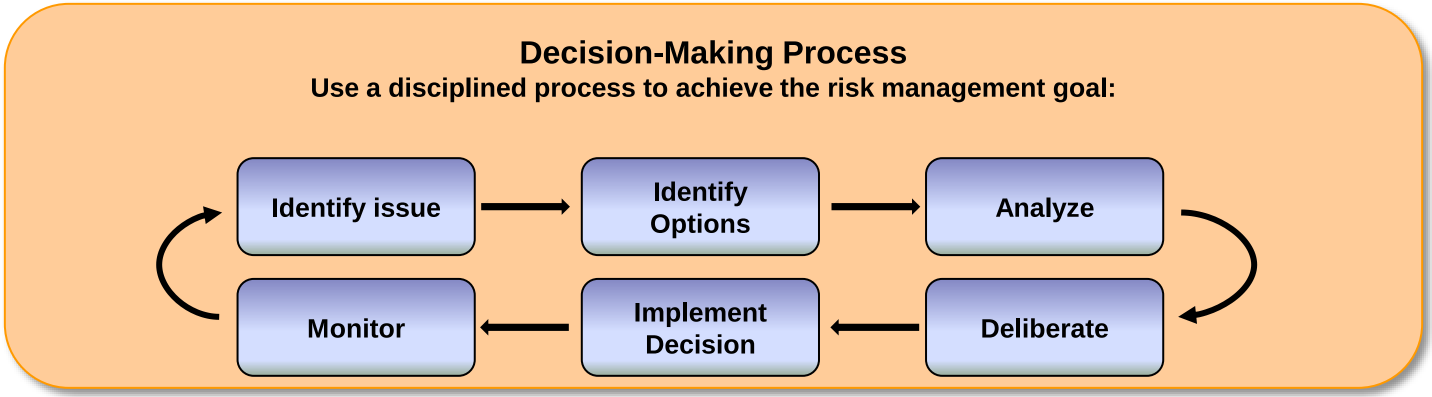
"*Objective*" dependence between *BEs*



Concluding remarks

The Decision Making process

- QRA results are one input to a subjective decision-making process
- Analytical results are debated and stakeholder values are included, within a deliberative process of decision-making



Adapted from G. Apostolakis, Workshop LA 2010 and ANS DC 2012

Concluding remarks

The one million euros question

€ € € € € €

"OK, these approaches are interesting, but does all of this actually make any practical difference in real-world decisions?"

€ € € € € €

(€ Are probability bounds/imprecise probabilities a more proper starting point than pure probability theory for robust and confident decision making, faithful to information and knowledge?€)

(€ How to do it in practice? information before knowledge for faithfulness to information and unbiased exploitation of knowledge– bounds "as large as justified by information" + expert knowledge (without forcing) to see the effects in a "sensitivity analysis- like process?€)

CENTRALE PARIS Supélec

POLITECNICO MILANO

...and nightmares

th[illegible]way on 22 July 2011, when a man placed a car-bomb outside the government office and massacred a number of people on the island of Utøya outside Oslo.

PERFECT STORMS

the eruption of the Icelandic volcano, which paralyzed the air traffic over the Atlantic and western Europe for a while in 2010

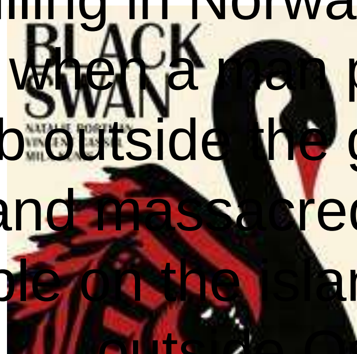
the failure of the BP Deepwater Horizon platform

the Fukushima Daiichi nuclear disaster in Japan in March 2011

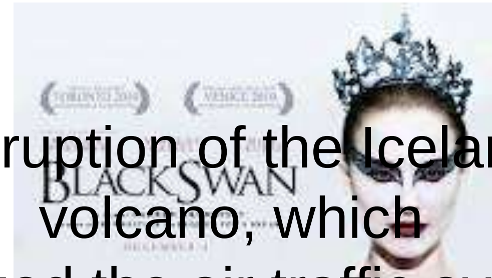
9/11 attacks on the US

the financial crisis that started in 2008

...and nightmares



the killing in Norway on 22 July 2011, when a man placed a car-bomb outside the government office and massacred a number of people on the island of Utøya outside Oslo.



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BLACK SWANS

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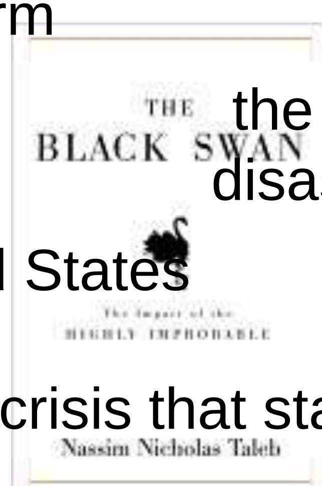


9/11 attacks on the United States

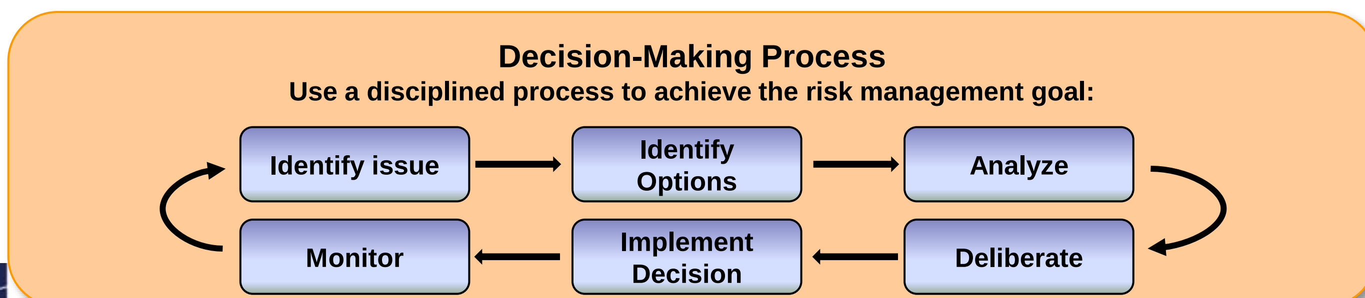
the financial crisis that started in 2008

Concluding remarks

The Decision Making process

- QRA results are one input to a subjective decision-making process
- Analytical results are debated and stakeholder values are included, within a deliberative process of decision-making

Coherently with safety concepts such as defense-in-depth, multiple barriers and design basis accidents, conservatism in the decisions is added where appropriate (to protect from the known and unknown unknowns)



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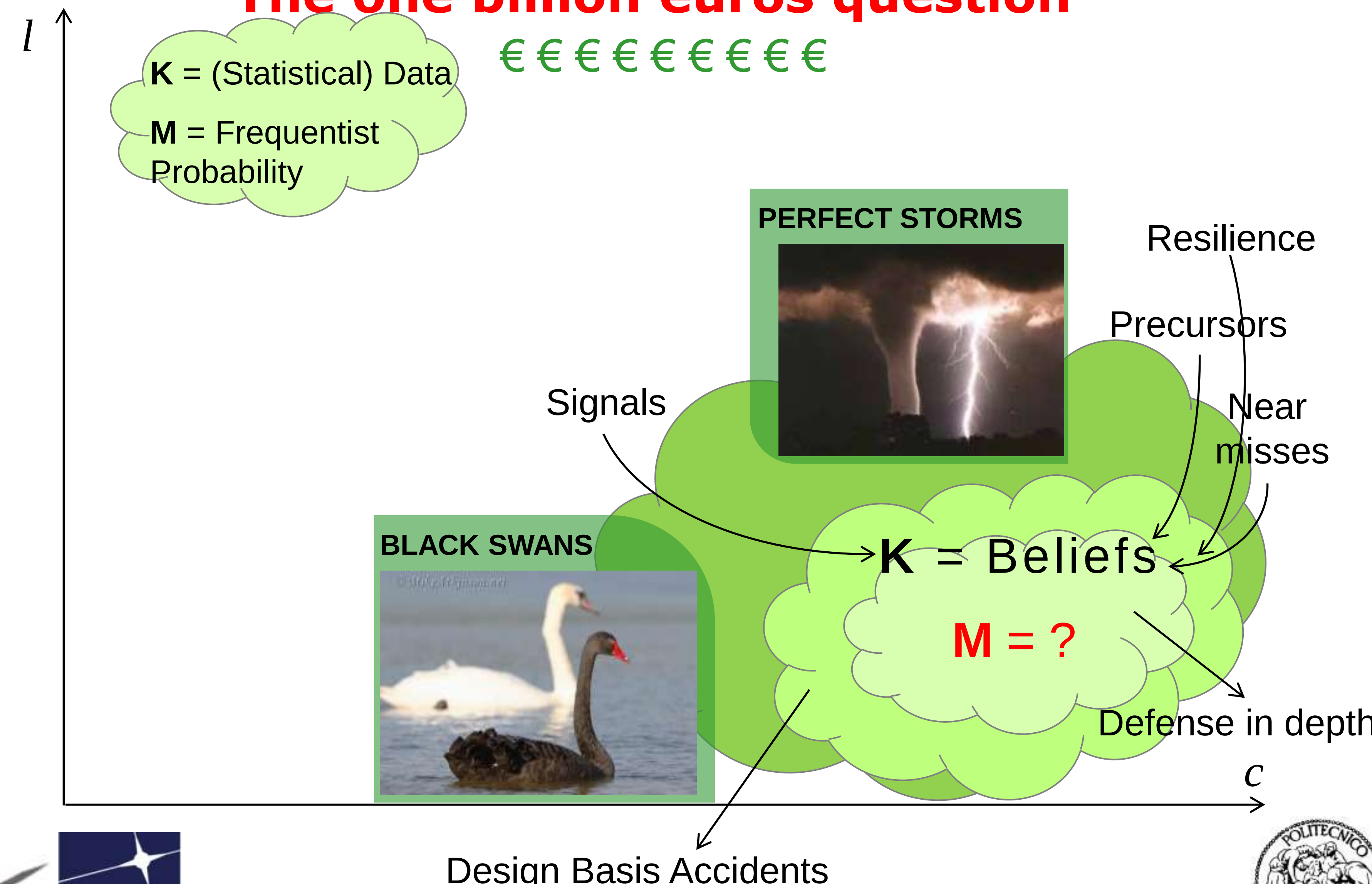
Concluding remarks

The one billion euros question



Aven, Pate'-Cornell 2012

~~Advertisement~~ Dedication

Special Conference Theme:

Treatment of Epistemic Uncertainty in RISK-Informed Decision-Making

A long-standing and often-expressed criticism of the Bayesian approach to uncertainty is its use of a (precise) probability distribution to represent epistemic uncertainty. Various alternatives have been proposed and explored over the years, some of which are extensions of the traditional Bayesian approach, such as robust Bayes. Others differ in that they do not rely on a precisely specified probability distribution to represent epistemic uncertainty. Some approaches in this latter category are imprecise probabilities, possibility theory, Dempster-Shafer theory, fuzzy sets, p-boxes, and interval-valued probabilities. A special issue of *Reliability Engineering and System Safety* was devoted to alternative approaches to uncertainty representation in 2004, and a workshop was held in Santa Monica on this topic in 2010.

Different views about these various approaches exist among researchers and practitioners; on the other hand, increasing specialization threatens to isolate the mainstream reliability and risk analysis community from important developments in the treatment of epistemic uncertainty, which may have an impact on the outcomes of the analyses.

To help build a common ground and development path, we are organizing a special theme for the upcoming PSAM 11/ESREL 12 conference (https://www.psam11.org/www/fi/ or www.esrahomepage.org). The theme is divided into the categories of Theory and Applications, as an indication that submissions of both theoretical and applied nature are sought. We especially welcome theoretical developments and related applications that illustrate the *practical* impact of the treatment of epistemic uncertainty on decision-making, in an effort to address the "one million Euro" question: "OK, these approaches are interesting, but does all of this actually make any practical difference in real-world decisions?"

We are looking forward to receiving your contribution.

Please direct any questions you might have to **Dana Kelly at Dana.Kelly@inl.gov**

Dana Kelly: 1959-2011

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Supélec

Thanks: the Unknown-ledgments

Final remarks

There are known knowns

One should expect that the expected can be prevented, but the unexpected should have been expected

But there are also unknown unknowns – the ones we don't know we don't know.

PERFECT STORMS

Precursors

Near misses

Signals

BLACK SWANS

We also know there are known unknowns; that is to say we know there are some things we do not know.

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Knowing ignorance is strength, ignoring knowledge is sickness

Final remarks

There are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns – the ones we don't know we don't know.

One should expect that the expected can be prevented, but the unexpected should have been expected.

Knowing ignorance is strength, ignoring knowledge is sickness.

There is no zero risk, there is no zero uncertainty.

PRA is a mature methodology, but there is still work to be done in order to render our systems safer, with confidence.

Let us keep discussing, also on fundamental issues.