Intelligent Systems for Decision Support

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Outline

- Decision support for intelligence analysis
  - Background and problems
  - Flexible compositional modelling
  - Plausible scenario based intelligence monitoring
- Component approaches
  - Fuzzy learning and feature selection
  - Fuzzy interpolative reasoning
  - Fuzzy risk assessment
- Conclusion and future challenges

Intelligence Analysis: Background

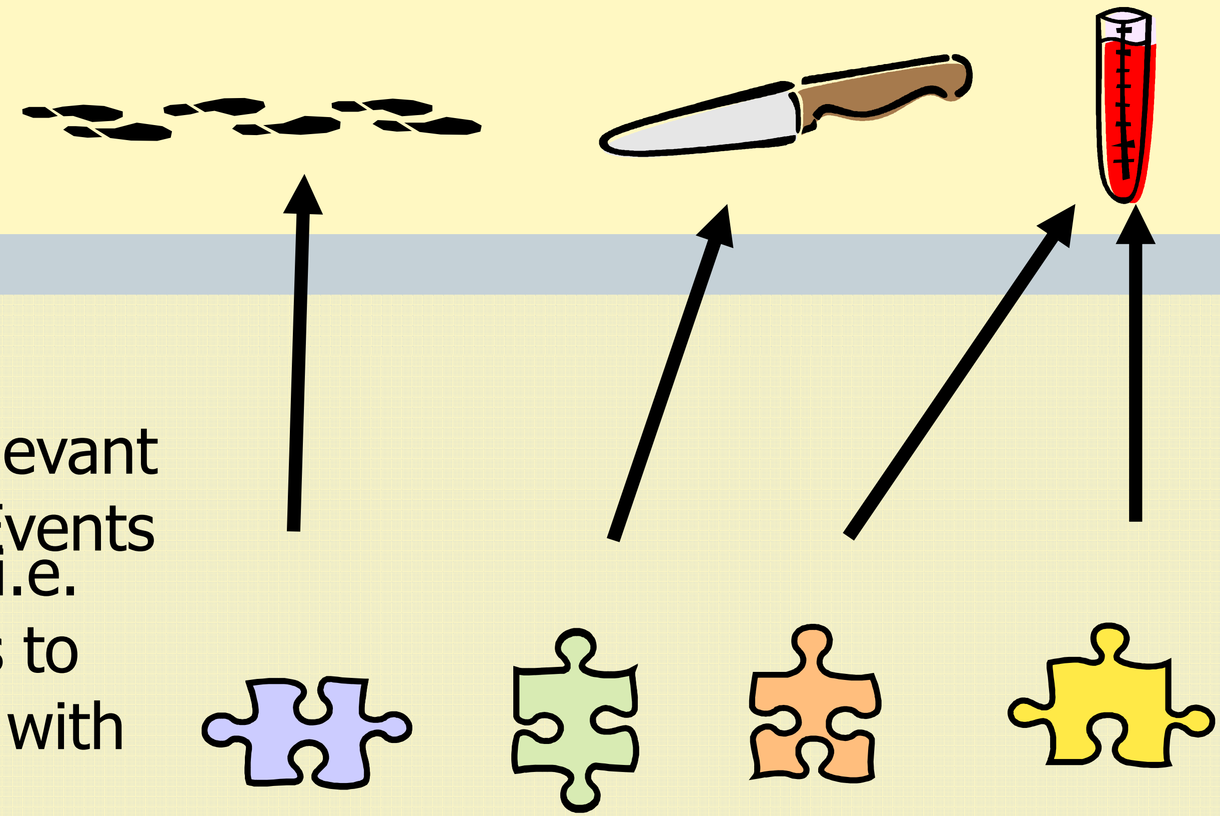
- Intelligence analysis aims to recognize a threat from collected intelligence and evidence
- A successful analysis can help minimizing damages
- It may even prevent revolting consequences
  - 9-11 terrorist attack
  - 7-7 London bombing

Intelligence Analysis: Problems

- Intelligence experts have agreed that
  - Failure in detecting a threat is not due to lack of intelligence data
  - But, due to difficulties in relating and interpreting the available data
    - Overwhelming amount of intelligence for human examination
    - Time pressure and subjective interpretation
- Computational intelligence techniques can help

Intelligence Analysis: Compositional Modelling

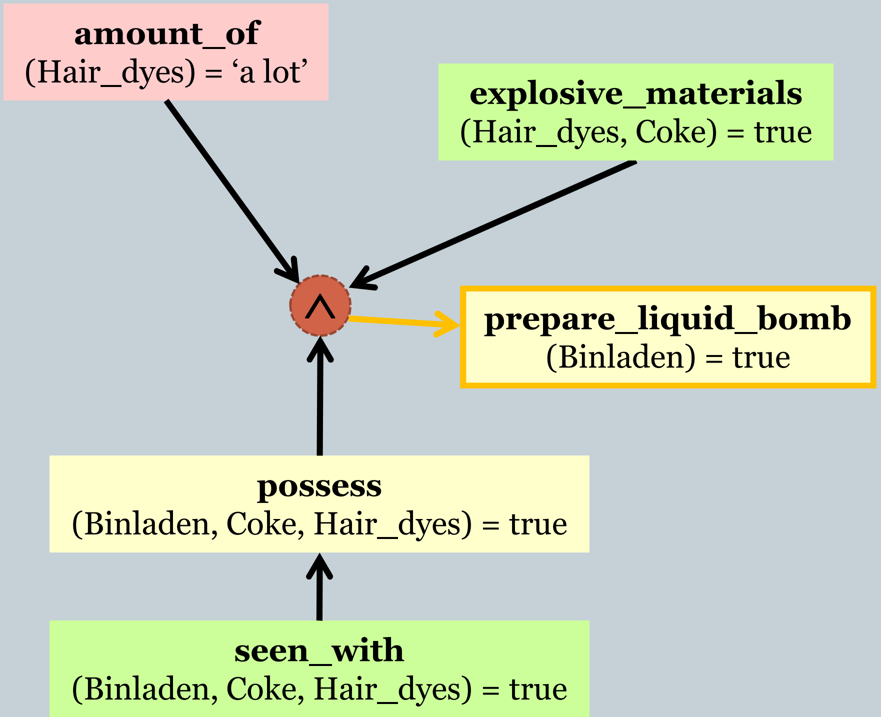
Intelligence



Plausible Relevant States and Events

Alternative ***scenarios***, i.e. explanations to intelligence, with different possibilities

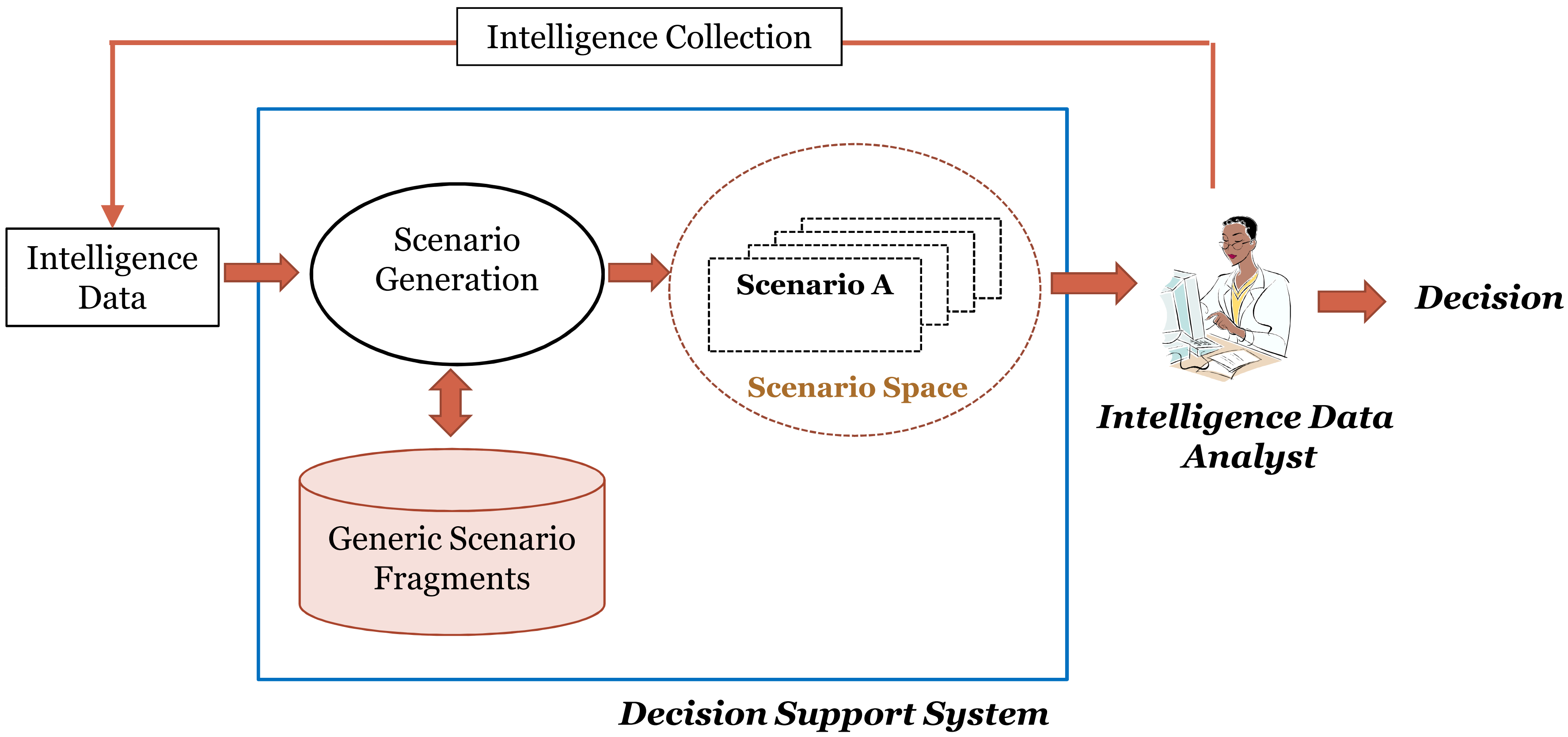
Intelligence Analysis: Plausible Scenarios



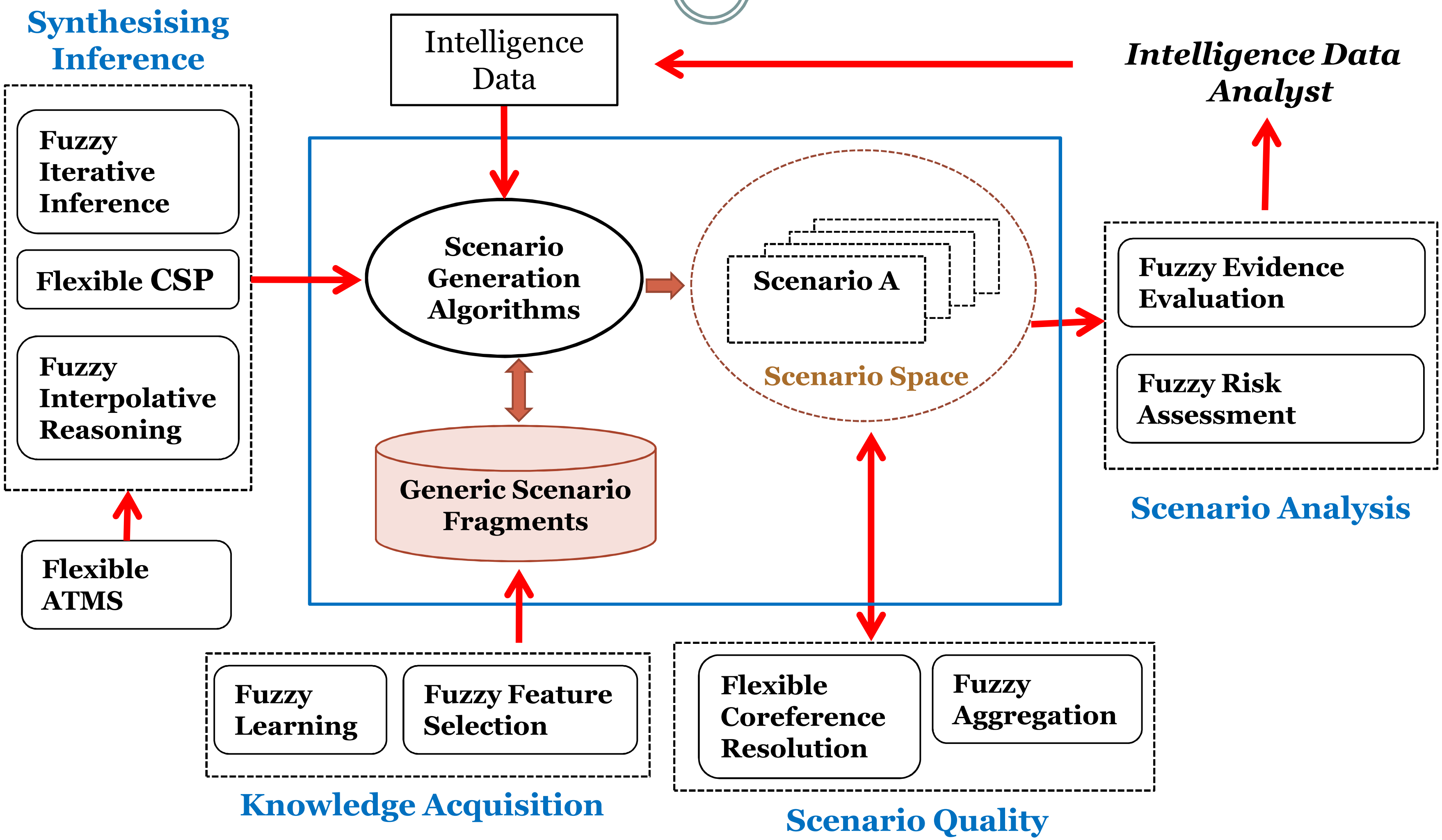
Notation: Evidence | Assumption | Consequence

- Situation awareness
  - How available intelligence is related and represents a threat
- Plausible scenario modelling
  - Hypothetical (re-)construction of possible scenarios, given evidence and *generic* knowledge components
- Decision support for
  - Risk assessment
  - Evidence evaluation
  - Information fusion
  - Conflict resolution

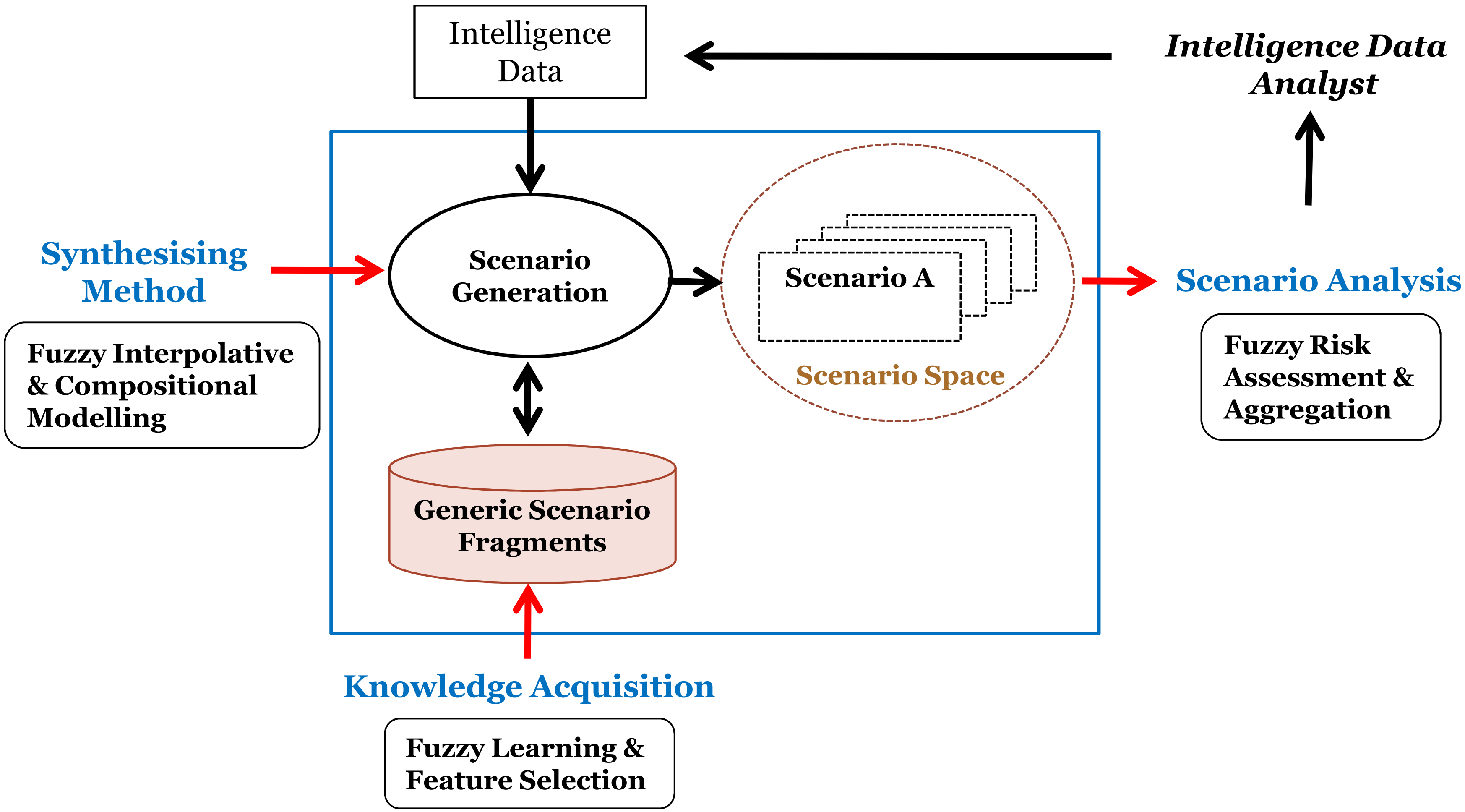
Plausible Scenario-Based DSS



Current Approaches



Focused Approaches

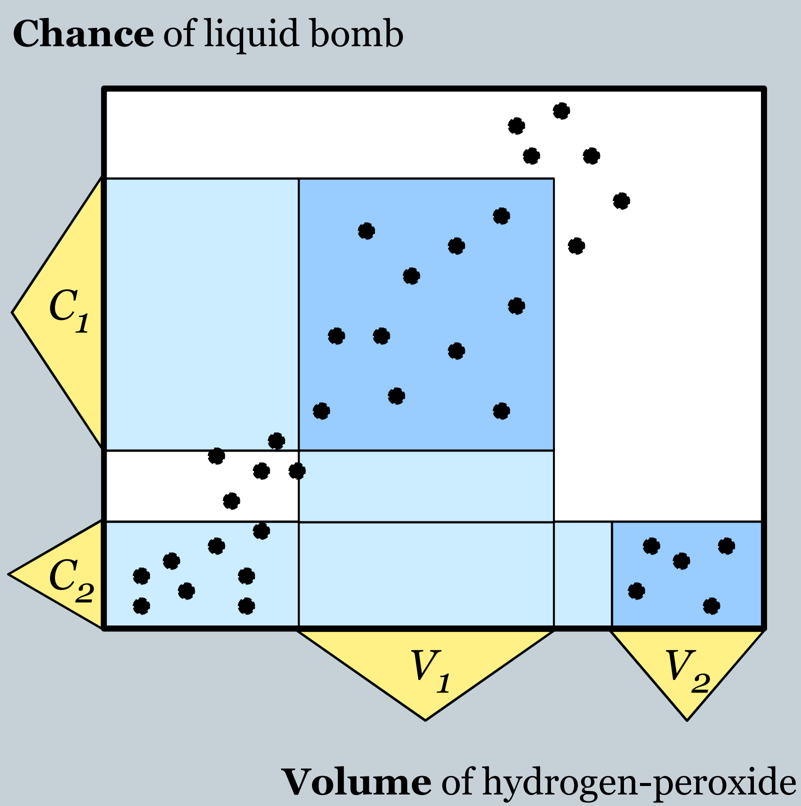


Fuzzy Learning: Model Fragments

- Fuzzy modelling
  - Turning data into machine-usable and human-comprehensible knowledge
  - Use of fuzzy sets to handle imprecise and ill-defined information
- Precise approach
  - Each fragment may have its own term set created from data
  - Accurate and efficient, but opaque

    If volume is Tri(32.41, 38.12, 49.18)

    Then chance is Tri(0.22, 0.45, 0.78)



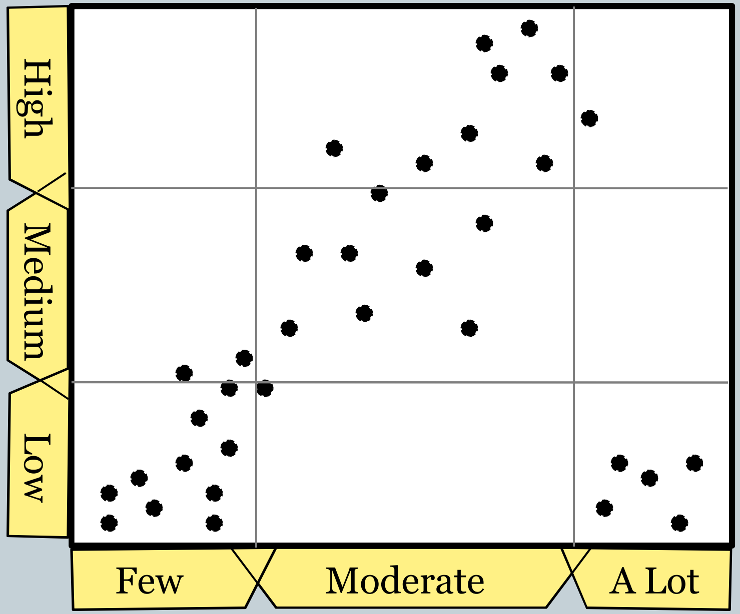
Fuzzy Learning: Model Fragments

- Linguistic approach
  - All fragments use predefined, linguistically labelled term set
  - Transparent, but less accurate and slow learning

If volume is Few
Then chance is Low

If volume is Moderate
Then chance is High

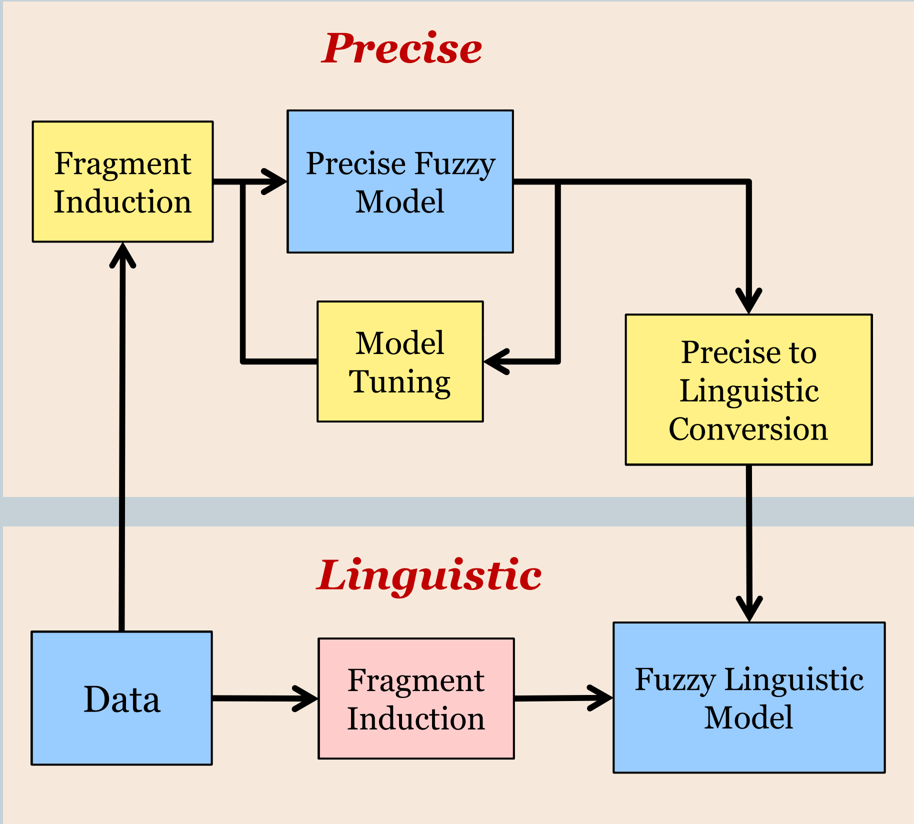
Chance of liquid bomb



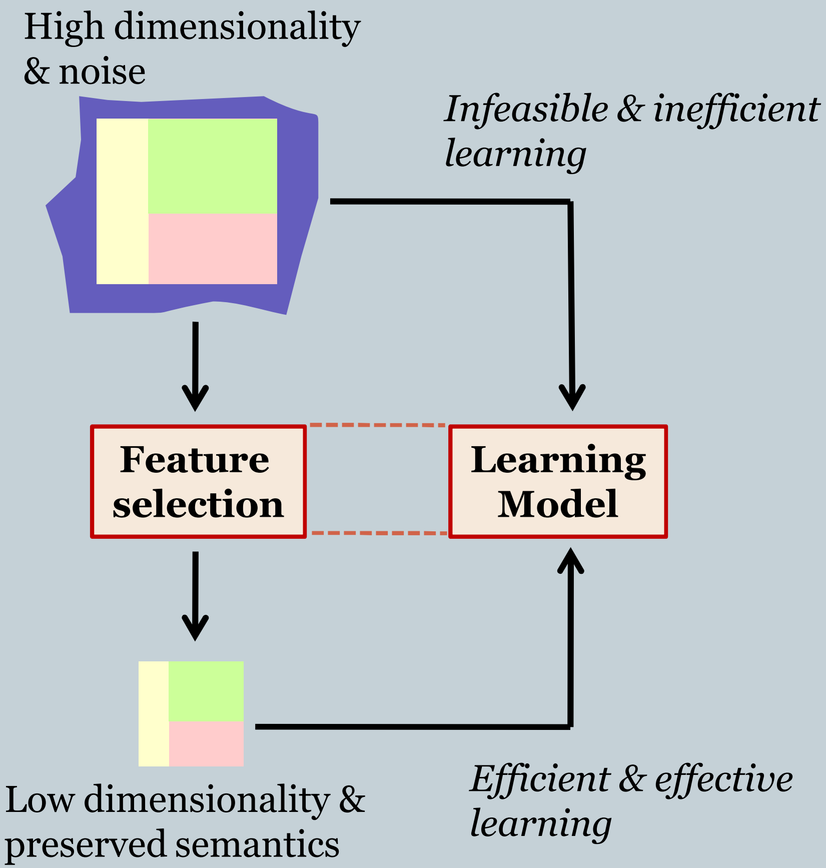
Volume of hydrogen-peroxide

Fuzzy Learning: Indirect Modelling

- Generate precise models by any standard precise method
- Translate precise to linguistic models using multi-objective optimisation (e.g. GAs, ACO)
- Overcome fixed grid 'grain' problem using linguistic hedges (aka. fuzzy quantifiers)
- Applicable to both models and model fragments



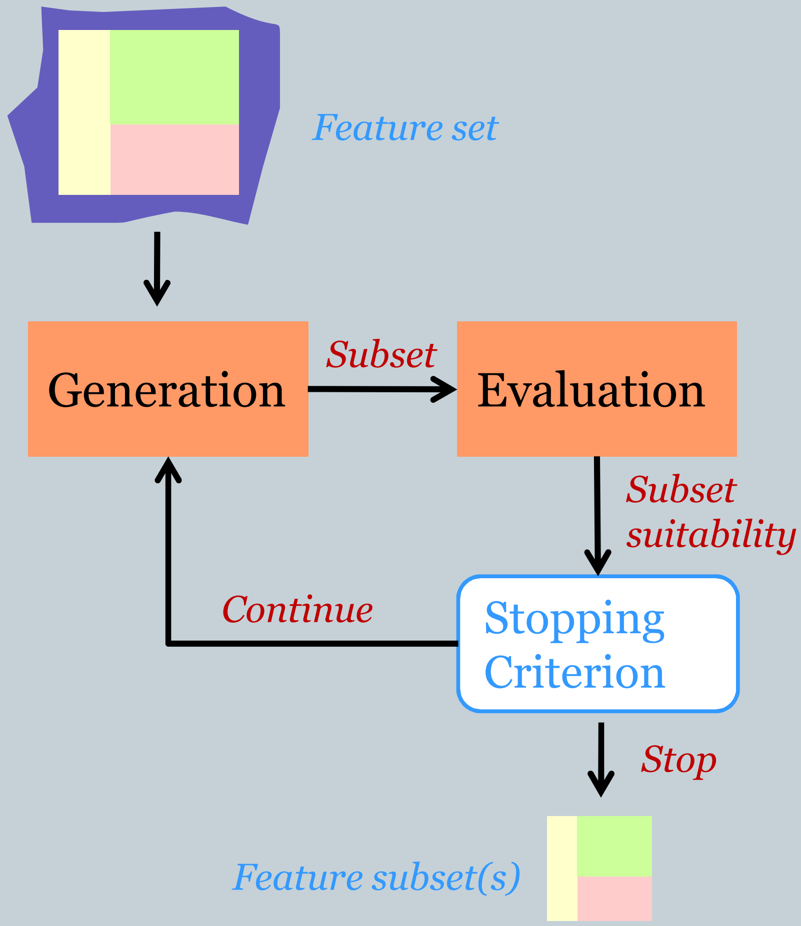
Feature Selection



- Semantics-preserving dimensionality reduction
  - To make acquisition process more ‘efficient’ with reduced complexity
  - To improve the ‘quality’ of knowledge, by removing noise and irrelevant data
- Variety of application domains

Feature Selection: Framework

- Subset generation
  - Searches forwards, backwards, stochastically …
- Evaluation function
  - Determines ‘goodness’ of subsets
- Stopping criterion
  - Decides when to stop subset search



Fuzzy-Rough Feature Selection

- Extend rough-set approach via fuzzy sets
- Fuzzy lower approximation:

$$\mu_{\underline{R_P}X}(x) = \inf_{y \in U} I(\mu_{R_P}(x,y),\ \mu_X(y))$$

- Fuzzy positive region:

$$\mu_{POS_P(Q)}(x) = \sup_{X \in U/Q} \mu_{\underline{P}X}(x)$$

- Evaluation function:

$$\gamma_P(Q) = \frac{|\mu_{POS_P(Q)}(x)|}{|U|} = \frac{\sum_{x \in U} \mu_{POS_P(Q)}(x)}{|U|}$$

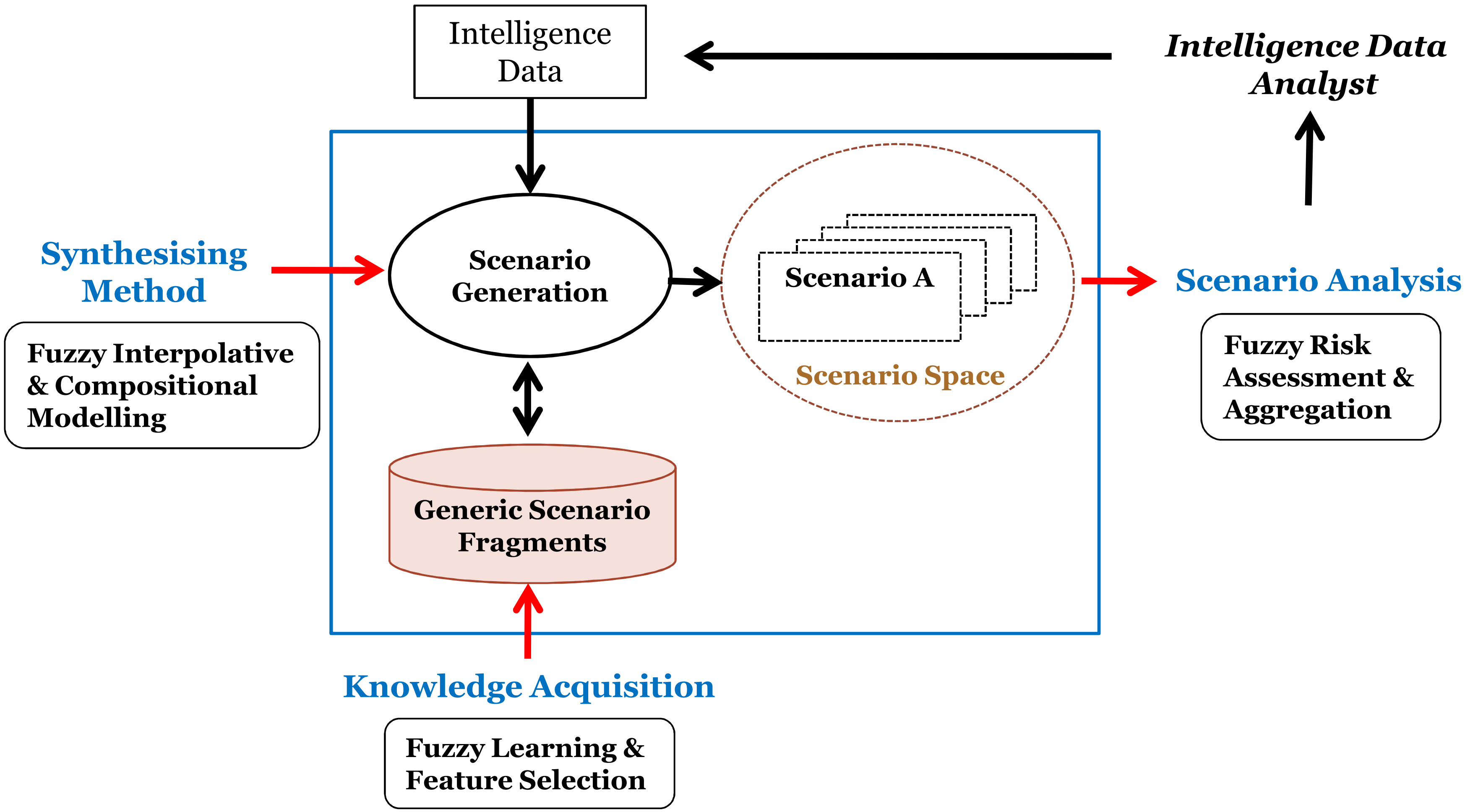
Fuzzy-Rough Feature Selection: Algorithm

- Subset generation
  - Greedy hill-climbing
- 'Goodness' evaluation
  - Fuzzy-rough dependency metric
- Stopping criterion
  - When no improvement in subset quality

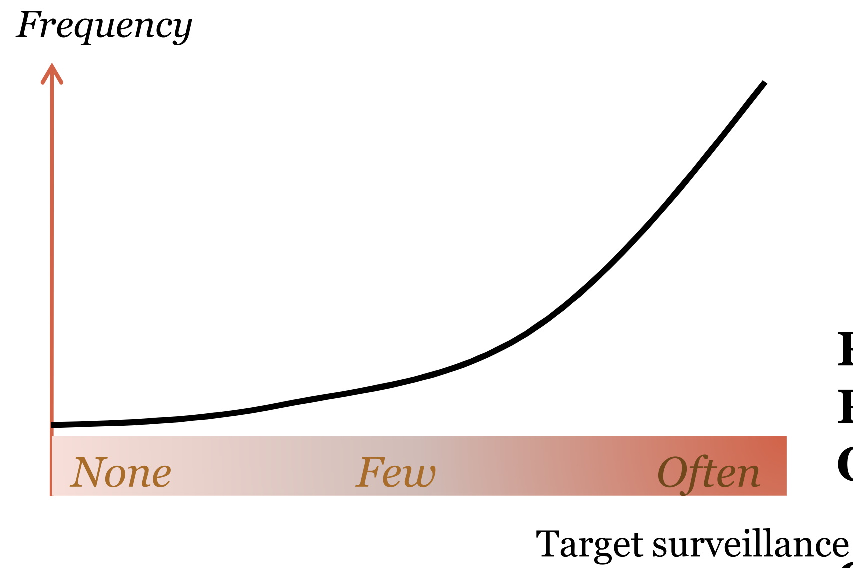
FRQuickReduct(C,D)
C, the set of all conditional features;
D, the set of decision features.

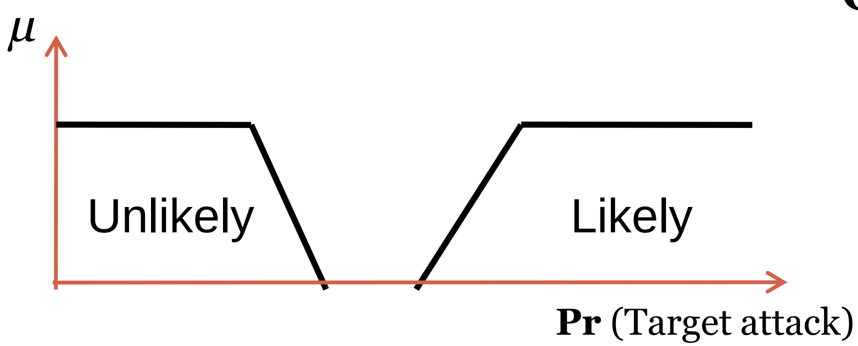
(1) $R \leftarrow \{\}$
(2) **do**
(3) $T \leftarrow R$
(4) $\gamma_{prev} = \gamma_{best}$
(5) $\forall x \in (C - R)$
(6) **if** $\gamma_{R \cup \{x\}}(D) > \gamma_T(D)$
(7) $T \leftarrow R \cup \{x\}$
(8) $\gamma_{best} = \gamma_T(D)$
(9) $R \leftarrow T$
(10) **until** $\gamma_{best} == \gamma_{prev}$
(11) **return** R

Focused Approaches



Interpolative Reasoning





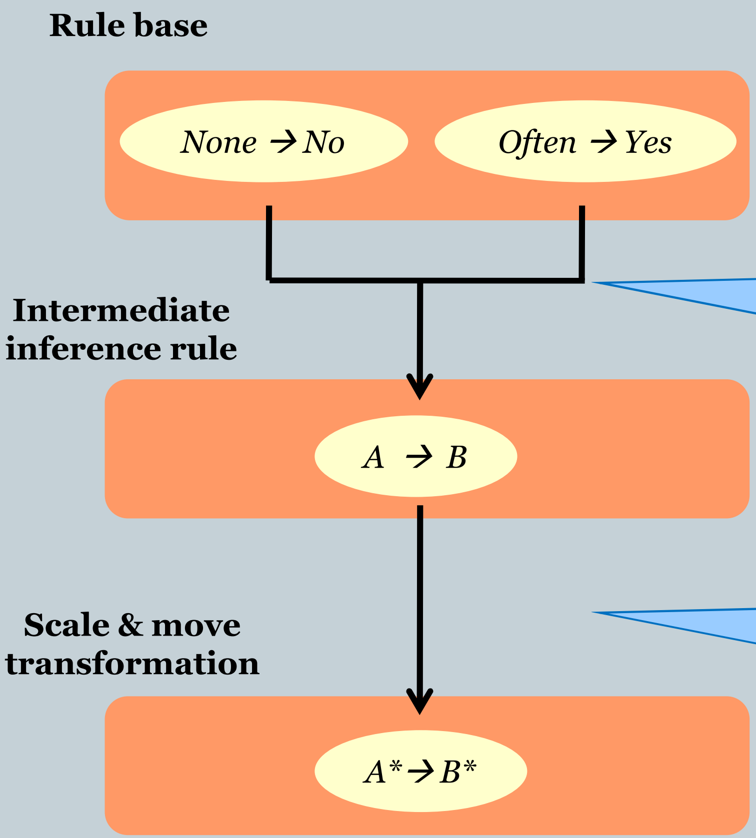
- To achieve approximate inference with a 'sparse' or 'incomplete' knowledge base

Rule$_i$: frequency is *None* → attack is *Unlikely*
Rule$_j$: frequency is *Often* → attack is *Likely*
Observation: frequency is *Few*

Question: Will there be an attack?

- Also useful to simplify knowledge bases by approximating fragments with their neighbours

Fuzzy Interpolation:
Similarity-Based Approach

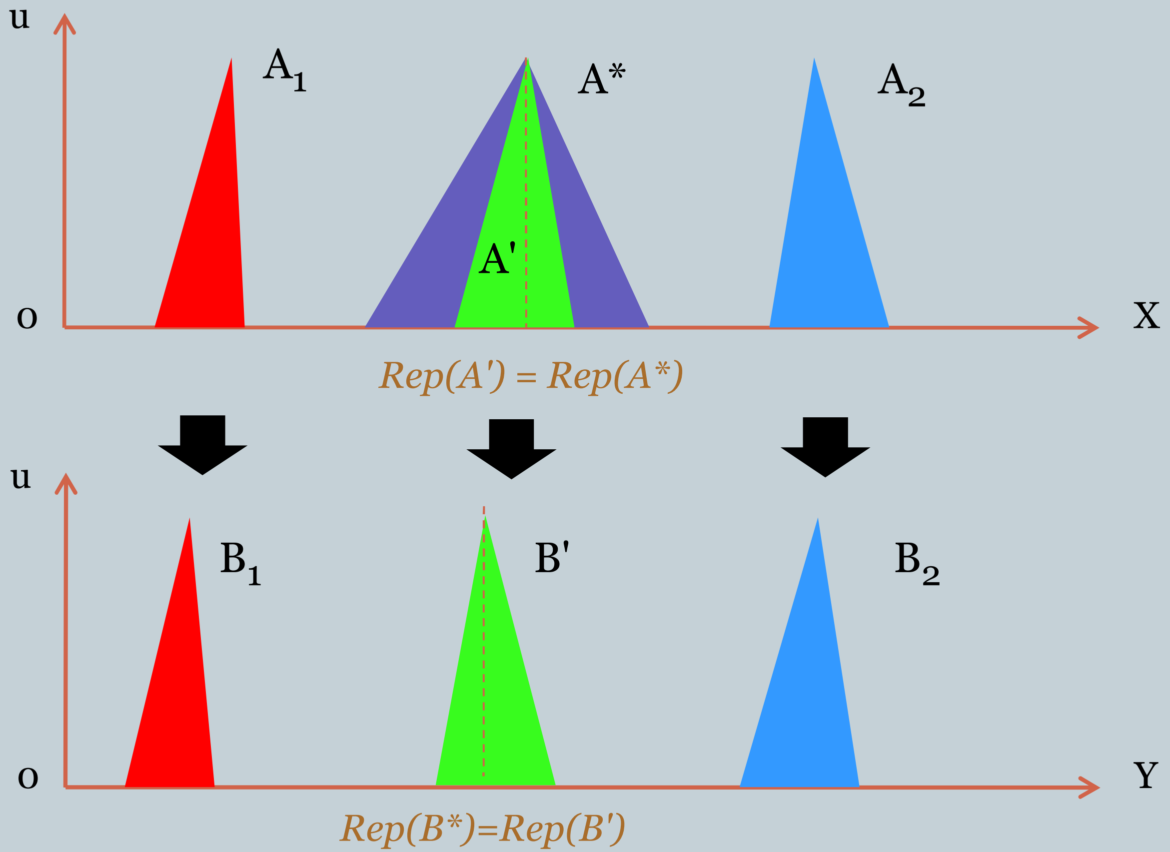


Creation of intermediate inference rule via linear interpolation, guided by observation A*

Derivation of conclusion via scale and move transformations, ensuring similarity

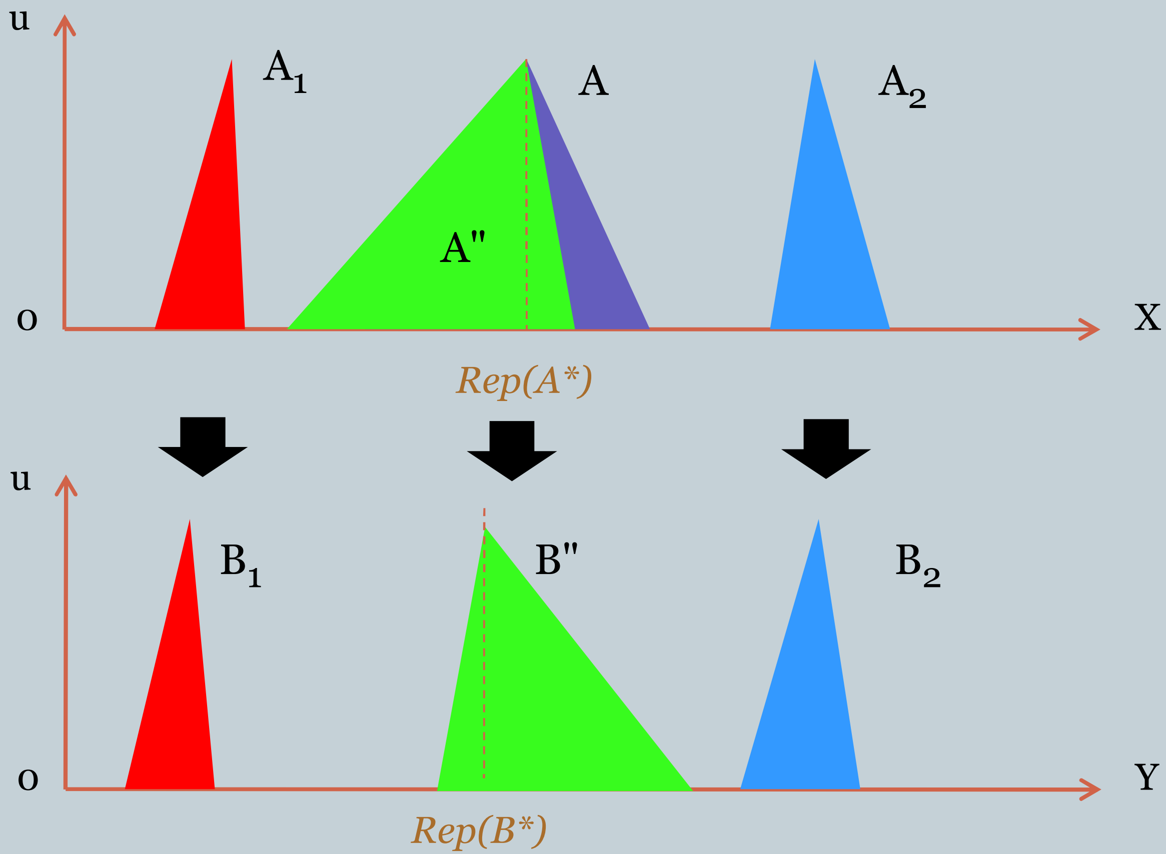
Fuzzy Interpolation: Intermediate Rule

- Guided by representative value of observation *A**; *Rep(A') = Rep(A*)*



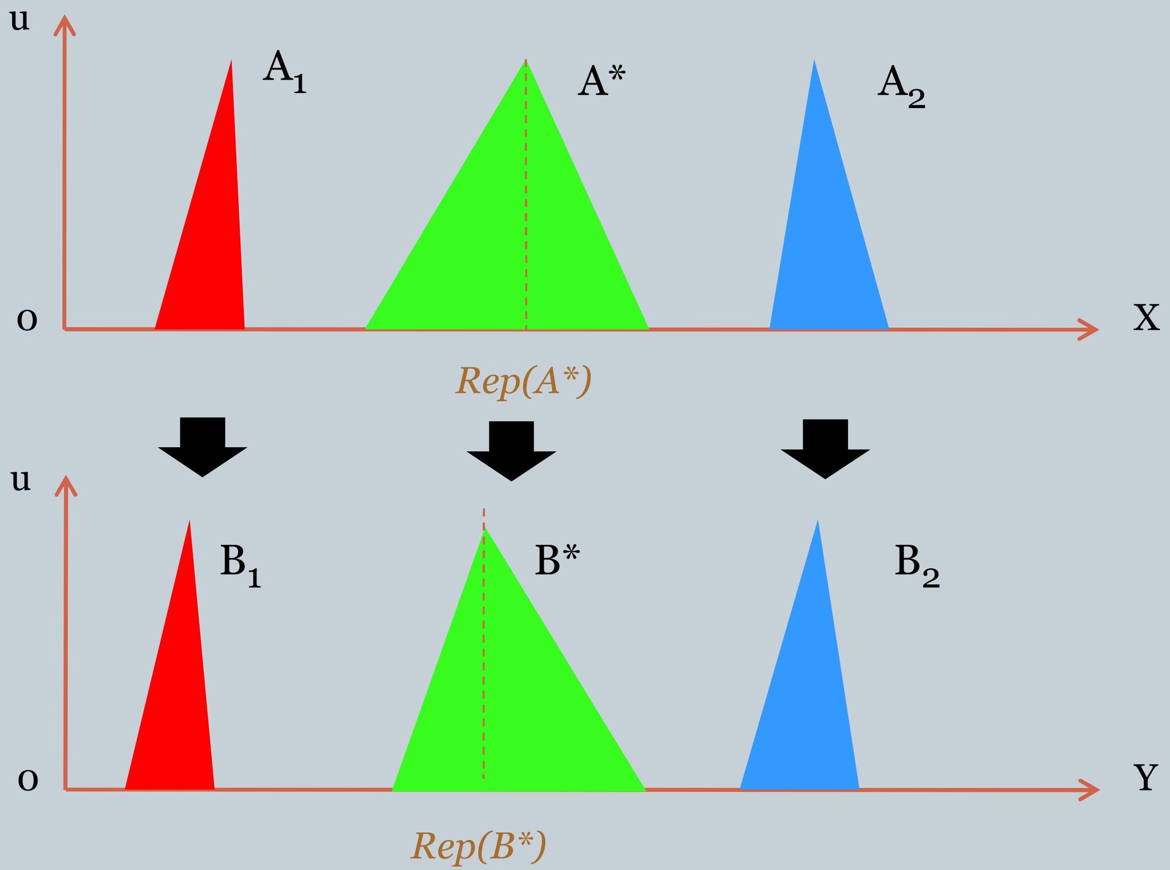
Fuzzy Interpolation: Scale Transformation

- Inferring by scale transformation

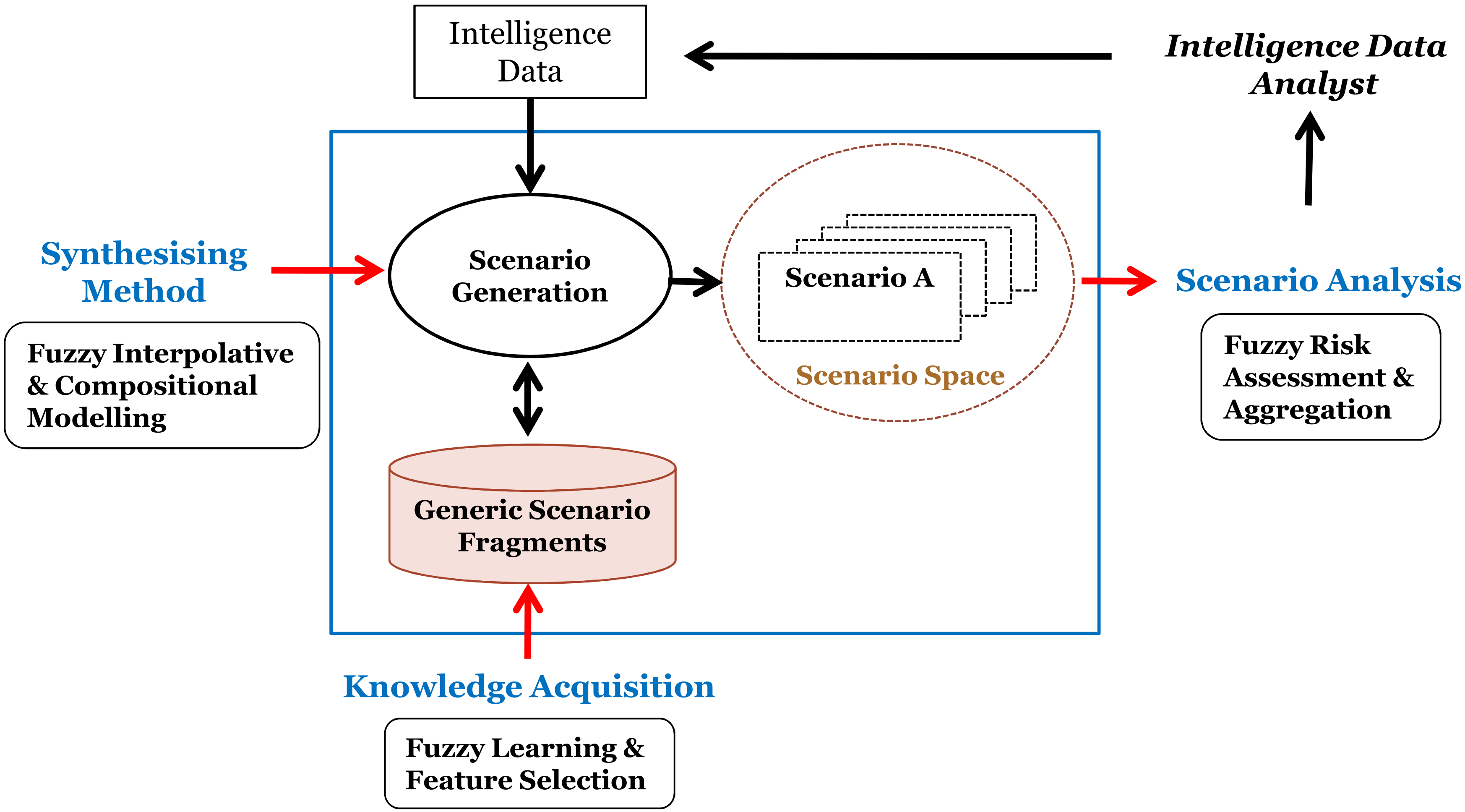


Fuzzy Interpolation: Move Transformation

- Inferring by move transformation



Focused Approaches



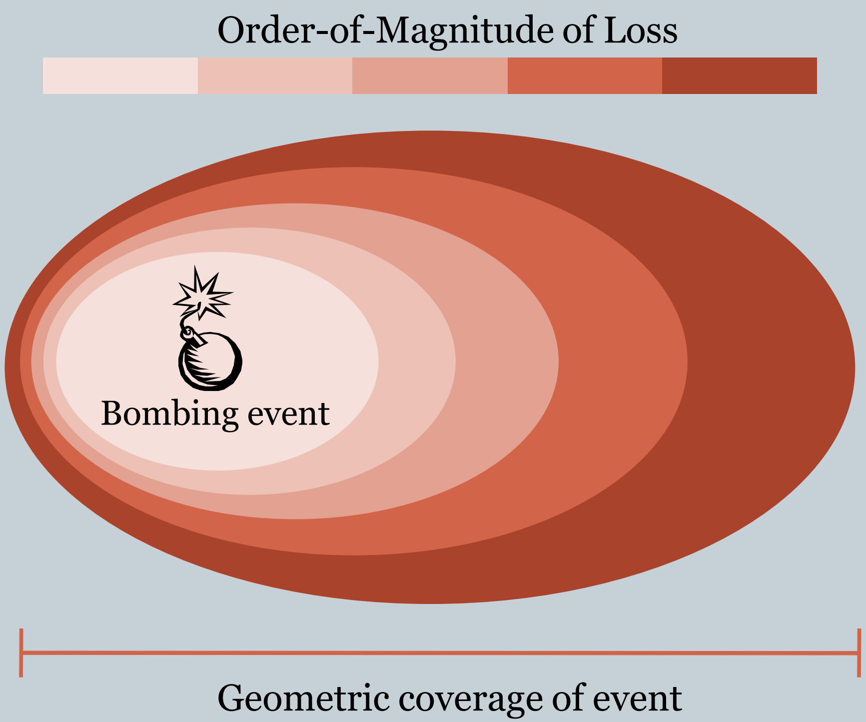
Risk Assessment

- Risk assessment is employed to 'differentiate' and 'prioritize' identified scenarios
- Counter measures, including further evidence gathering, can be efficiently deployed
- Estimating the risk of a plausible event requires dealing with 'randomness and fuzziness'

Risk Assessment: Loss

- Plausible occurrence of an event is considered ‘random’
- Losses by such an event are judged linguistically and expressed as values of ‘fuzzy random variables’
- Loss
  - Damages to property or business
  - Number of casualties (actual human cost cannot be measured)

Risk Assessment: Fuzzy Loss

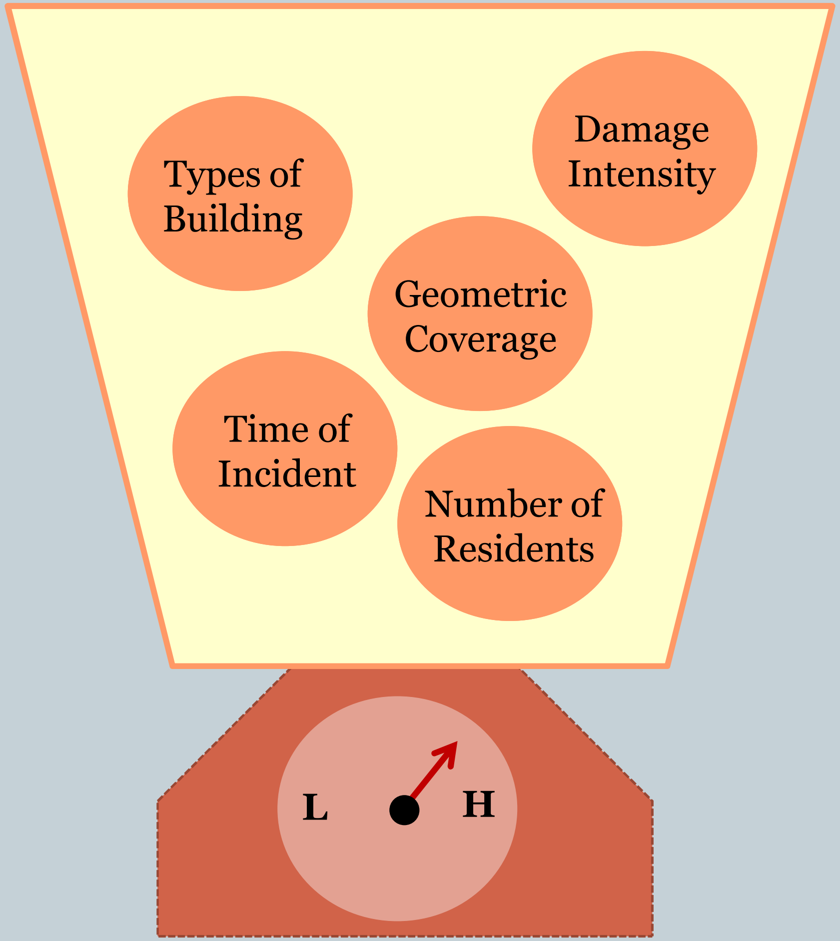


- Loss caused by an event is represented as a function $\xi : \Omega \rightarrow \Im$

$$\xi(\omega) = \begin{cases} n_s, P\{\omega = Success\} \\ n_f, P\{\omega = Failure\} \end{cases}$$

  - Ω = {Success, Failure} is a sample space of plausible events
  - n_s, $n_f \in \Im$, which is a set of nonnegative fuzzy variables

Risk Assessment: Fuzzy Risk



- Estimated as mean chance of a fuzzy random event over a confidence level *x*, for an individual type of loss:

$$Risk(x) = Ch\{\xi \geq x\}$$

- Risk aggregation
- Other assessment criteria

Current Approaches

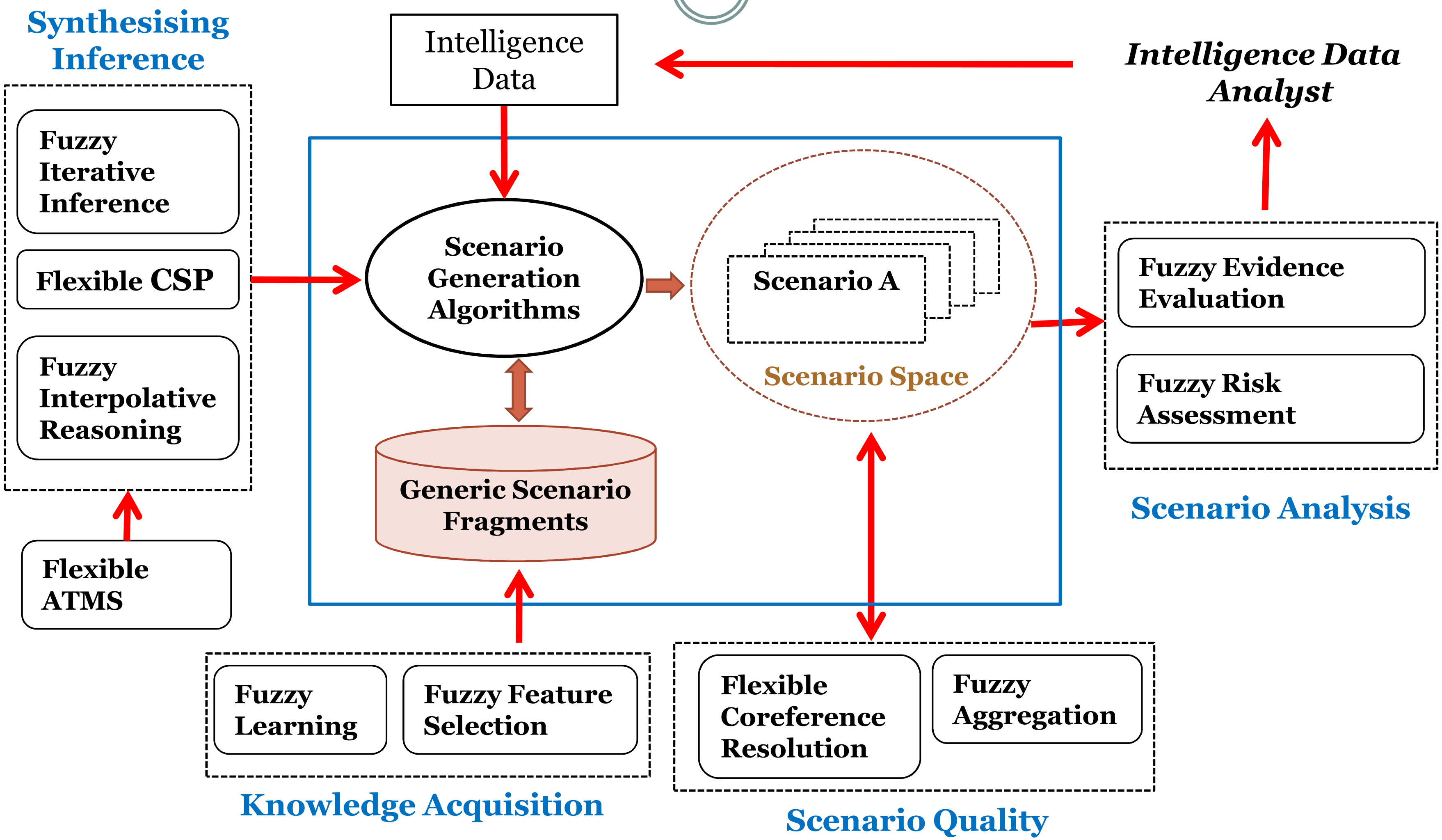


Illustration: Intelligence Data

Collected intelligence – preparation of 'liquid bomb'

Hydrogen-peroxide Vol.	Observed Time	Observed Location	Suspect Gender	Liquid Bomb
100 ml	12:45	airport	Male	YES
113 ml	08:50	airport	Male	YES
10 ml	13:01	airport	Male	NO
140 ml	20:38	airport	Female	YES
20 ml	09:23	airport	Female	NO
...	...	...	...	...

Illustration: Feature Selection

Remove ‘irrelevant’ data and noise

Hydrogen-peroxide Vol.	Observed Time	Observed Location	Suspect Gender	Liquid Bomb
100 ml	~~1[illegible]:45~~	~~airport~~	~~Male~~	YES
113 ml	~~08:[illegible]0~~	~~airport~~	~~Male~~	YES
10 ml	~~13:0[illegible]~~	~~airport~~	~~Male~~	NO
140 ml	~~20:[illegible]3~~	~~airport~~	~~Female~~	YES
20 ml	~~0[illegible]:23~~	~~airport~~	~~Female~~	NO
…	…	…	…	…

Illustration: Rule Learning

Hydrogen-peroxide Vol.	Liquid Bomb
100 ml	YES
113 ml	YES
10 ml	NO
140 ml	YES
20 ml	NO
…	…

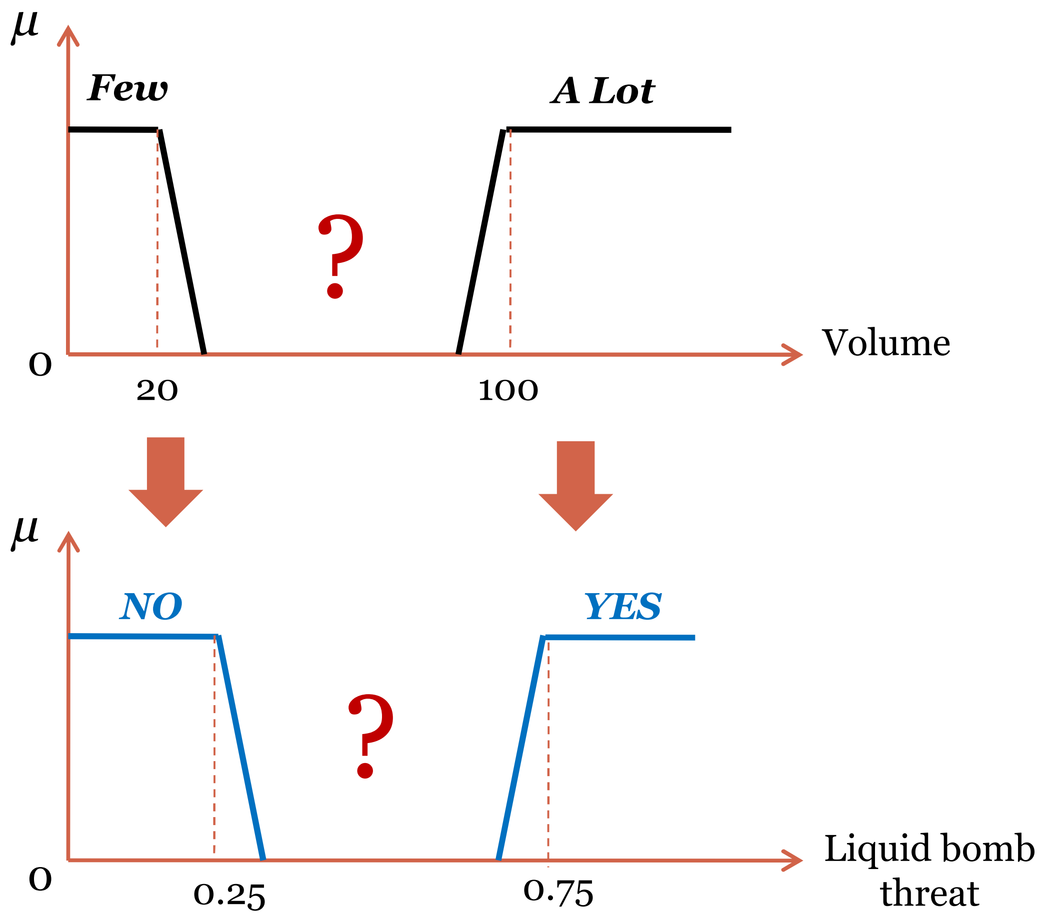


Illustration: Interpolative Reasoning

Rule$_1$: Volume = *Few* → Threat = *NO*
Rule$_2$: Volume = *A Lot* → Threat = *YES*
Observation: Volume = *A*

Question: What may be Threat level?
Approximation: Threat = *B*

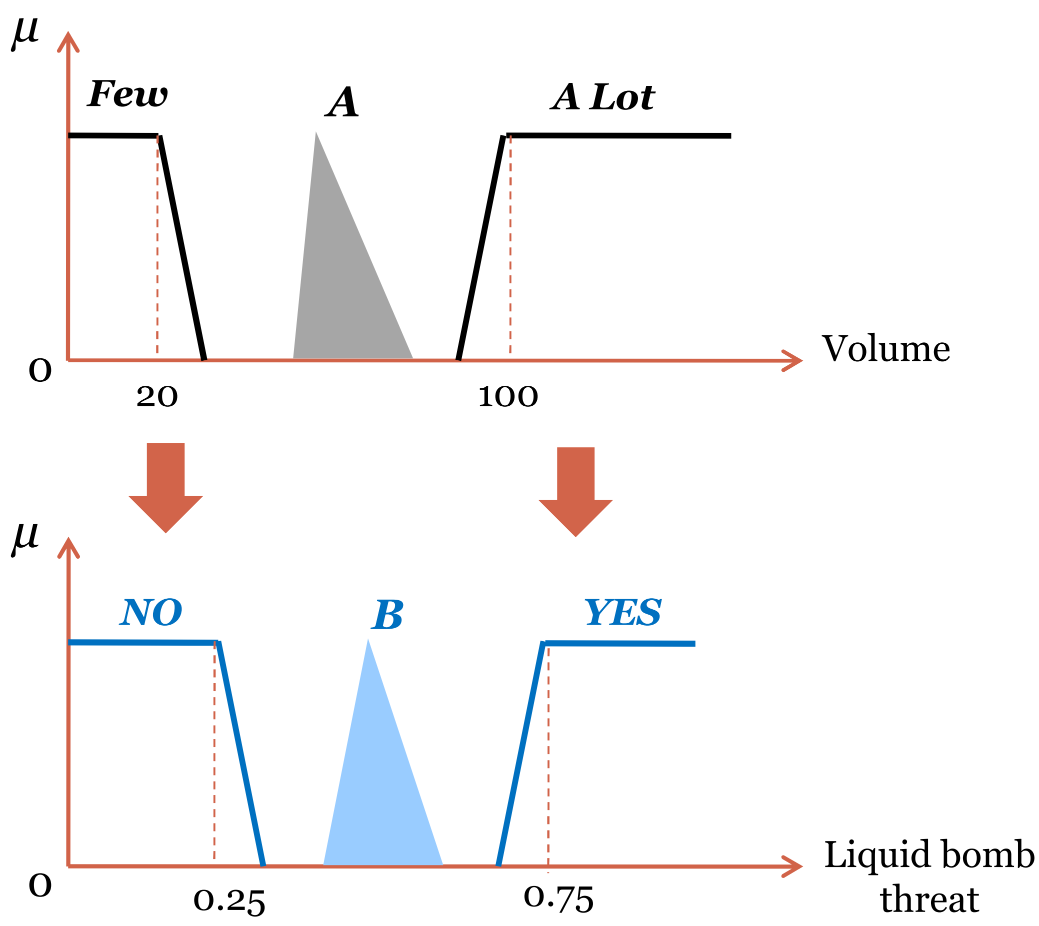


Illustration: Scenario Synthesis

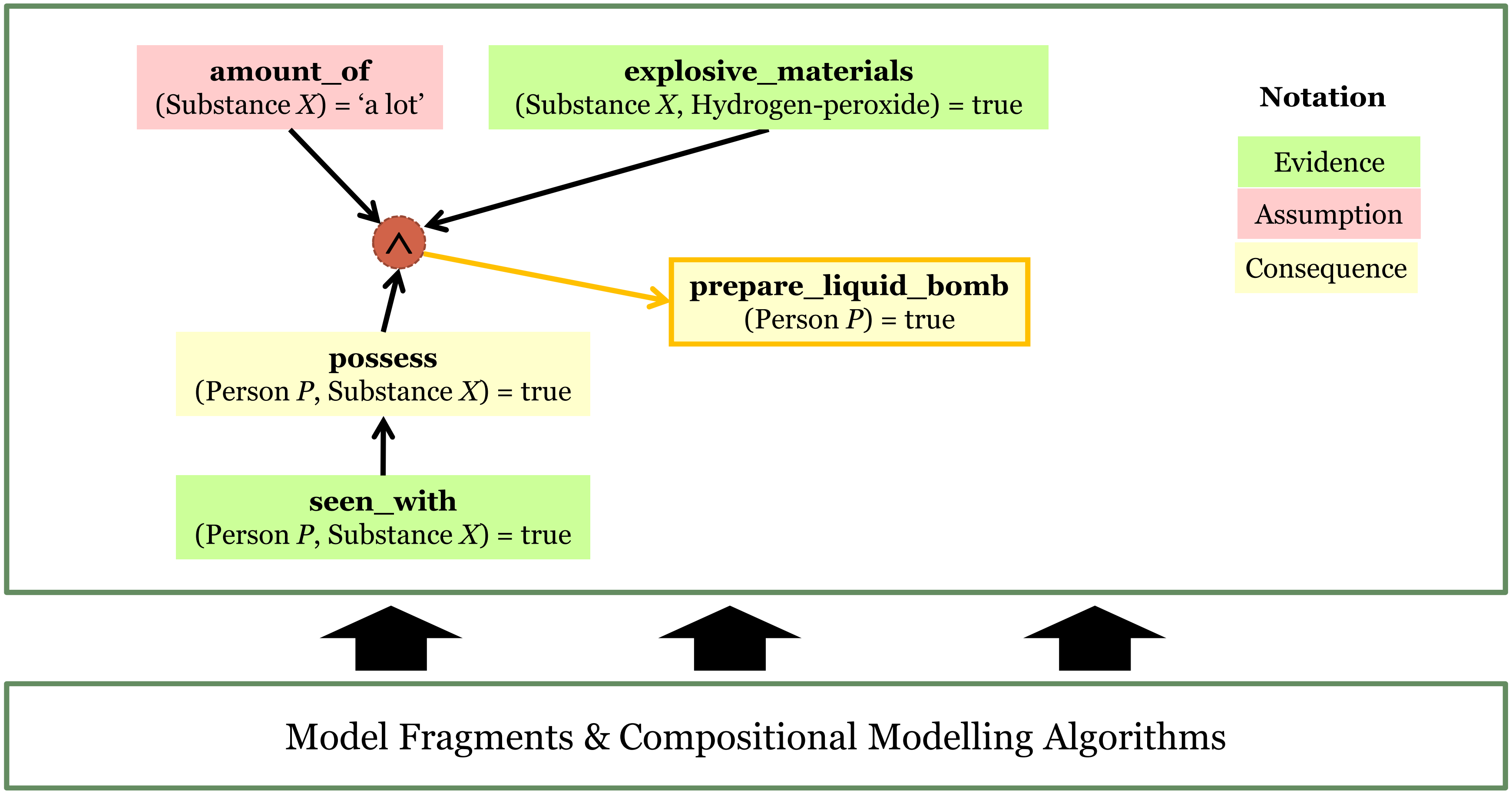
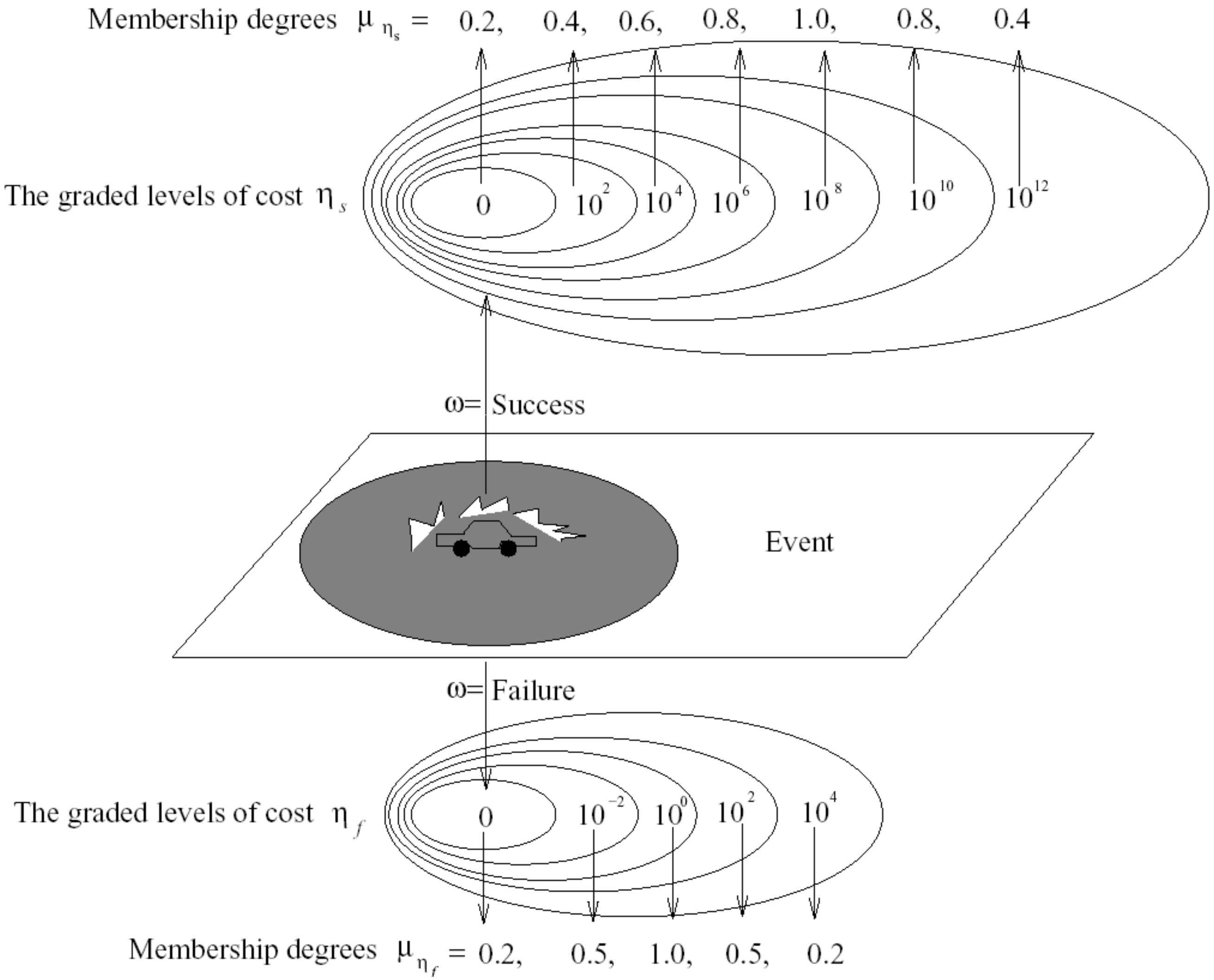


Illustration: Risk Assessment



Conclusion

- Computational intelligence in general, and fuzzy systems in particular helpful to *capture*, *learn* & *reason* with (intelligence data under) uncertainty
- Evidence-driven plausible scenario synthesis helpful for decision support (in intelligence monitoring)
- Fuzzy techniques successful (within a common decision support framework) for:
  - Fragment induction
  - Feature selection
  - Interpolative reasoning
  - Model composition
  - Constraint satisfaction
  - Truth maintenance
  - Co-reference resolution
  - Information aggregation
  - Evidence evaluation
  - Risk assessment
- However, important research remains …

Future Research and Challenges

- Learning hierarchical model fragments
- Hierarchical & ensemble feature selection
- Unification of scenario generation algorithms
- Dynamic coreference resolution & information fusion
- Evidence-driven risk-guided scenario generation
- Reconstruction of reasoning process
- Discovery of rare cases
- Meta-feature learning and selection for scenario synthesis
- …
- Further applications
  - Investigator training
  - Policy formulating
  - Multi-modal profiling
  - Adaptation to other domains (e.g. academic, financial)
  - …

Sample References

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Further Information and Contact?

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