UNIVERSITÉ DE RENNES 1

On belief functions implementations

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UMR IRISA

Plan

- Natural order
- Smets codes
- General framework
- How to obtain bbas?
  - Random bbas
  - Distance based model
  - probabilistic based model

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Natural order or Binary order

Discernment frame: $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$
Power set: all the disjunctions of Ω:
$2^\Omega = \{\emptyset, \{\omega_1\}, \{\omega_2\}, \{\omega_1 \cup \omega_2\}, \ldots, \Omega\}$

Natural order:

$$\begin{aligned} 2^\Omega \quad = \quad & \{\emptyset, \{\omega_1\}, \{\omega_2\}, \{\omega_1 \cup \omega_2\}, \\ & \{\omega_3\}, \{\omega_1 \cup \omega_3\}, \{\omega_2 \cup \omega_3\}, \{\omega_1 \cup \omega_2 \cup \omega_3\}, \\ & \{\omega_4\}, \ldots, \Omega\} \end{aligned}$$

Natural order or Binary order

Natural order:

$\emptyset$ 0	ω_1 1	ω_2 2	$\omega_1 \cup \omega_2$ $3 = 2^2 - 1$
ω_3 $4 = 2^{3-1} + 1$	$\omega_1 \cup \omega_3$ 5	$\omega_2 \cup \omega_3$ 6	$\omega_1 \cup \omega_2 \cup \omega_3$ $7 = 2^3 - 1$
ω_4 $8 = 2^{4-1} + 1$	$\dots$	$\dots$	$\dots$
ω_i $2^{i-1} + 1$	$\dots$	$\dots$	Ω $2^n - 1$

Natural order or Binary order

Bba in Matlab:

Example: $m_1(\omega_1) = 0.5$, $m_1(\omega_3) = 0.4$, $m_1(\omega_1 \cup \omega_2 \cup \omega_3) = 0.1$
$m_2(\omega_3) = 0.4$, $m_2(\omega_1 \cup \omega_3) = 0.4$

```
F1=[1 4 7]';
F2=[4 5]';
M1=[0.5 0.4 0.1]';
M2=[0.4 0.6]';
```

Natural order or Binary order

Combination

$$m_{\text{Conj}}(X) = \sum_{Y_1 \cap Y_2 = X} m_1(Y_1) m_2(Y_2) \quad (1)$$

$\omega_1 \cap (\omega_1 \cup \omega_3)$: $1 \cap 5$
In binary with 3 digits for a frame of 3 elements: 1=100 and 5=101=100 |001
$100 \& 101 = 100$

Natural order or Binary order

In Matlab:

```
sizeDS=3;
F1=[1 4 7]';
F2=[4 5]';
M1=[0.5 0.4 0.1]';
M2=[0.4 0.6]';
Fres=[];
Mres=[];
for i=1:size(F1)
   for j=1:size(F2)
      Fres=[Fres bi2de(de2bi(F1(i),sizeDS)&de2bi(F2(j),sizeDS))];
      Mres=[Mres M1(i)*M2(j)];
   end
end
```

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Smets codes for DST

Smets gaves the codes of the Mobius transform (see Only_Mobius_Transf) for conversions:

- bba and belief: mtobel, beltom
- bba and plausibility: mtopl, pltom
- bba and communality: mtoq, qtom
- bba and implicability: mtob, btom
- bba to pignistic probability: mtobetp
- etc...

e.g. in Matlab:
m1=[0 0.4 0.1 0.2 0.2 0 0 0.1]';
mtobel(m1)
gives: 0 0.4000 0.1000 0.7000 0.2000 0.6000 0.3000 1.0000

Smets code

For s bbas m_j

Conjunctive combination

$$m_{\text{Conj}}(X) = \sum_{Y_1 \cap \ldots \cap Y_s = X} \prod_{j=1}^{s} m_j(Y_j)$$

The practical way:

$$q(X) = \prod_{j=1}^{s} q_j(X)$$

Disjunctive combination

$$m_{\text{Dis}}(X) = \sum_{Y_1 \cup \ldots \cup Y_s = X} \prod_{j=1}^{s} m_j(Y_j)$$

The practical way:

$$b(X) = \prod_{j=1}^{s} b_j(X)$$

DST code

In Matlab

For the conjunctive rule of combination:

```
m1=[0 0.4 0.1 0.2 0.2 0 0 0.1]';
m2=[0 0.2 0.3 0.1 0.1 0 0.2 0.1]';
q1=mtoq(m1);
q2=mtoq(m2);
qConj=q1.*q2;
mConj=qtom(qConj)
mConj =
   0.4100 0.2200 0.2000 0.0500 0.0900 0 0.0200 0.0100
```

DST code

In Matlab

For the disjunctive rule of combination:

```
m1=[0 0.4 0.1 0.2 0.2 0 0 0.1]';
m2=[0 0.2 0.3 0.1 0.1 0 0.2 0.1]';
b1=mtob(m1);
b2=mtob(m2);
bConj=b1.*b2;
bDis=b1.*b2;
mDis=btom(bDis)
mDis =
   0 0.0800 0.0300 0.3100 0.0200 0.0800 0.1300 0.3500
```

DST code

Once bbas are combined, to decide just use the functions mtobel, mtopl or mtobetp, etc.

In Matlab

mtopl(mConj)

0 0.2800 0.2800 0.5000 0.1200 0.3900 0.3700 0.5900

mtobetp(mConj)

0.4209 0.4040 0.1751

mtopl(mDis)

0 0.8200 0.8200 0.9800 0.5800 0.9700 0.9200 1.0000

mtobetp(mDis)

0.3917 0.3667 0.2417

DST code

DST code for the combination:

- criteria=1 Smets criteria
- criteria=2 Dempster-Shafer criteria (normalized)
- criteria=3 Yager criteria
- criteria=4 disjunctive combination criteria
- criteria=5 Dubois criteria (normalized and disjunctive combination)
- criteria=6 Dubois and Prade criteria (mixt combination)
- criteria=7 Florea criteria
- criteria=8 PCR6
- criteria=9 Cautious Denoeux Min for non-dogmatics functions
- criteria=10 Cautious Denoeux Max for separable functions
- criteria=11 Hard Denoeux for sub-normal functions
- criteria=12 Mean of the bbas

DST code

decisionDST code for the decision:

- criteria=1 maximum of the plausibility
- criteria=2 maximum of the credibility
- criteria=3 maximum of the credibility with rejection
- criteria=4 maximum of the pignistic probability
- criteria=5 Appriou criteria

DST code

test.m:

```
m1=[0 0.4 0.1 0.2 0.2 0 0 0.1]';
m2=[0 0.2 0.3 0.1 0.1 0 0.2 0.1]';
m3=[0.1 0.2 0 0.4 0.1 0.1 0 0.1]';

m3d=discounting(m3,0.95);

M_comb_Smets=DST([m1 m2 m3d],1);
M_comb_PCR6=DST([m1 m2],8);

class_fusion=decisionDST(M_comb_Smets',1)
class_fusion=decisionDST(M_comb_PCR6',1)
class_fusion=decisionDST(M_comb_Smets',5,0.5)
```

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General framework

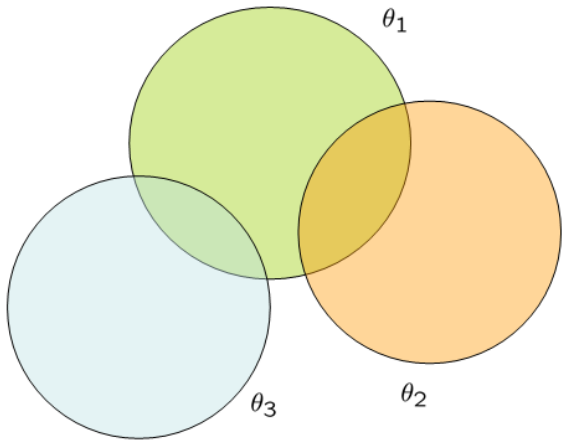
- Main problem of the DST code: all elements must be coded (not only the focal elements)
- Only usable for belief functions defined on power set (2^Ω)
- General belief functions framework works for power set and hyper power set (D^Ω)

DSmT introduced by Dezert, 2002.

- D^Ω closed set by union and intersection operators
- D^Ω is not closed by complementary, $A \in D^\Omega \nRightarrow \overline{A} \in D^\Omega$
- if $|\Omega| = n$: $2^\Omega << D^\Omega << 2^{2^\Omega}$
- D_r^Ω: reduced set considering some constraints ($\omega_2 \cap \omega_3 \equiv \emptyset$)

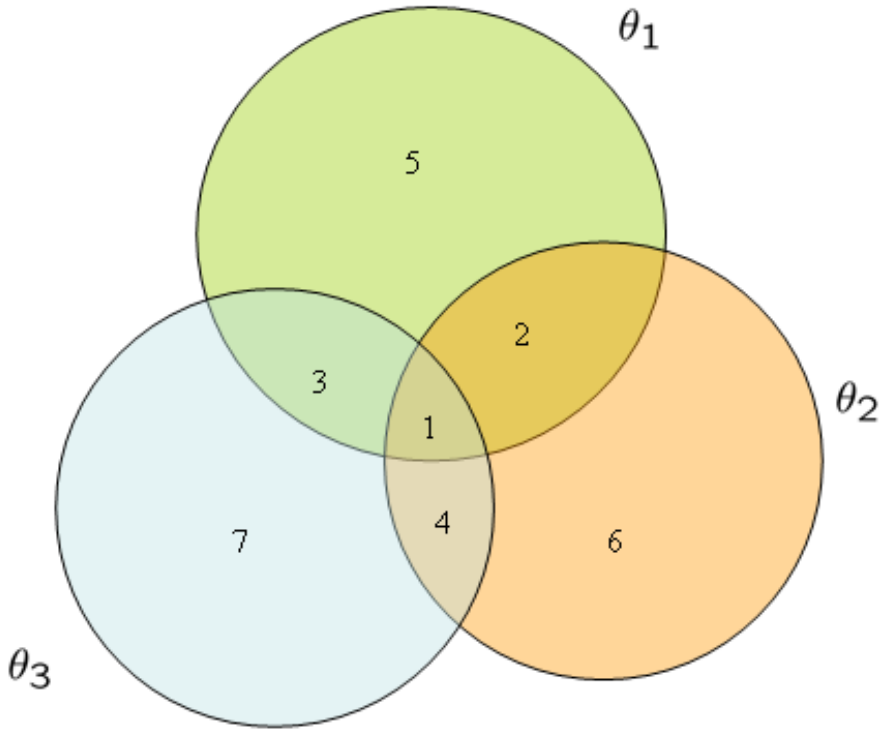
$$\mathrm{GPT}(X) = \sum_{Y \in D_r^\Omega, Y \not\equiv \emptyset} \frac{\mathcal{C}_\mathcal{M}(X \cap Y)}{\mathcal{C}_\mathcal{M}(Y)} m(Y)$$

where $\mathcal{C}_\mathcal{M}(X)$ is the cardinality of X in D_r^Ω



General framework: codification

A simple codification (Martin, 2009)
Affect an integer of $[1; 2^n - 1]$ to each distinct part of Venn diagram de Venn ($n = |\Omega|$)

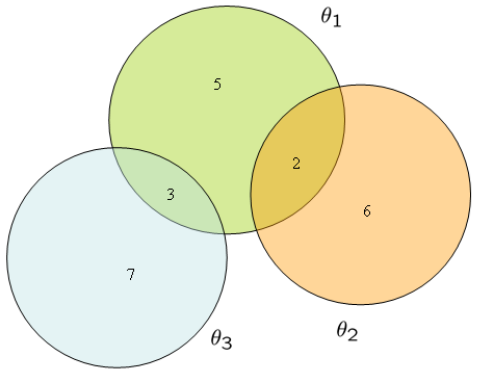


$$\Omega = \{[1\ 2\ 3\ 5], [1\ 2\ 4\ 6], [1\ 3\ 4\ 7]\}$$

General framework: codification

Adding a constraint: if $\Omega = \{[1\ 2\ 3\ 5], [1\ 2\ 4\ 6], [1\ 3\ 4\ 7]\}$ and we know $\omega_2 \cap \omega_3 \equiv \emptyset$ (*i.e.* $\omega_2 \cap \omega_3 \notin D_r^\Omega$)
The parts 1 and 4 of Venn diagram do not exist:

$$\Omega_r = \{[2\ 3\ 5], [2\ 6], [3\ 7]\}$$



Operations on focal elements

$$\omega_1 \cap \omega_3 = [3]$$
$$\omega_1 \cup \omega_3 = [2\ 3\ 5\ 7]$$
$$(\omega_1 \cap \omega_3) \cup \omega_2 = [2\ 3\ 6]$$

The cardinality $\mathcal{C}_\mathcal{M}(X)$: the number of intergers in the codification of X

Gives an easy Matlab programmation of the combination rules and the decision functions

General framework: codification

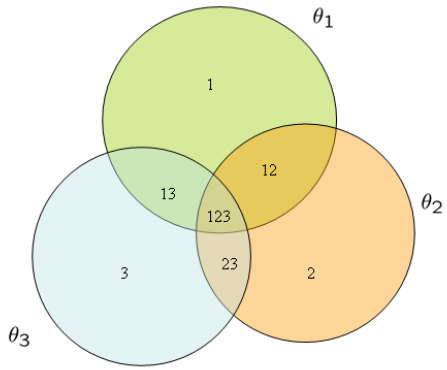
Decoding: to present the decision or a result to the human - *The codification is not understandable*

If the decision set is given, we just have to sweep the corresponding part of D_r^Ω

Without any knowledge of the element to decode:

1. We can use the Smarandache condification more lisible but less practical in Matlab

2. We sweepp all D_r^Ω (first considering 2^Ω). There is a combinatorial risk.



General framework

Description of the problem frame='A','B','C','D';
% list of experts with focal elements and associated bba
expert(1).name='Source 1';
expert(1).focal='1' '2u3u4' '1u2u3u4';
expert(1).bba=[0.47 0.18 0.35];
expert(1).discount=1; % No discount

expert(1).name='Source 2';
expert(2).focal={'1' '2' '1u3' '1u2u3'};
expert(2).bba=[0.3 0.4 0.2 0.1];
expert(1).discount=0.1; % high discount

constraint={''}; % set of empty elements e.g. '1n2'

General framework

In test.m

Description of the problem

elemDec={'A'}; % set of decision elements:

- list of elements on which we can decide,
- A for all,
- S for singletons only,
- F for focal elements only,
- SF for singleton plus focal elements,
- Cm for given specificity, e.g. elemDec={'Cm' '1' '4'}; minimum of cardinality 1, maximum=4,
- 2T for only 2^{Ω} (DST case)

General framework

Parameters

Combination citerium

criteriumComb = is the combination criterium

- criteriumComb=1 Smets criterium
- criteriumComb=2 Dempster-Shafer criterium (normalized)
- criteriumComb=3 Yager criterium
- criteriumComb=4 disjunctive combination criterium
- criteriumComb=5 Florea criterium
- criteriumComb=6 PCR6
- criteriumComb=7 Mean of the bbas

Parameters

Combination citerium

criteriumComb = is the combination criterium

- criteriumComb=8 Dubois criterium (normalized and disjunctive combination)
- criteriumComb=9 Dubois and Prade criterium (mixt combination)
- criteriumComb=10 Mixt Combination (Martin and Osswald criterium)
- criteriumComb=11 DPCR (Martin and Osswald criterium)
- criteriumComb=12 MDPCR (Martin and Osswald criterium)
- criteriumComb=13 Zhang's rule

General framework

Parameters

Decision citerium

criteriumDec = is the combination criterium

- criteriumDec=0 maximum of the bba
- criteriumDec=1 maximum of the pignistic probability
- criteriumDec=2 maximum of the credibility
- criteriumDec=3 maximum of the credibility with reject
- criteriumDec=4 maximum of the plausibility
- criteriumDec=5 Appriou criterium
- criteriumDec=6 DSmP criterium

General framework

Parameters

Mode of fusion

mode='static'; % or 'dynamic'

Display

display = kind of display

- display = 0 for no display,
- display = 1 for combination display,
- display = 2 for decision display,
- display = 3 for both displays,
- display = 4 for a comparison decision display,
- display = 5 for a comparison decision display with figures

Backup

nameTest = name of the test. No parameter, no backup

Wframe = to display with the complet frame legend

General framework

Fusion

fuse(expert,constraint,frame,criteriumComb,criteriumDec,mode, elemDec,display)

Called functions:

- Coding: call coding, addConstraint, codingExpert
- Combination: call combination
- Decision: call decision
- Display: call decodingExpert, decodingFocal

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Random bbas (see RandomMass.m)

In Matlab:

1. OmegaSize=3;
2. nbFocalElement=4;
3. ind=randperm(2^OmegaSize);
4. indFocalElement=ind(1:nbFocalElement);
5. randMass=diff([0; sort(rand(nbFocalElement-1,1)); 1]);
   We take the difference between 3 ordered random number in [0,1], e.g. diff([0; [0.3; 0.9] ; 1]) gives 0.3 0.6 0.1
6. MasseOut(indFocalElement,i)=randMass;

Random bbas (see RandomMass.m)

- focal elements can be evrywhere:
  ind=randperm(2^OmegaSize);
- focal elements not on the emptyset:
  ind =1+randperm(2^OmegaSize-1);
- no dogmatic mass: one focal element is on Omega (ignorance):
  ind =[2^OmegaSize randperm(2^OmegaSize-1)];
- no dogmatic mass: one focal element is on Omega (ignorance) and focal elements are not on the emptyset
  ind =[2^OmegaSize (1+randperm(2^OmegaSize-2))]
  (nbFocalElement==OmegaSize):
- all the focal elements are the singletons:

```
ind=[ ];
for i=1:OmegaSize
   ind=[ind; 1+2^(i-1)];
end
```

Distance based model (Denœux 1995)

Only ω_i and Ω are focal elements, $n * m$ sources (experts)

- Prototypes case ($\mathbf{x}_i$ center of ω_i). For the observation x

$$\begin{aligned} m_j^i(\omega_i) &= \alpha_{ij} \exp[-\gamma_{ij} d^2(x, \mathbf{x}_i)] \\ m_j^i(\Omega) &= 1 - \alpha_{ij} \exp[-\gamma_{ij} d^2(x, \mathbf{x}_i)] \end{aligned}$$

  - $0 \leq \alpha_{ij} \leq 1$: discounting coefficient and $\gamma_{ij} > 0$, are parameters to play on the quantity of ignorance and on the form of the mass functions
  - The distance allows to give a mass to x higer according to the proximity to ω_i
- belief k-nn: we consider the k-nearest neigborhs insteed to $\mathbf{x}_i$
- Then we combine the bbas

Distance based model (Denœux 1995)

In Matlab (Denœux codes)

See ExampleIris.m

```
load iris
ind=randperm(150);
xapp=x(ind(1:100),:);
Sapp=S(ind(1:100));
xtst=x(ind(101:150),:);
Stst=S(ind(101:150));
[gamm,alpha] = knndsinit(xapp,Sapp); % initialization
[gamm,alpha,err] = knndsfit(xapp,Sapp,5,gamm,0); % parameter
                                                 optimization
[m,L] =knndsval(xapp,Sapp,5,gamm,alpha,0,xtst); % test
[value,Sfind]=max(m);
[mat_conf,vect_prob_classif,vect_prob_error]=build_conf_matrix(Sfind,Stst)
```

Probabilistic based model $^{(1/6)}$

- Need to estimate $p(S_j|\omega_i)$
- 2 models proposed by Appriou according to both axioms:
  1. the $n * m$ couples $[M_i^j, \alpha_{ij}]$ are distinct information sources where focal elements are: ω_i, ω_i^c and Ω
  2. If $M_i^j = 0$ and the information is valid $(\alpha_{ij} = 1)$ then it is certain that ω_i is not true.

Probabilistic based model (2/6)

Model 1: $m^i_j(\omega_i) = M^j_i$ $\quad$ $m^i_j(\omega^c_i) = 1 - M^j_i$

Model 2: $m^i_j(\Omega) = M^j_i$ $\quad$ $m^i_j(\omega^c_i) = 1 - M^j_i$

Adding the reliability α_{ij} with the discounting:

Model 1:

$$\begin{aligned} m^i_j(\omega_i) &= \alpha_{ij} M^j_i \\ m^i_j(\omega^c_i) &= \alpha_{ij}(1 - M^j_i) \\ m^i_j(\Omega) &= 1 - \alpha_{ij} \end{aligned}$$

Model 2:

$$\begin{aligned} m^i_j(\omega_i) &= 0 \\ m^i_j(\omega^c_i) &= \alpha_{ij}(1 - M^j_i) \\ m^i_j(\Omega) &= 1 - \alpha_{ij}(1 - M^j_i) \end{aligned}$$

Probabilistic based model (3/6)

How to find M_i^j?
3th axiom:

3 Conformity to the Bayesian approach (case where $p(S_j|\omega_j)$ is exactly the reality ($\alpha_{ij} = 1$) for all i, j) and all the *a priori* probabilities $p(\omega_i)$ are known)

Probabilistic based model (4/6)

Model 1: $M_i^j = \dfrac{R_j p(S_j|\omega_j)}{1 + R_j p(S_j|\omega_j)}$

$$\begin{aligned} m_j^i(\omega_i) &= \frac{\alpha_{ij} R_j p(S_j|\omega_j)}{1 + R_j p(S_j|\omega_j)} \\ m_j^i(\omega_i^c) &= \frac{\alpha_{ij}}{1 + R_j p(S_j|\omega_j)} \\ m_j^i(\Omega) &= 1 - \alpha_{ij} \end{aligned}$$

with $R_j \geq 0$ a normalization factor.

Probabilistic based model (5/6)

Model 2: $M_i^j = R_j p(S_j|\omega_j)$

$$\begin{aligned} m_j^i(\omega_i) &= 0 \\ m_j^i(\omega_i^c) &= \alpha_{ij}(1 - R_j p(S_j|\omega_j)) \\ m_j^i(\Omega) &= 1 - \alpha_{ij}(1 - R_j p(S_j|\omega_j)) \end{aligned}$$

with $R_j \in [0, (\max_{S_j,i}(p(S_j|\omega_j)))^{-1}]$

In practical:

- α_{ij}: discounting coefficient fixed near 1 and $p(S_j|\omega_j)$ can be given by the confusion matrix
- Adapted to the cases where we learn one class against all the others

Probabilistic based model (6/6)

In Malab:

- take the previous confusion matrix or mat_conf=[68 12 22 ; 9 42 5 ; 8 2 87]
- mat_mass= bbaType(mat_conf,alpha,model): gives all the possible bbas (*i.e.* number of classes) for the given confusion matrix, alpha (a constant such as 0.95) and the model (1 or 2)
- bbas=buildBbas(Stst,mat_conf,alpha,model): gives the bbas resulting of the founded classes given in Stst

Probabilistic vs Distance

Difficulties:

- Appriou: learning the probabilities $p(S_j|\omega_j)$
- Denœux: choice of the distance $d(x, \mathbf{x}_i)$

Easiness:

- $p(S_j|\omega_j)$ easer to estimate on decisions with the confusion matrix of the classifiers
- $d(x, \mathbf{x}_i)$ easer to choose on the numeric outputs of classifiers (ex.: Euclidean distance)

References

- Toolboxes: on http://www.bfasociety.org
  iBelief: R package:
  https://cran.rstudio.com/web/packages/ibelief/index.html
- a lot of papers on: http://www.bfasociety.org

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