Knowledge Propagation in Information Fusion Processes

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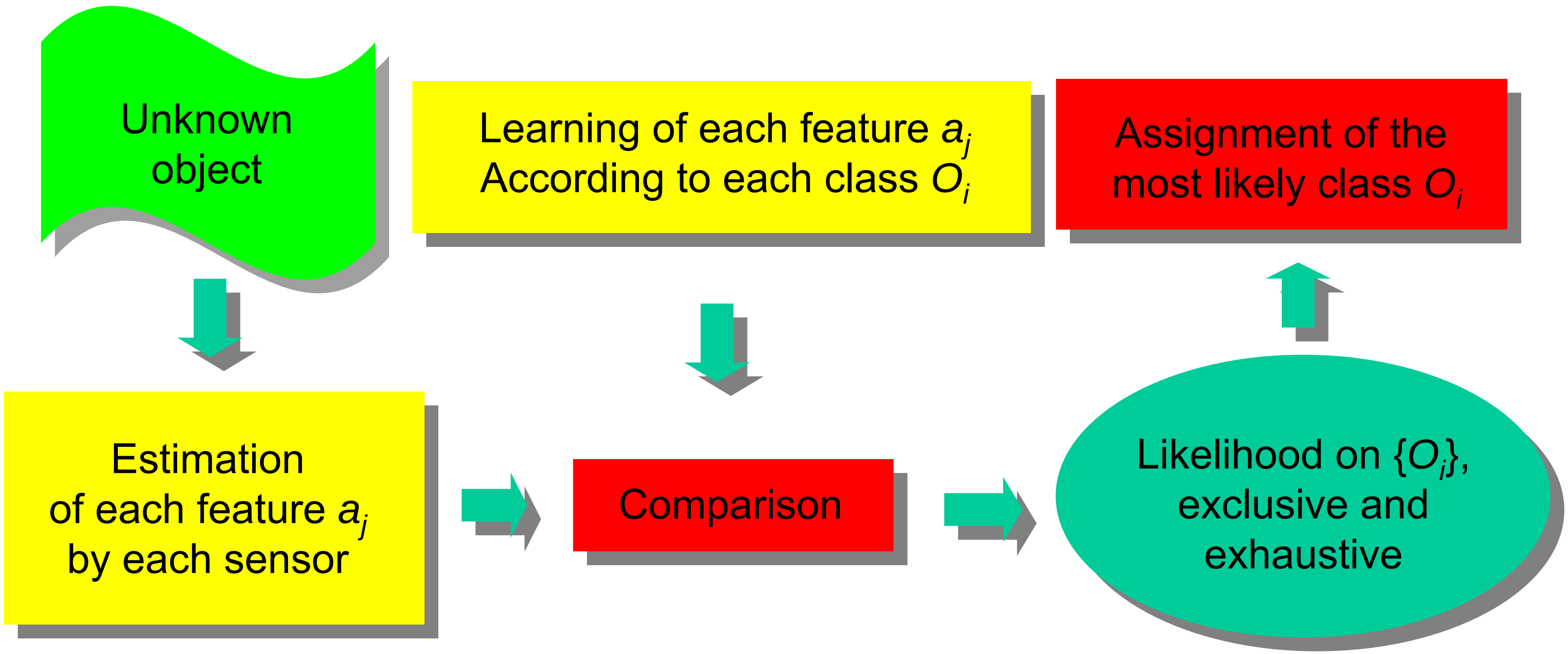
THE FRENCH AEROSPACE LAB

return on innovation

Classical Classification Process



Further Needs in Classification

Independent assessment of a variety of properties H_i about an unknown object by the sensors, eventually at different times

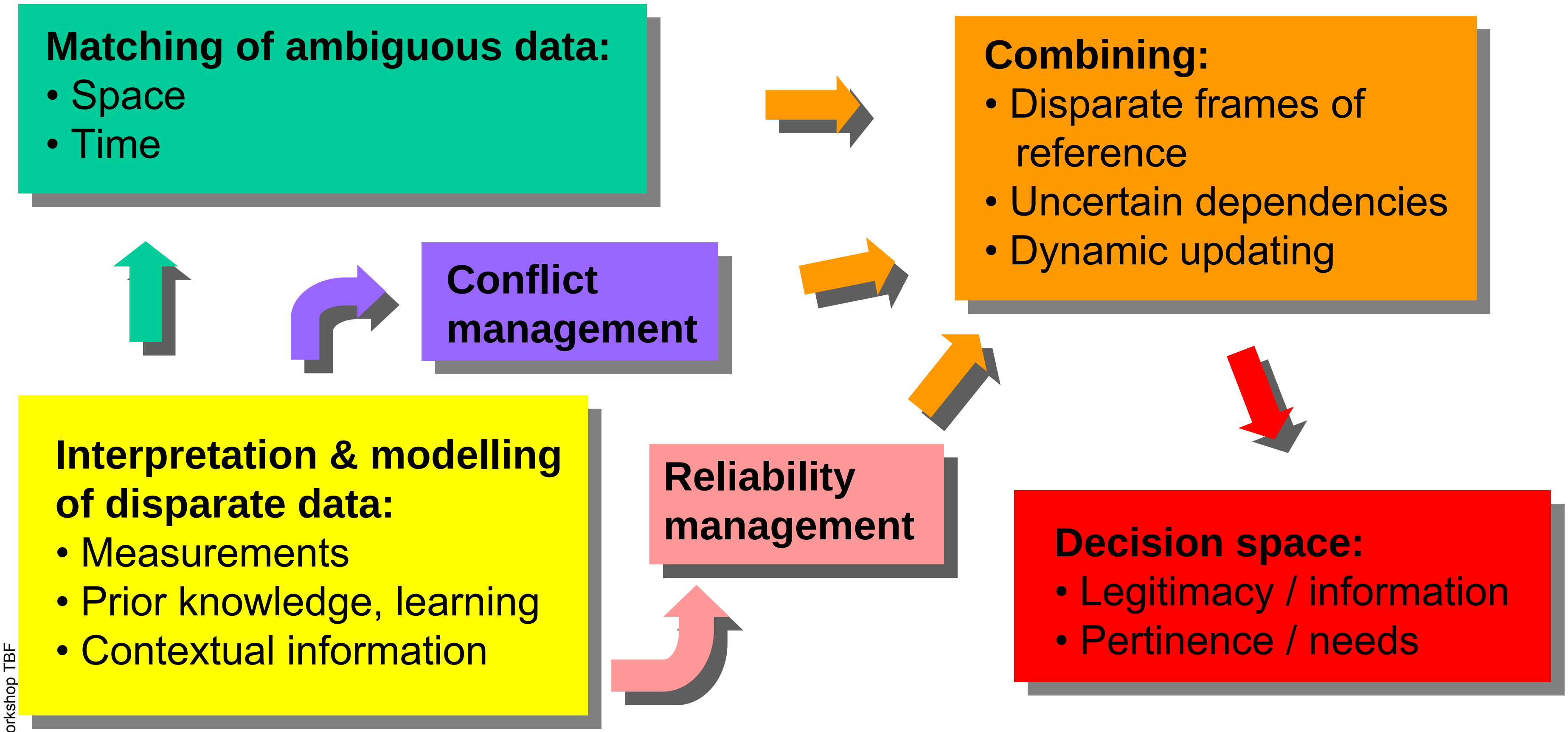
→ Likelihoods on $\{H_i, \neg H_i\}$

→ Transposition at a same time & combination

→ Likelihood on $\{O_j\}$, exclusive & exhaustive

→ Selection of a set of classes that most likely includes the right one

Frames of Reference in Fusion Processes



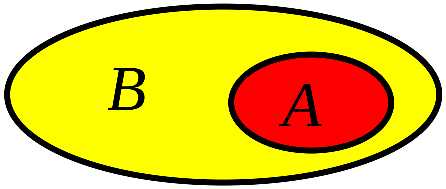
Foundations

Frame of discernment : $E = \{H_i\}, \quad i \in [1, I]$ Exclusive, exhaustive

Mass function : $2^E \rightarrow [0,1]$, $\sum_{A \subseteq E} m(A) = 1$, $m(\emptyset) = 0$

Belief function : minimum likelihood

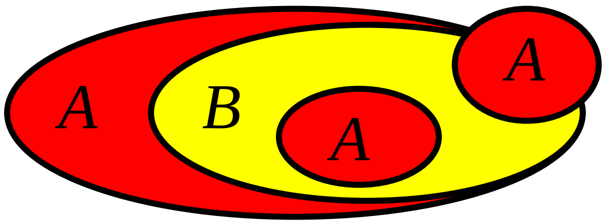
$$Bel(B) = \sum_{A \subseteq B} m(A)$$



Plausibility function : maximum likelihood

$$Pl(B) = \sum_{A \cap B \neq \emptyset} m(A)$$

$$Pl(B) = 1 - Bel(\neg B)$$



Focal element :

$A \subseteq E$,
such that $m(A) \neq 0$

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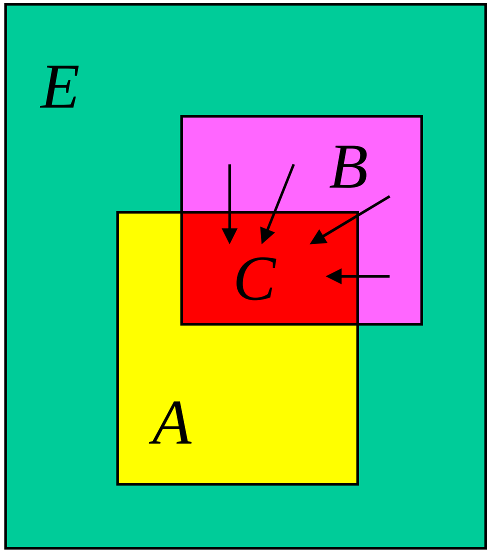
Conditioning - Deconditioning

Conditioning

$m(.)$ on E
A certain, $A \subset E$

$$m(C/A) = \frac{\sum_{B \cap A = C} m(B)}{\sum_{B \cap A \neq \emptyset} m(B)}$$

$$Pl(B/A) = \frac{Pl(B \cap A)}{Pl(A)}$$



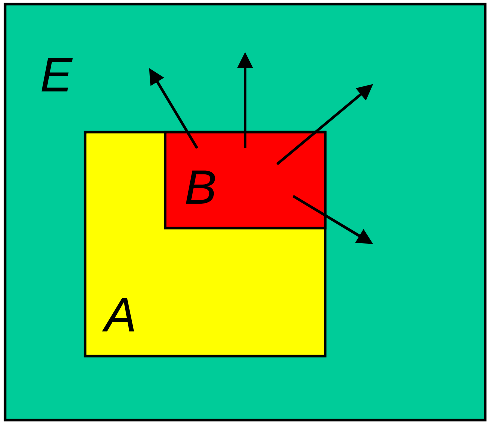
Deconditioning

$\forall B \subseteq A,\ Pl(B) = Pl(B/A)\ \underbrace{Pl(A)}_{?}$

$\forall B \not\subset A,\ Pl(B) = ?$

Minimal commitment

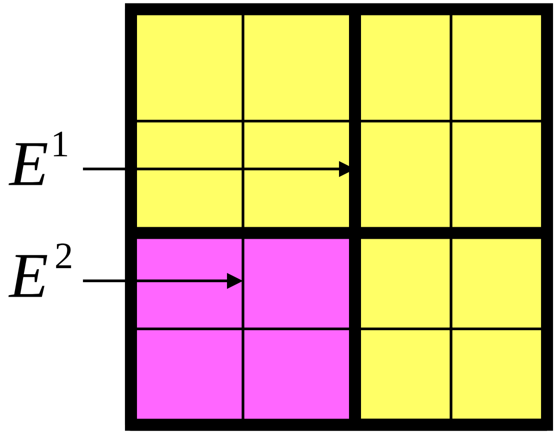
$$\forall B \subseteq A,\ m(B \cup \neg A) = m(B/A)$$



Refinement - Coarsening

$$E^1 = \{H_1^1, \ldots, H_{I1}^1\} \xrightarrow{R} E^2 = \{H_1^2, \ldots, H_{I2}^2\}$$

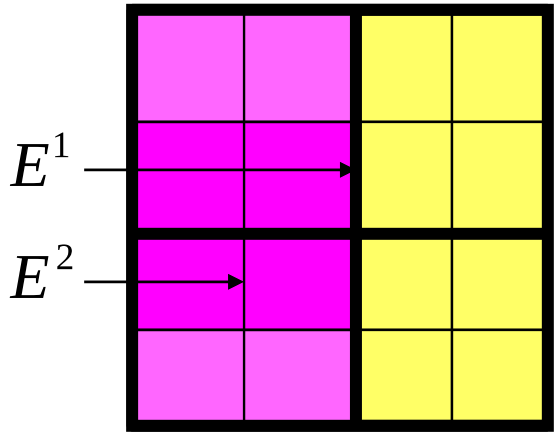
$$\{R(H_1^1), \ldots, R(H_{I1}^1)\} = \text{Partition of } E^2$$



Refinement:

$$m^1(.) \text{ on } E^1 \xrightarrow{R} m^2(.) \text{ on } E^2$$

$$\forall A \subseteq E^1, \quad m^2(R(A)) = m^1(A)$$



Coarsening:

$$m^2(.) \text{ on } E^2 \xrightarrow{R^{-1}} m^1(.) \text{ on } E^1$$

$$m^1(A) = \sum_{\substack{B \subseteq E^2 \\ A = \{H_i^1 / R(H_i^1) \cap B \neq \emptyset\}}} m^2(B)$$

A Federative Approach

Conditioning
Deconditioning

Refinement
Coarsening

Elaboration →
← Particular cases

Extension

Evidence transfer from one frame to another:
- Classification
- Indirect assessment
- Knowledge propagation
- Updating
- Prediction

Elaboration of coherent operators:
- Reliability management
- Disparate sources combination
- Decision

Related developments:
- Data modelling
- Conflict management
- Matching of ambiguous data

Management of Disparate Frames of Discernment and Dependencies

$Pl_e(.)$, $Pl_s(./B \subseteq E_e)$, $Pl_{sr}(.)$, incomplete

$Pl_e(.)$ on E_e

$Pl_s(./B \subseteq E_e)$ on E_s

$E_r \subseteq E_e$: elements with links to E_s

Extension

$m_s(.)$ on E_s

1 $Pl_{sr}(A \times B) = \dfrac{Pl_s(A/B \subseteq E_r)\, Pl_e(B)}{Pl_e(E_r)}$ on $E_s \times E_r$

2 $m_{sr}(.)$ of minimal commitment on $E_s \times E_r$ with respect to $Pl_{sr}(.)$

3 Coarsening from $E_s \times E_r$ to E_s :

$$m_s(A) = \sum_{B \subseteq E_r} m_{sr}(A \times B)$$

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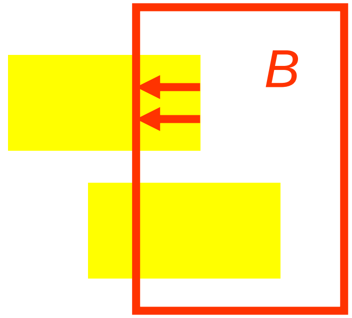
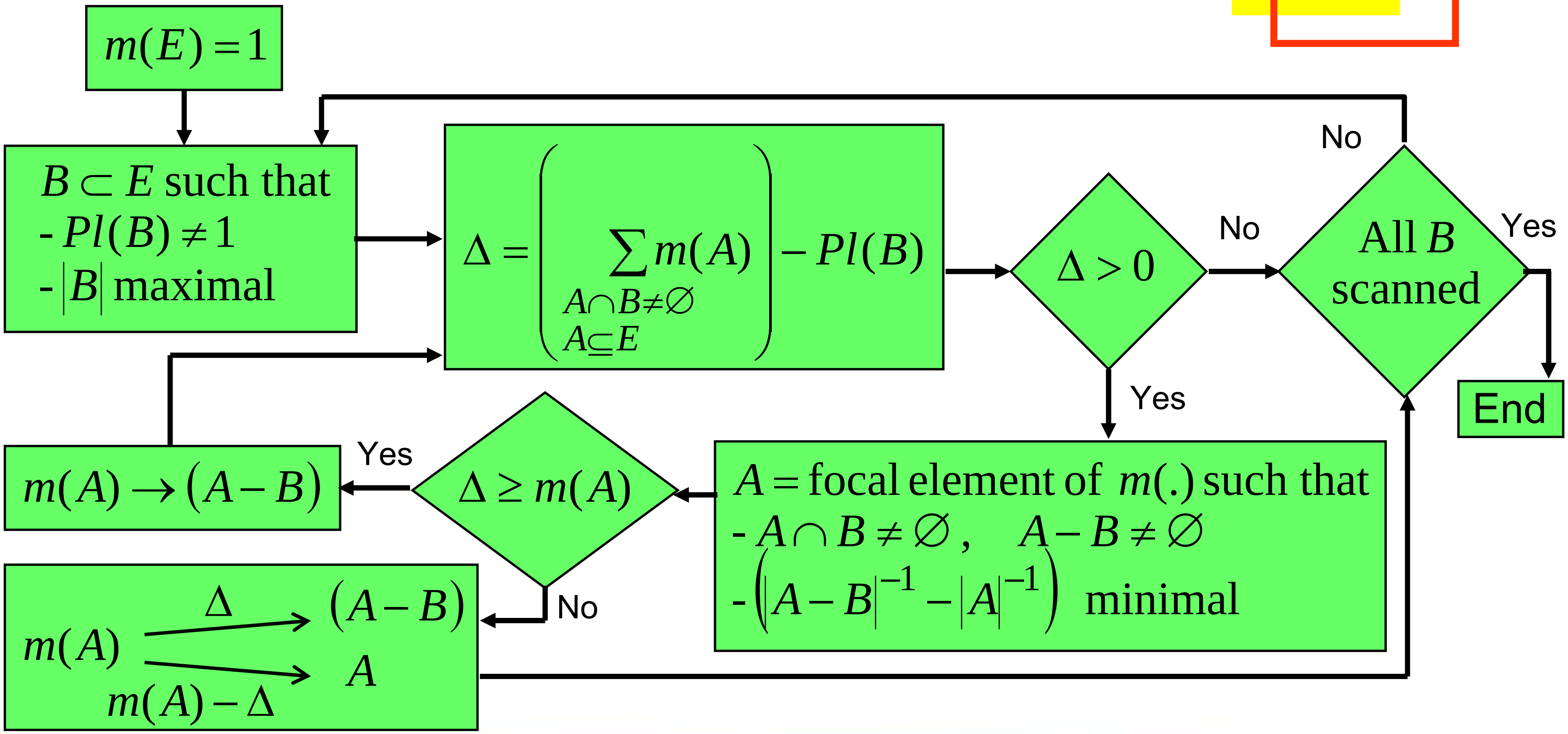
Determination of *m*(.) with Minimal Commitment

Incomplete $Pl(.)$ on E ➡ Complete $m(.)$ minimizing

$$Sp(m) = \sum_{A \subseteq E} \frac{m(A)}{|A|}$$





Example

Input

$Pl(H_2 \cup H_3) = 0.6$

$Pl(H_1 \cup H_2) = 0.9$

$Pl(H_2) = 0.3$

$Pl(H_1) = 0.8$

$m(E) = 1$

$E = \{H_1, H_2, H_3\}$

$Pl(H_2 \cup H_3) = 0.6 \rightarrow$ $m(E) = 0.6$, $m(H_1) = 0.4$

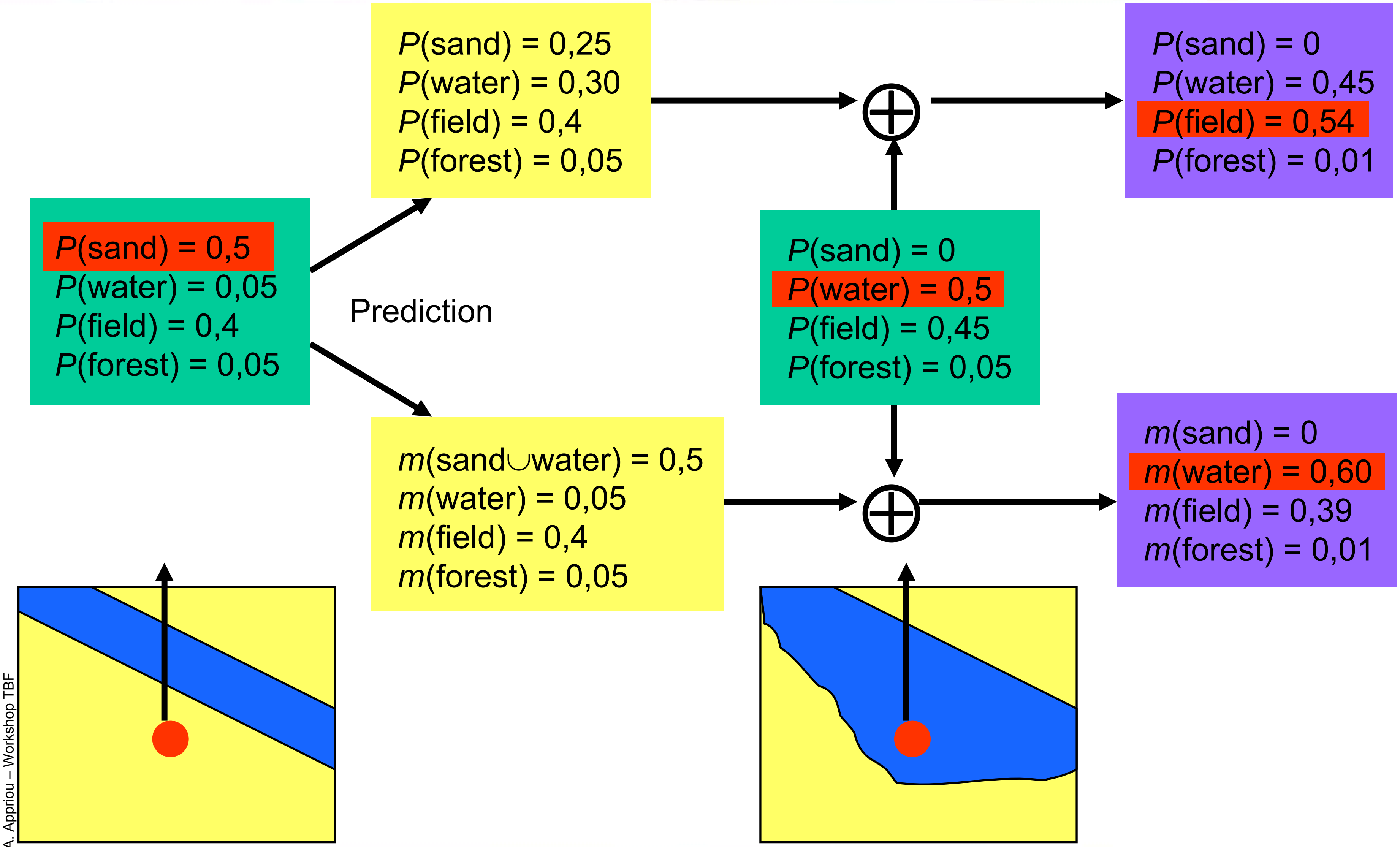
$Pl(H_1 \cup H_2) = 0.9 \rightarrow$ $m(E) = 0.5$, $m(H_1) = 0.4$, $m(H_3) = 0.1$

$Pl(H_2) = 0.3 \rightarrow$ $m(E) = 0.3$, $m(H_1 \cup H_3) = 0.2$, $m(H_1) = 0.4$, $m(H_3) = 0.1$

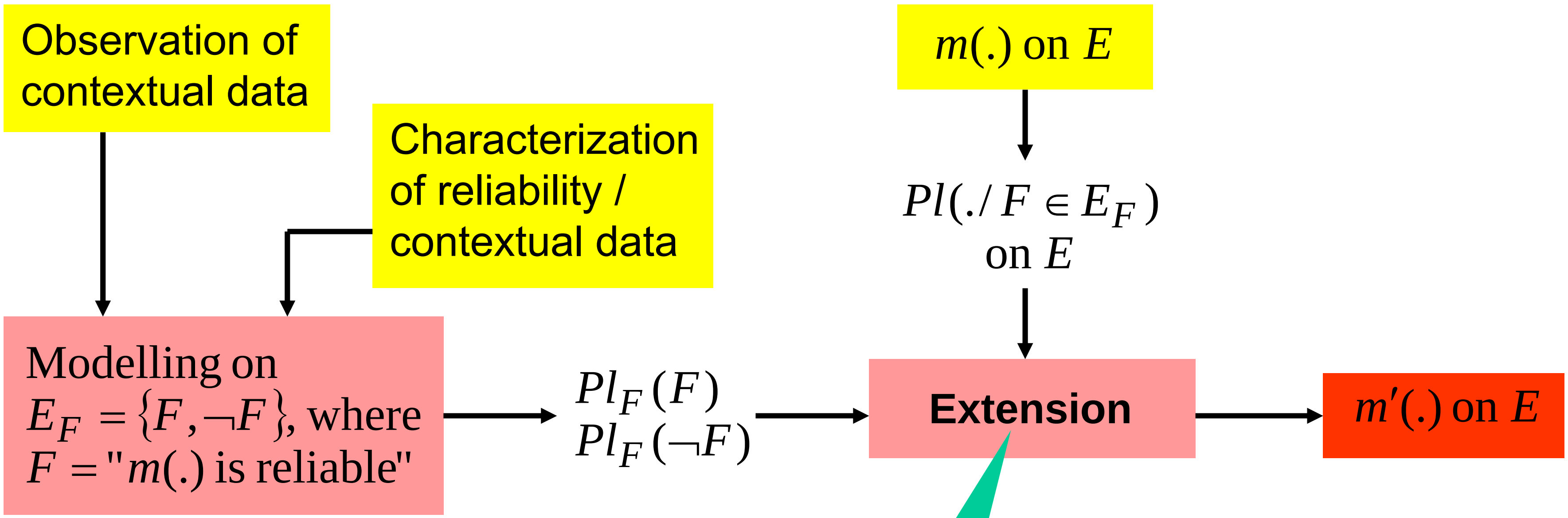
$Pl(H_1) = 0.8 \rightarrow$ $m(E) = 0.2$, $m(H_1 \cup H_3) = 0.2$, $m(H_2 \cup H_3) = 0.1$, $m(H_1) = 0.4$, $m(H_3) = 0.1$

Unique solution

Multidate Image Classification



Reliability Management



Discounting $(1 - Pl_F(F))$:

$m'(A) = Pl_F(F)\, m(A) \quad \forall A \subset E$

$m'(E) = 1 - Pl_F(F)\,(1 - m(E))$

→ Optimal solution if $m_F(.)$ Bayesian ($m_{sr}(.)$ of minimal commitment)

→ Suitable but suboptimal solution otherwise

Pixel Classification in Multispectral Images

2 IR sensors : 2 - 2,3 μm, 0,4 - 0,6 μm

2 hypotheses : Asphalt, Vegetation

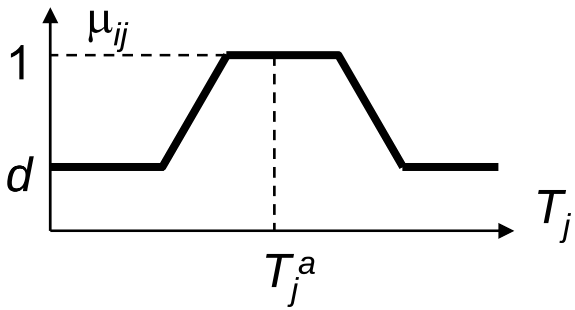
1 contextual variable / sensor *j* :

water vapor transmittance T_j

Learning in summer :

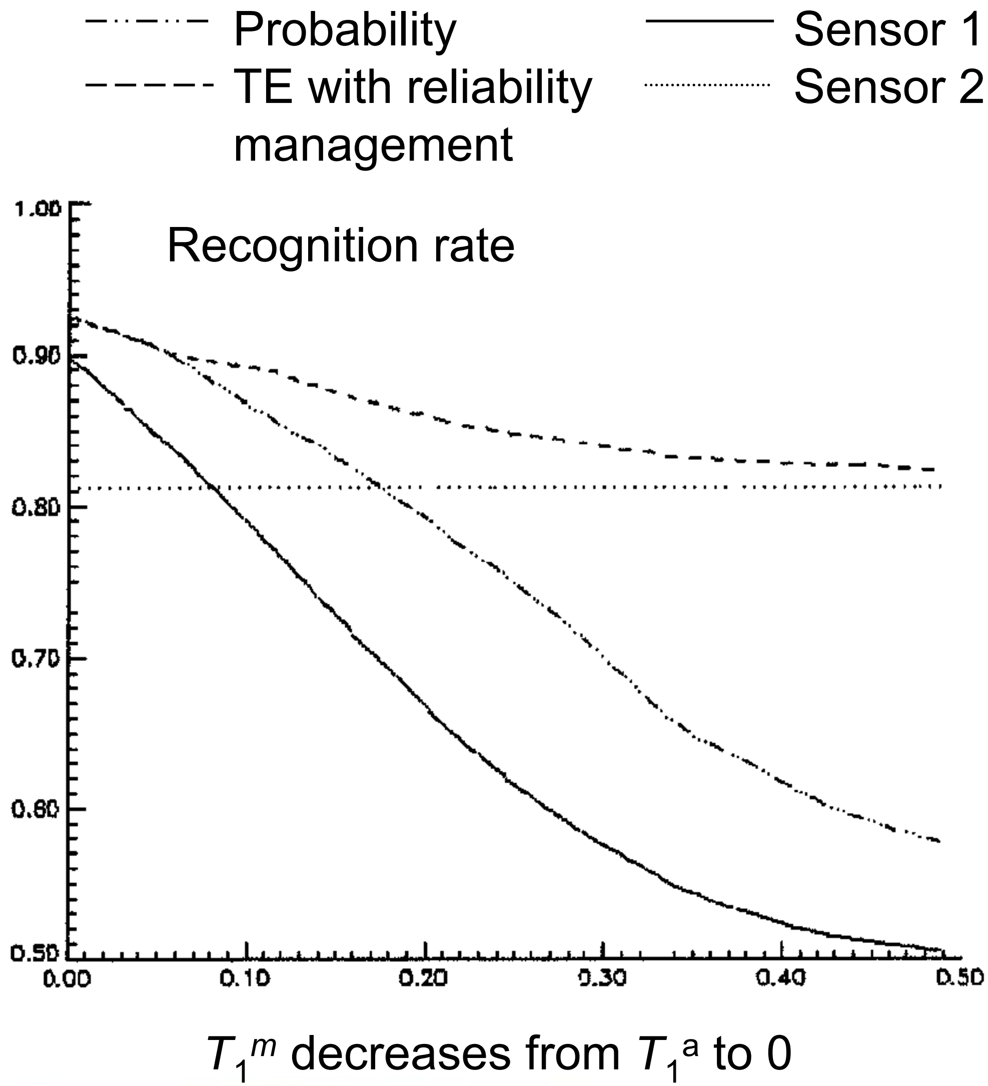
$$p_a(s_j / H_i, T_j^a)$$

Validity Domain / sensor *j* :



Real data in winter

Transmittance observation : T_j^m



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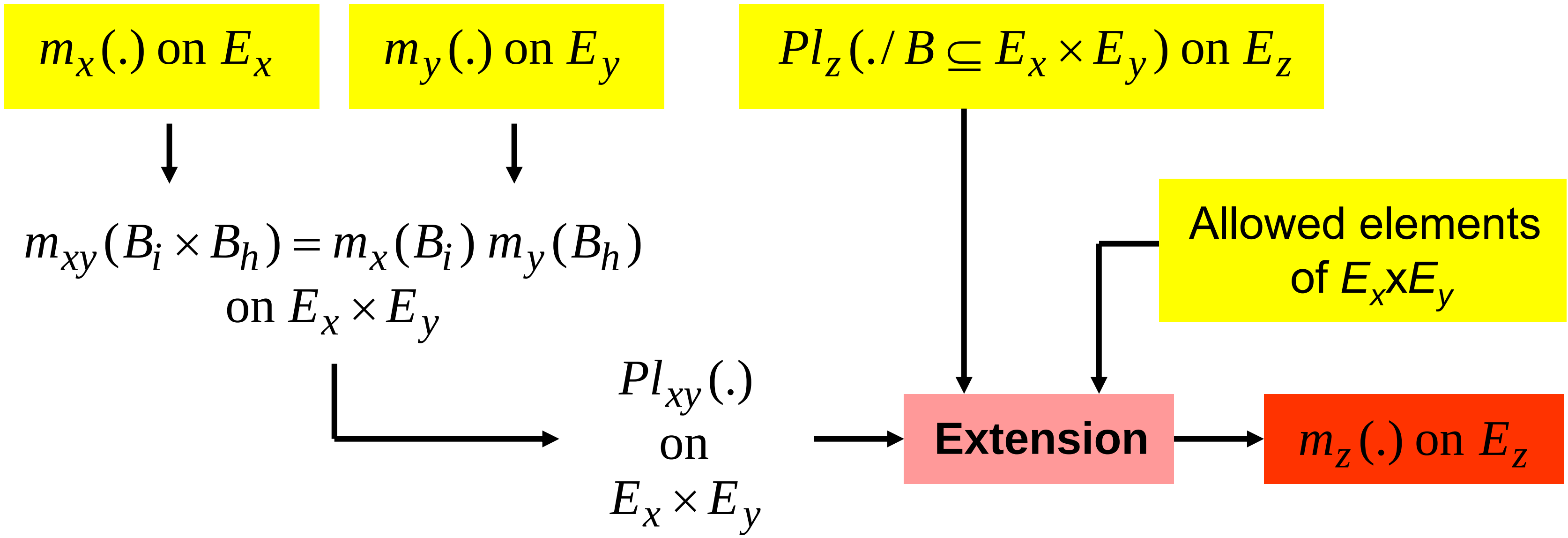
Disparate Source Combination



Definition of :

- Particular relations between E_x, E_y, and E_z
- $Pl_z(./B \subseteq E_x \times E_y)$
- Allowed elements of $E_x \times E_y$

Particular rules of combination

Examples of Particular Rules of Combination

$$E_x = E_y = E_z$$

$$Pl_z(A / B_i \times B_h \subseteq E_x \times E_y) = 1 \text{ if it "covers" at least one allowed link}$$
$$Pl_z(A / B_i \times B_h \subseteq E_x \times E_y) = 0 \text{ otherwise}$$

Combination Rule	Allowed Links	Allowed elements
Orthogonal Sum	$B_i x B_h \rightarrow A = B_i \cap B_h$	(X_i, Y_h), $X_i = Y_h$
Disjunction	$B_i x B_h \rightarrow A = B_i \cup B_h$	$E_x x E_y$
Dubois & Prade	$B_i x B_h \rightarrow A = B_i \cap B_h$, if $B_i \cap B_h \neq \emptyset$ $B_i x B_h \rightarrow A = B_i \cup B_h$, if $B_i \cap B_h = \emptyset$	$E_x x E_y$
Yager	$B_i x B_h \rightarrow A = B_i \cap B_h$, if $B_i \cap B_h \neq \emptyset$ $B_i x B_h \rightarrow E_z$, if $B_i \cap B_h = \emptyset$	$E_x x E_y$

Information management

Conflict management

Conflict → Modelling & interpretation according to axioms

Conflict → Specific combination rule, to exploit available information

Synthesis of Binary Estimations

Discrimination on $E = \{H_1, \cdots, H_i, \cdots, H_N\}$

$N \times (N-1)/2$ sources S_{ij}
each on $E_{ij} = \{H_i, H_j\}$

Combination of one-to-one comparisons:

$$P_{ij}(H_i) + P_{ij}(H_j) + P_{ij}(ign.) = 1$$
$$i \in [1, N-1], \quad j \in [i+1, N]$$

$$Pl\left(A \subseteq E \,/\, B = \{H^k\} \subseteq \prod_{S_{ij} \in S} E_{ij} \right)$$
$= 1$ if $\exists H_i \in A, \; H^{ij} = H_i \; \forall j$
$= 0$ otherwise

Allowed elements H^k of $\prod_{S_{ij}} E_{ij}$:

$H^k = (H^{12}, \cdots, H^{ij}, \cdots), \; H^{ij} \in E_{ij}$

such that : $\exists H_i \in E, \; H^{ij} = H_i, \; \forall j$

$$m_{ij}(H_i) = P_{ij}(H_i)$$
$$m_{ij}(H_j) = P_{ij}(H_j)$$
$$m_{ij}(E_{ij}) = P_{ij}(ind.)$$

Combination with respect to *i* & *j*

$$Pl(H_i) = \frac{\prod_{\substack{j \in [1,N] \\ j \neq i}} \left[P_{i,j}(H_i) + P_{i,j}(ind.) \right]}{1 - K}$$

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Fusion of Binary Classifiers

$$Pl(A/B \subseteq E_{12} \times E_{23} \times E_{31}) = 1 \text{ if it "covers":}$$
$$\text{either}: (H_1, H_j, H_1) \to H_1$$
$$\text{or}: (H_2, H_2, H_j) \to H_2$$
$$\text{or}: (H_j, H_3, H_3) \to H_3$$
$$Pl(A/B \subseteq E_{12} \times E_{23} \times E_{31}) = 0 \text{ otherwise}$$

Allowed elements:
$$(H_1, H_j, H_1)$$
$$(H_2, H_2, H_j)$$
$$(H_j, H_3, H_3)$$

$$E_{12} = \{H_1, H_2\}$$
$$m_{12}(H_1) = 0{,}4$$
$$m_{12}(H_2) = 0{,}6$$

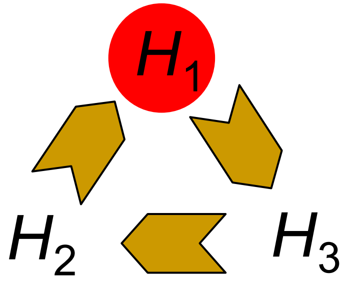
$$E_{23} = \{H_2, H_3\}$$
$$m_{23}(H_2) = 0{,}3$$
$$m_{23}(H_3) = 0{,}7$$

$$E_{31} = \{H_3, H_1\}$$
$$m_{31}(H_3) = 0{,}3$$
$$m_{31}(H_1) = 0{,}7$$

Combination

$$E = \{H_1, H_2, H_3\}$$
$$m(H_1) = 0{,}42$$
$$m(H_2) = 0{,}27$$
$$m(H_3) = 0{,}31$$

$S_{ij} \to$ Discrimination between H_i et H_j
Distance / learning $\to P_{ij}(H_i)+P_{ij}(H_j)=1$



Combination of Preferences in Multicriteria Decision

$Pl(A/B \subseteq E_{12} \times E_{23} \times E_{31}) = 1$ if it "covers":
either : $(H_1, H_j, H_1) \rightarrow H_1$
or : $(H_2, H_2, H_j) \rightarrow H_2$
or : $(H_j, H_3, H_3) \rightarrow H_3$
$Pl(A/B \subseteq E_{12} \times E_{23} \times E_{31}) = 0$ otherwise

Allowed elements :
(H_1, H_j, H_1)
(H_2, H_2, H_j)
(H_j, H_3, H_3)

$E_{12} = \{H_1, H_2\}$
$m_{12}(H_1) = 0{,}2$
$m_{12}(H_2) = 0{,}5$
$m_{12}(E_{ij}) = 0{,}3$

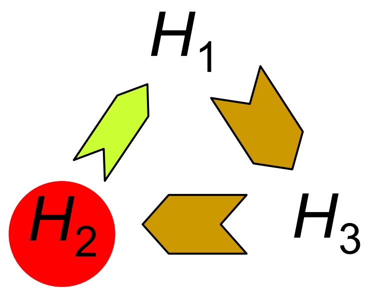
$E_{23} = \{H_2, H_3\}$
$m_{23}(H_2) = 0{,}4$
$m_{23}(H_3) = 0{,}6$

$E_{31} = \{H_3, H_1\}$
$m_{31}(H_3) = 0{,}4$
$m_{31}(H_1) = 0{,}6$

Combination

$E = \{H_1, H_2, H_3\}$
$Pl(H_1) \cong 0{,}30$
$Pl(H_2) \cong 0{,}32$
$Pl(H_3) \cong 0{,}24$

S_{ij} : Survey about preferences between H_i and H_j
→ Statsitics of opinions:
$P_{ij}(H_i)+P_{ij}(H_j)+P_{ij}(ign.)=1$



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Conflict: Back to Zadeh's Paradox

$E_1 = E_2 = E = \{H_1, H_2, H_3\}$
$H_1 = \text{Meningitis}$
$H_2 = \text{Contusion}$
$H_3 = \text{Brain tumor}$

$m_1(H_1) = 0{,}99$
$m_1(H_2) = 0$
$m_1(H_3) = 0{,}01$

$m_2(H_1) = 0$
$m_2(H_2) = 0{,}99$
$m_2(H_3) = 0{,}01$

Orthogonal Sum

$m(H_1) = 0$
$m(H_2) = 0$
$m(H_3) = 1$

Combination

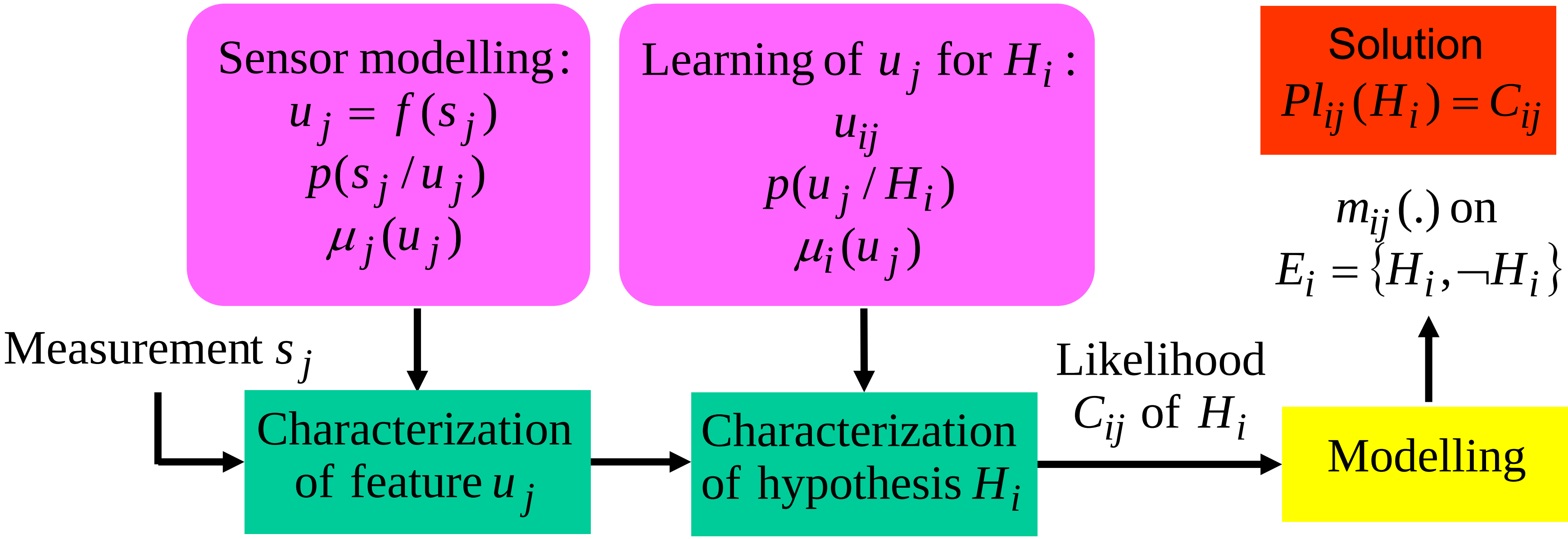
$m_z(H_1) = 0$
$m_z(H_2) = 0$
$m_z(H_3) = 0{,}0001$
$m_z(H_{12}) = 0{,}9801$
$m_z(H_{23}) = 0{,}0099$
$m_z(H_{31}) = 0{,}0099$

$Pl(A/B \subseteq E \times E) = 1$ if it "covers":
either $(H_i, H_i) \to H_i$
or $(H_i, H_j) \to H_{ij} = H_i \cup H_j$
$Pl(A/B \subseteq E \times E) = 0$ otherwise

$E_z = \{H_1, H_2, H_3, H_{12}, H_{23}, H_{31}\}$

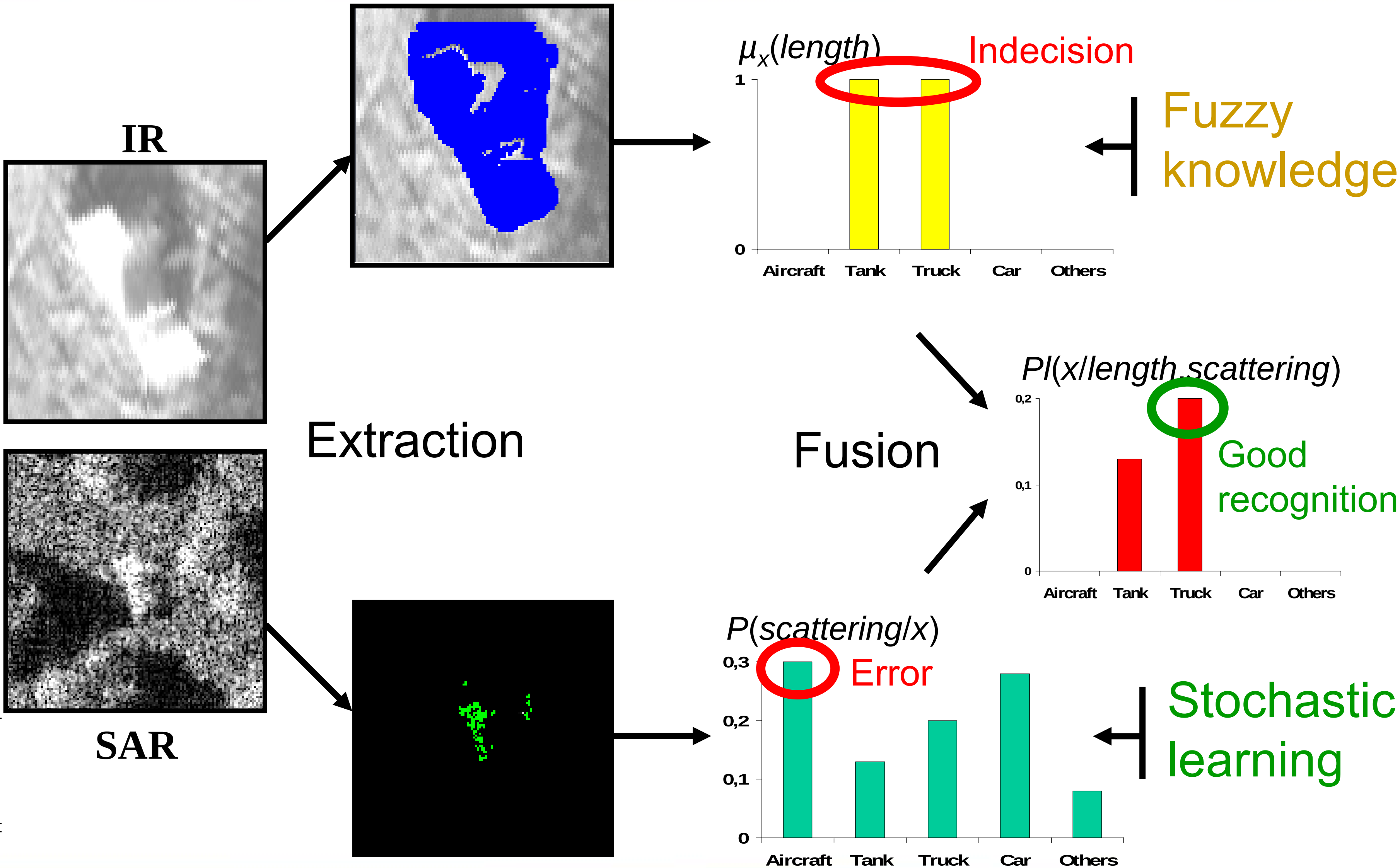
Data Modelling

Principle : separate assessment of each hypothesis or proposition



- Potential variety of inputs
- Incomplete information processing - Modularity - Evolutivity
- Reasoning on disparate propositions
- Separate reliability management for each hypothesis
- Contextual data processing: $E_i \rightarrow E_F = \{F, \neg F\}$

Image Fusion for Aerial Recognition



Decision : the Dilemma

Choice of the most likely hypothesis

$E = \{H_1, \ldots, H_I\}$
$m(.)$ on E

$$\max_i \left(\sum_{A \subseteq E} \lambda(H_i, A)\, m(A) \right)$$

…   …

$\lambda(H_i, A) = 1$ if $A = H_i$
$\lambda(H_i, A) = 0$ if $A \neq H_i$

Maximum of Belief

$\lambda(H_i, A) = \frac{1}{|A|}$ if $H_i \in A$
$\lambda(H_i, A) = 0$ if $H_i \notin A$

Pignistic criterion

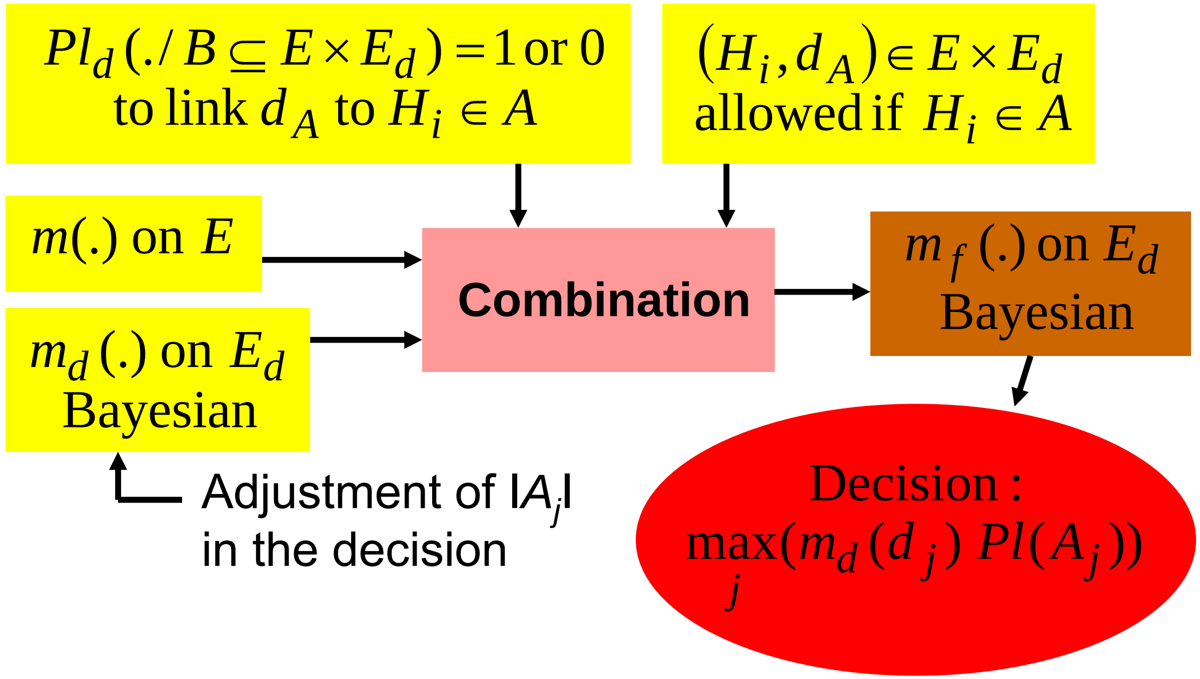
$\lambda(H_i, A) = 1$ if $H_i \in A$
$\lambda(H_i, A) = 0$ if $H_i \notin A$

Maximum of Plausibility

Decision : Set of the most Likely Hypotheses

$$E = \{H_1, \dots, H_I\}$$
$$E_d = \{d_1, \dots, d_D\}$$

$$H_i = \text{Hypothesis}$$
$$d_j = \text{Choice of } A_j \subseteq E$$



- Set of hypotheses that includes most likely the right one
  (≠ set of the best hypotheses considered separately)
- Adjustable compromise between likelihood and precision
- Ambiguities :
  - Parametric adjustment
  - Use of a secondary criterion :

$$\min_j \{m_d(d_{j'} / A_{j'} = \neg A_j)\ Pl(\neg A_j)\}$$

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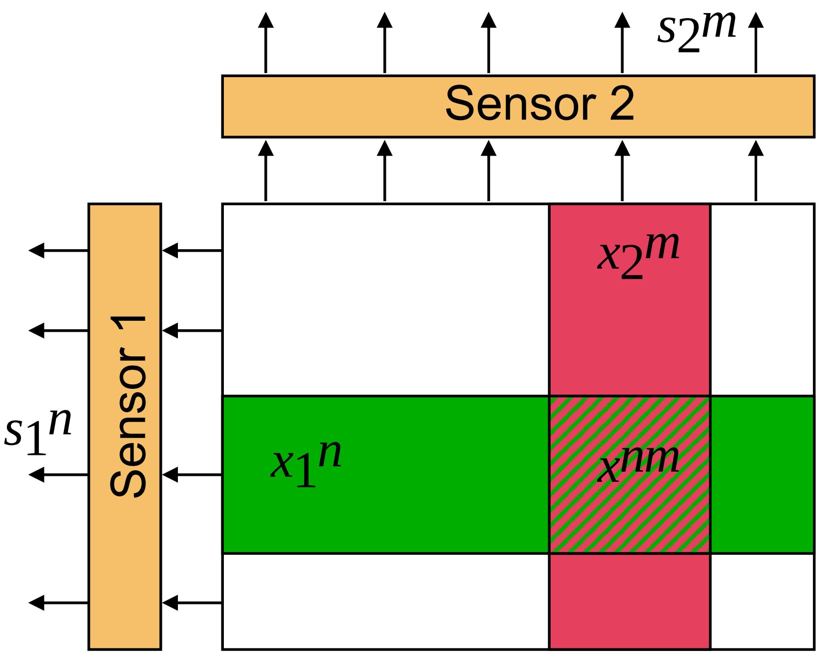
A Few Didactic Examples

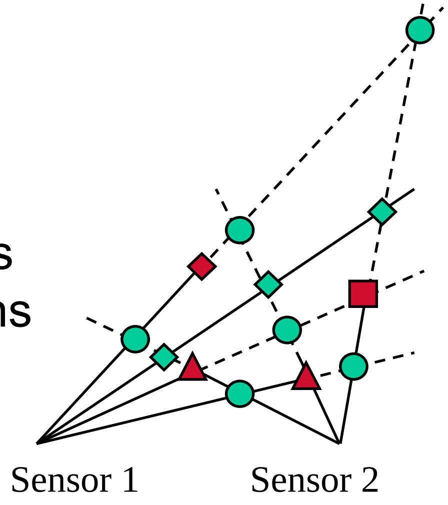
$m(H_1)$	0,2	0,1	0,4
$m(H_2)$	0,1	0	0
$m(H_3)$	0,3	0,3	0
$m(H_1 \cup H_2)$	0,2	0,5	0
$m(H_2 \cup H_3)$	0,1	0,1	0,6
$m(E)$	0,1	0	0
Solution(s) with $\lvert . \rvert=1$	H_1, H_2, H_3	H_1, H_2	H_2, H_3
Solution(s) with $\lvert . \rvert=2$	$H_1 \cup H_3$	$H_1 \cup H_3$	$H_1 \cup H_2$, $H_1 \cup H_3$
Secondary criterion	H_3	H_1	H_2, H_3
Pignistic criterion	H_3	H_1, H_3	H_1

Ambiguous Observation Matching

Orthogonal spatial resolutions :
- Localization
- Discrimination of multiple targets



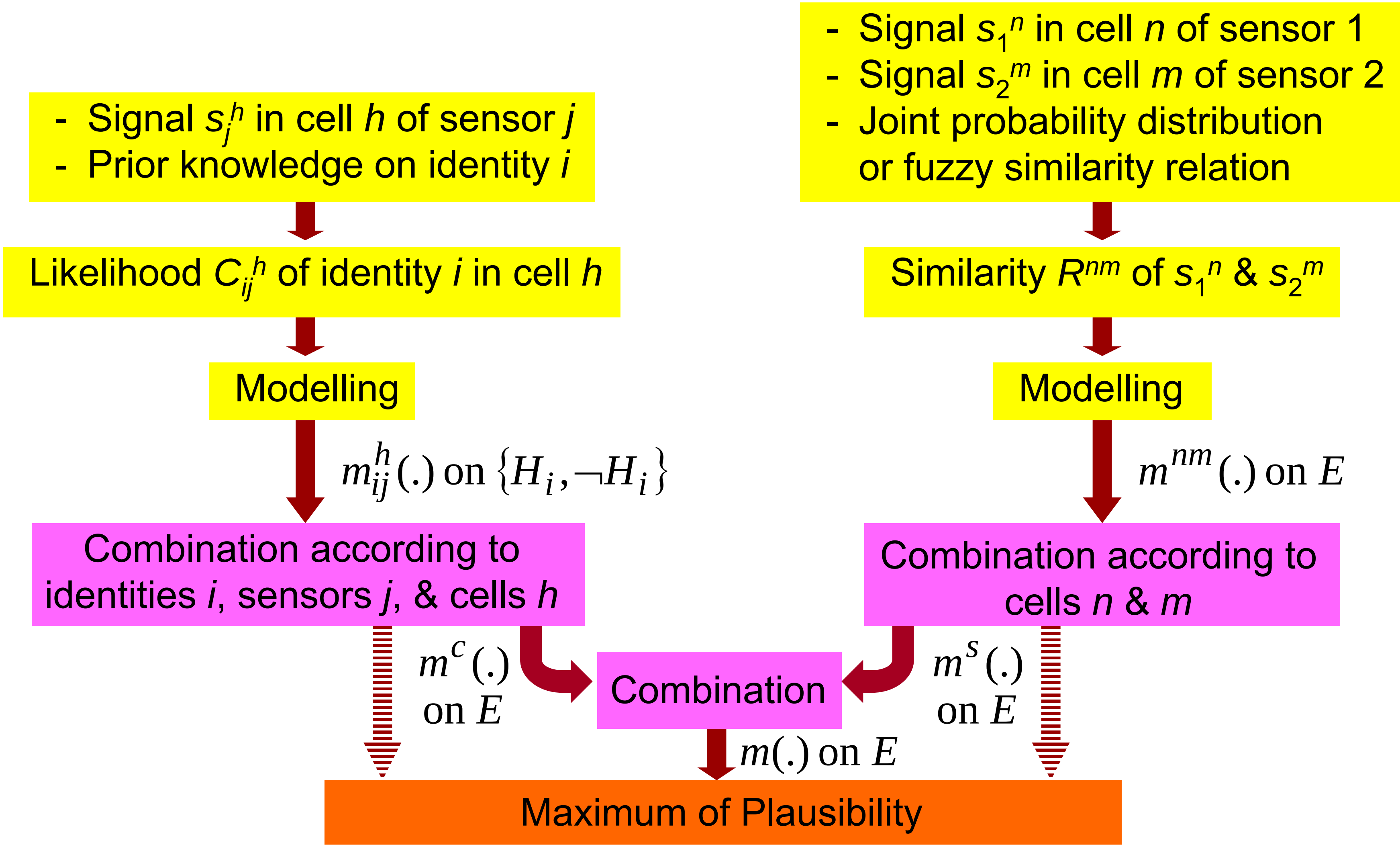
Difficulties :
- Ghosts
- False Alarms
- Hidden targets
- Non-Detections



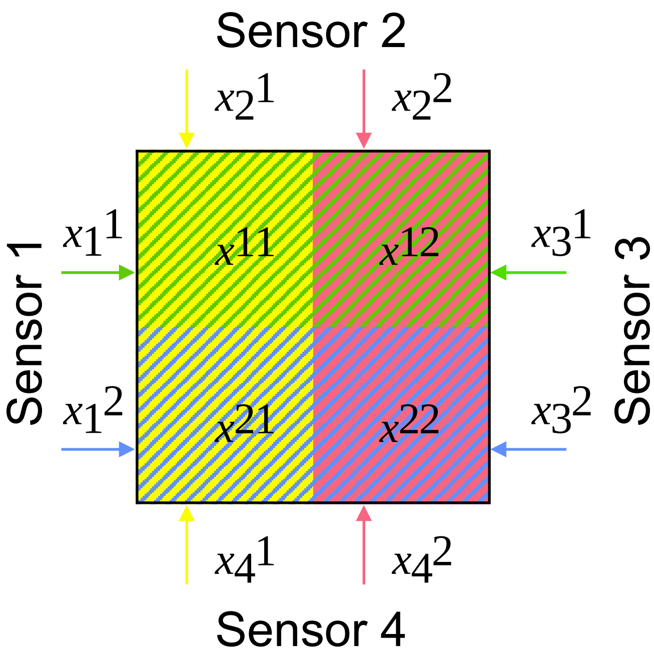
Formulation :
Look for the most likely singleton in the set *E* of identity distributions over cell intersections

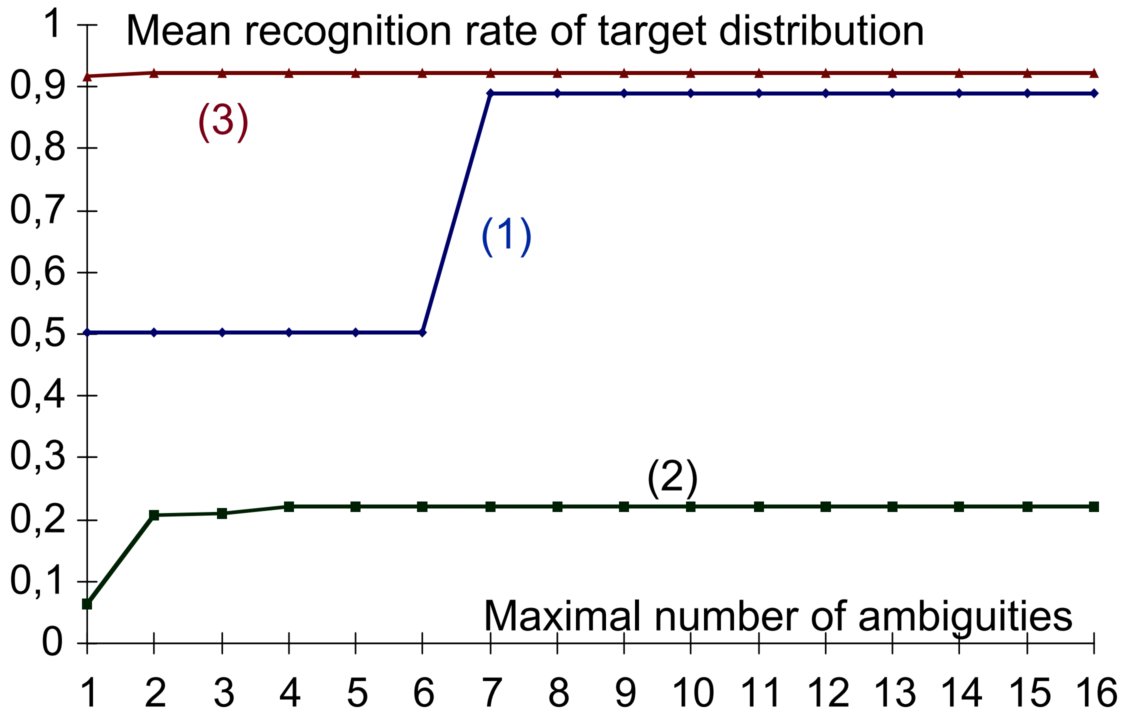
Simultaneous detection, localization, counting, identification of all targets

Matching Process



Application to Detection



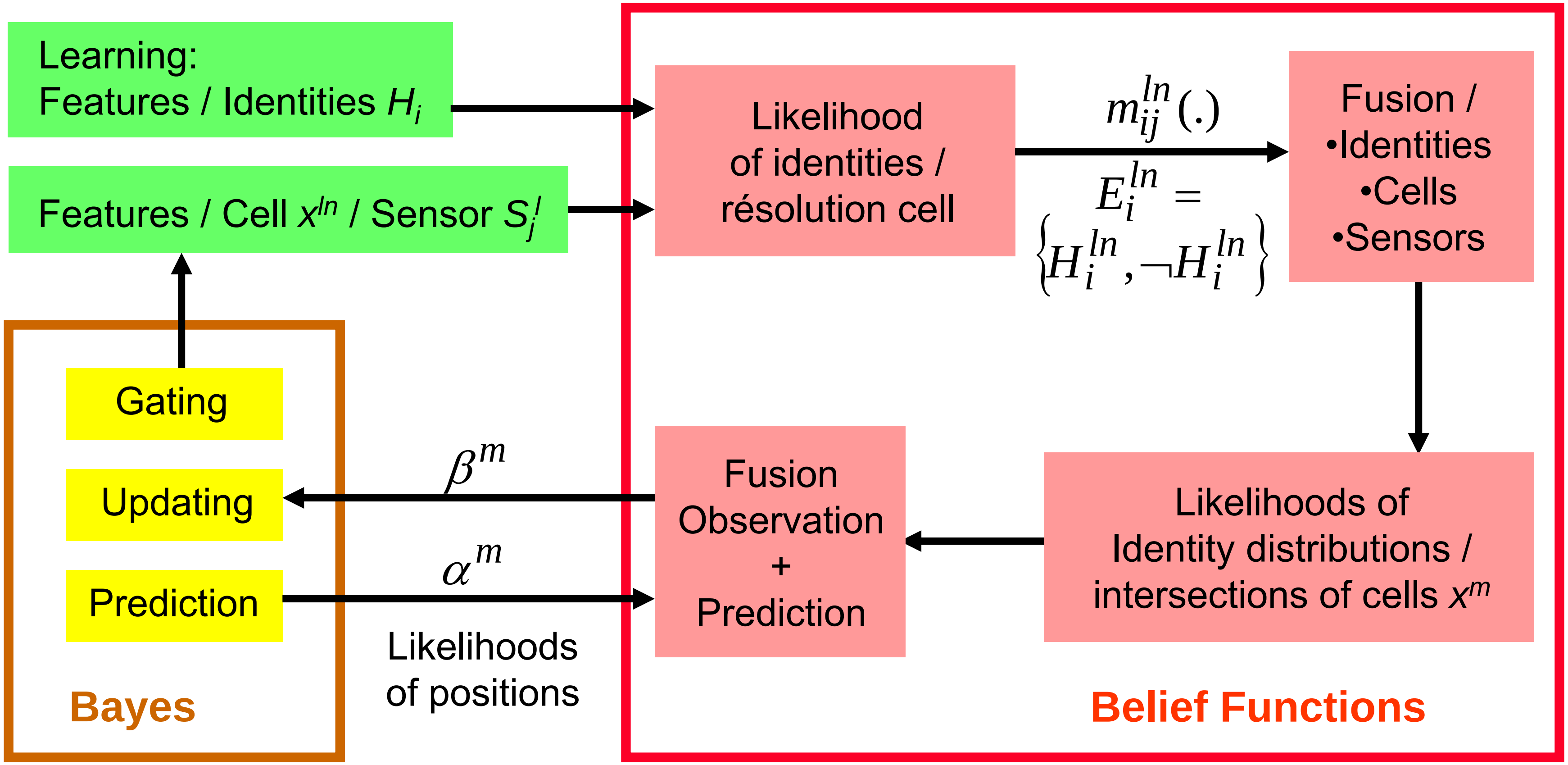


- Statistical learning of signals with and without target
- Fuzzy similarity relation between signals of sensors looking at a same target

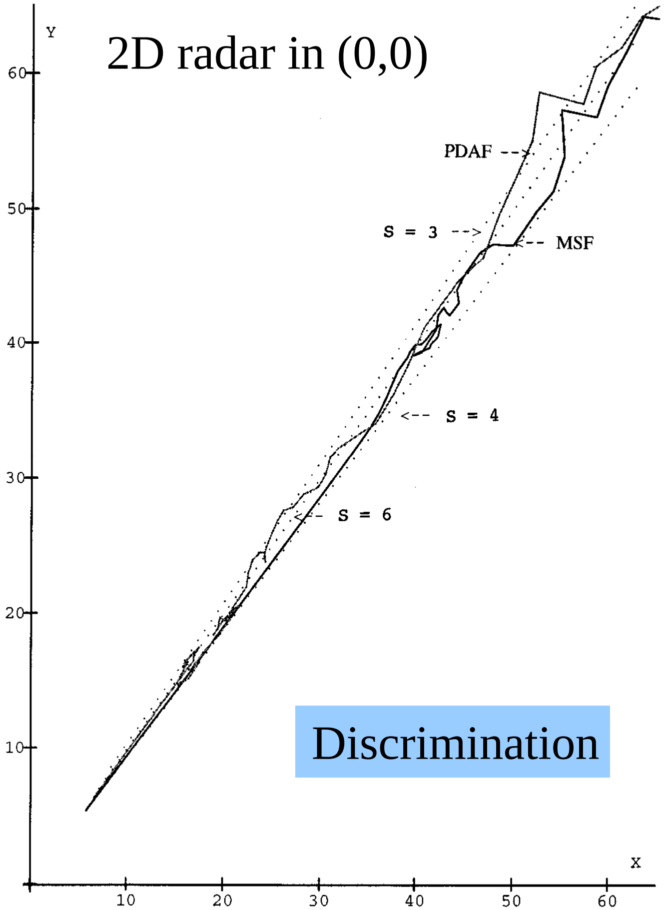
(1) Classification criterion
(2) Similarity criterion
(3) Global criterion

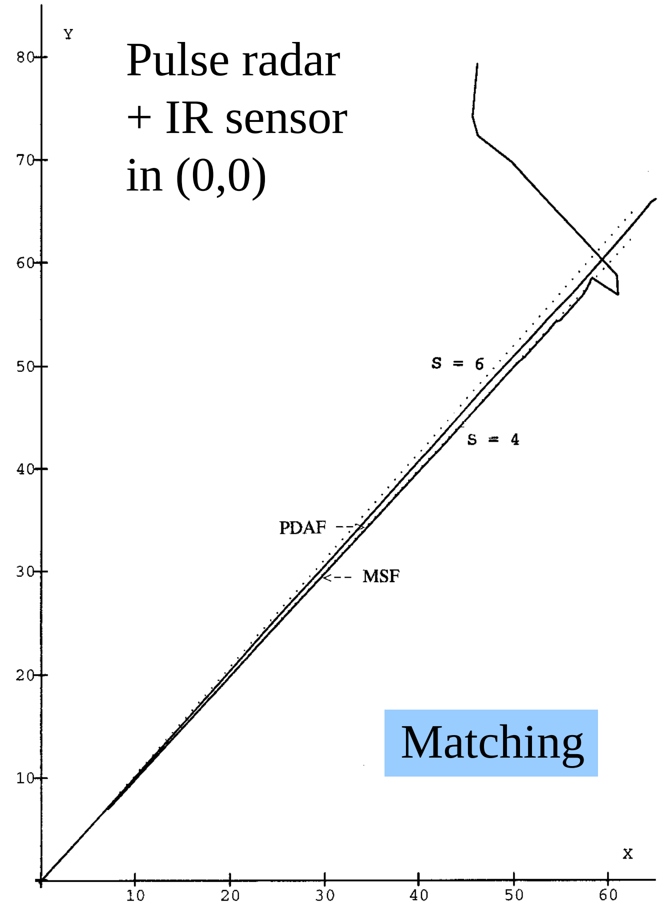
Tracking in Dense Environment

A global approach: Multiple Signal Filter (MSF)



Examples





Signals:

N(0,1) No target in the cell

N(*S*,1) Target level *S* in the cell

- Reliable statistical learning
- Initialization error only
- Tracking of target *S*=4

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Concluding Remarks

Collection of coherent operators that meets emerging fusion needs

- Independent interpretation of heterogeneous data in a same process
- Integration of contextual observations
- Reliability management
- Management of disparate frames of reference and dependencies
- Conflict and information management
- Ambiguous data matching
- Open decision principles