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Non-specificity-based Supervised Discretization for Possibilistic Classification

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Context and Motivation

MAL - Decision Intelligence

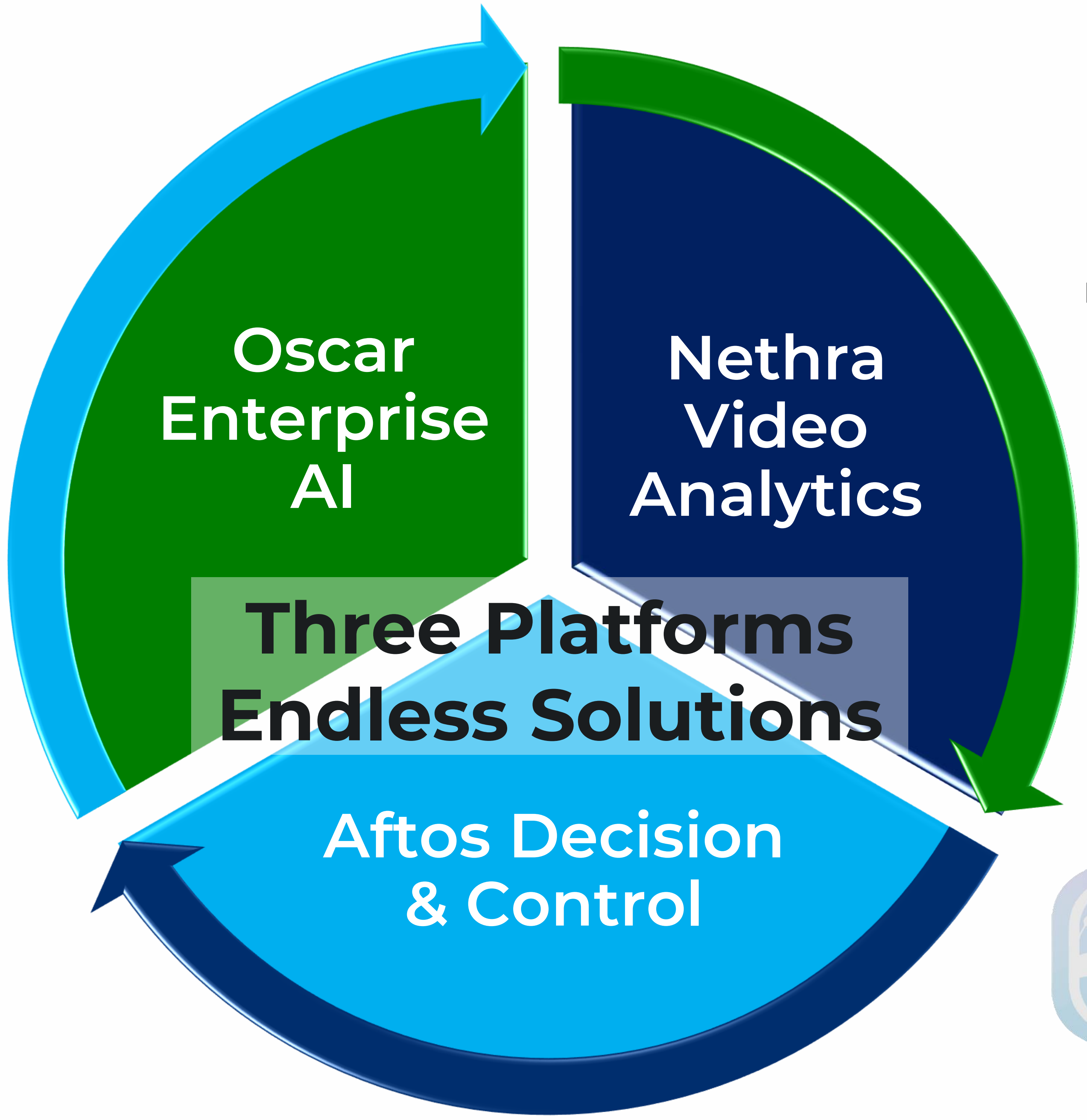
Massive Analytic is a Deep-tech Scale-up specialising in Decision Intelligence.

MAL's suite of platforms can be integrated for implementation to generate world-beating decision support and control outputs.

Combine and Analyse

- Data Fusion
- Data Processing
- Analysis and learning
- Create models

OSCAR
DATA SCIENCE



NETHRA
VIDEO ANALYTICS

Generate Data from video and imagery

- Extract information from video imagery
- Objects, movement and behaviour
- Flexible models and complex workflows

AFTOS
ROBOTICS

Automate, Simulate, Predict, Decide and Control

- Complex scenarios
- Many actors and variable
- Simulate and predict scenarios
- Real-time operations
- Strategic option analysis

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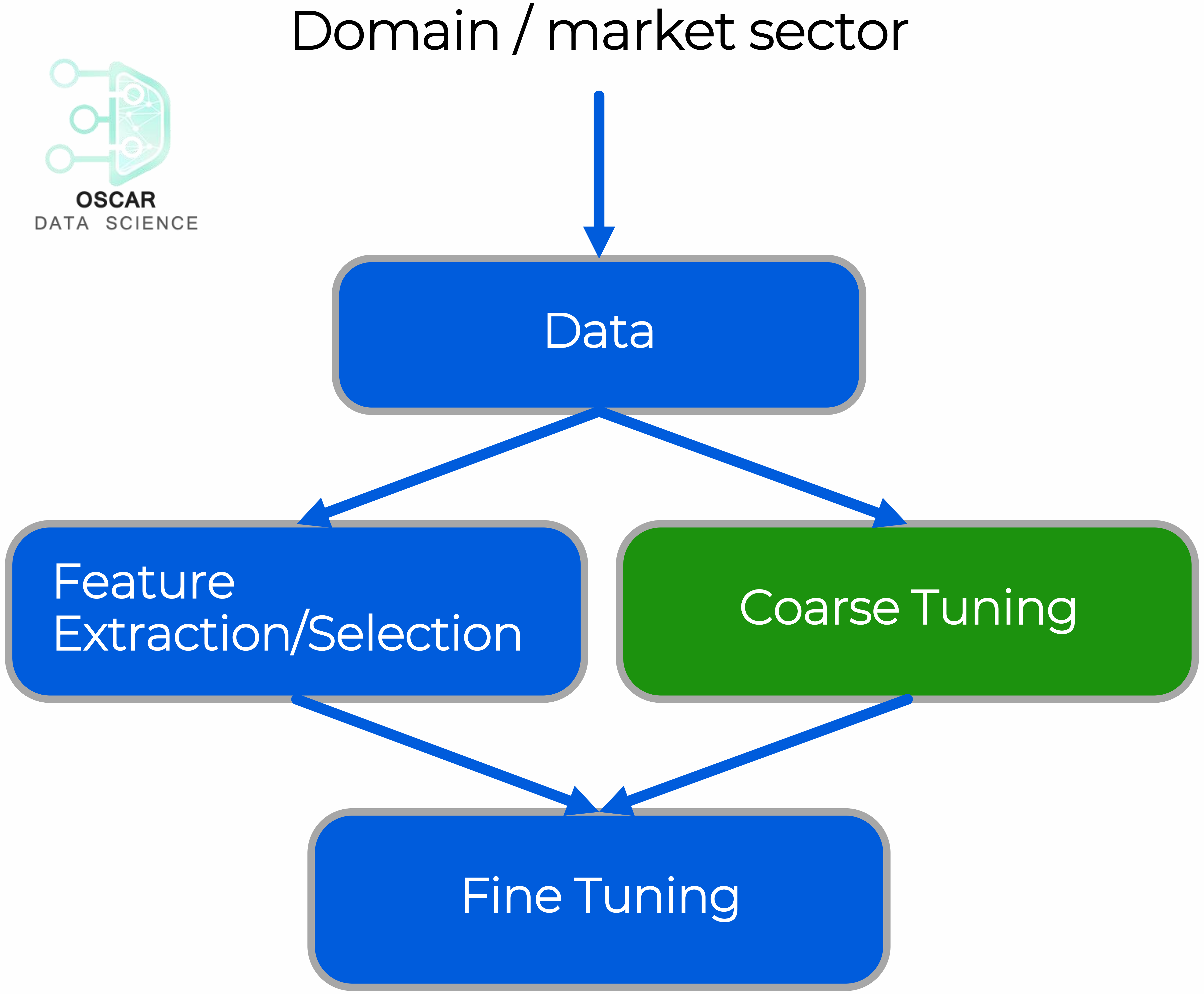
OSCAR Workflow

- Coarse Tuning: deploy possibilistic algorithms not available in competitive platforms
- Feature Extraction/Selection: extend the performance and explainability of in-house solutions with new datasets
- Fine Tuning: Outperform competitive platforms in the achieved accuracies of AI pipelines

OSCAR
DATA SCIENCE



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Problem Statement & Objective

- Real Data: multiple formats (numerical, categorical, mixed)
- Possibilisitc Decision Trees [Jenhani et al. 2008] ONLY handle Categorical features.
- Discretization of numeric features requires ignoring the possibilistic labels!

How to discretize numeric features without ignoring the uncertainty in the class labels?

Possibilistic Datasets and Non-Specificity based Possibilistic Decision Trees (NSPDT)

Jenhani I., Ben Amor N., Elouedi Z. :**Decision Trees as Possibilistic Classifiers**, *International Journal of Approximate Reasoning*, 48(3):784–807, 2008.

Standard Dataset Vs. Possibilistic Dataset

n instances; m features; c class labels

Standard dataset

	Feature 1	Feature 2	…	Feature m	Class label
1	23.5	0	…	Low	C_2
2	13.75	1	…	Average	C1
…	…	…	…	…	…
n	20	1	…	High	C_1

Ground truth: each instance belongs to only one category and we know it with certainty

Possibilistic dataset

	Feature 1	Feature 2	…	Feature m	C_1	C_2	…	C_c
1	23.5	0	…	Low	0	1	…	.4
2	13.75	1	…	Average	1	0	…	0
…	…	…	…	…	…	…	…	…
n	20	1	…	High	1	1	…	0

Ground truth: each instance belongs to only one category but we are uncertain about it

Possibilistic Dataset

Notations π

- Ω : the universe of discourse (e.g. $\{C_1, \ldots, C_c\}$)
- x : a variable with an unknown value (e.g. The class label of an object)
- ω : an element of Ω (e.g. C_2)
- L : the possibilistic scale (e.g. [0, 1])

	Feature 1	Feature 2	…	Feature m	C_1	C_2	…	C_c
1	23.5	0	…	Low	0	1	…	.4
2	13.75	1	…	Average	1	0	…	0
…	…	…	…	…	…	…	…	…
n	20	1	…	High	1	1	…	0

Possibility distribution π

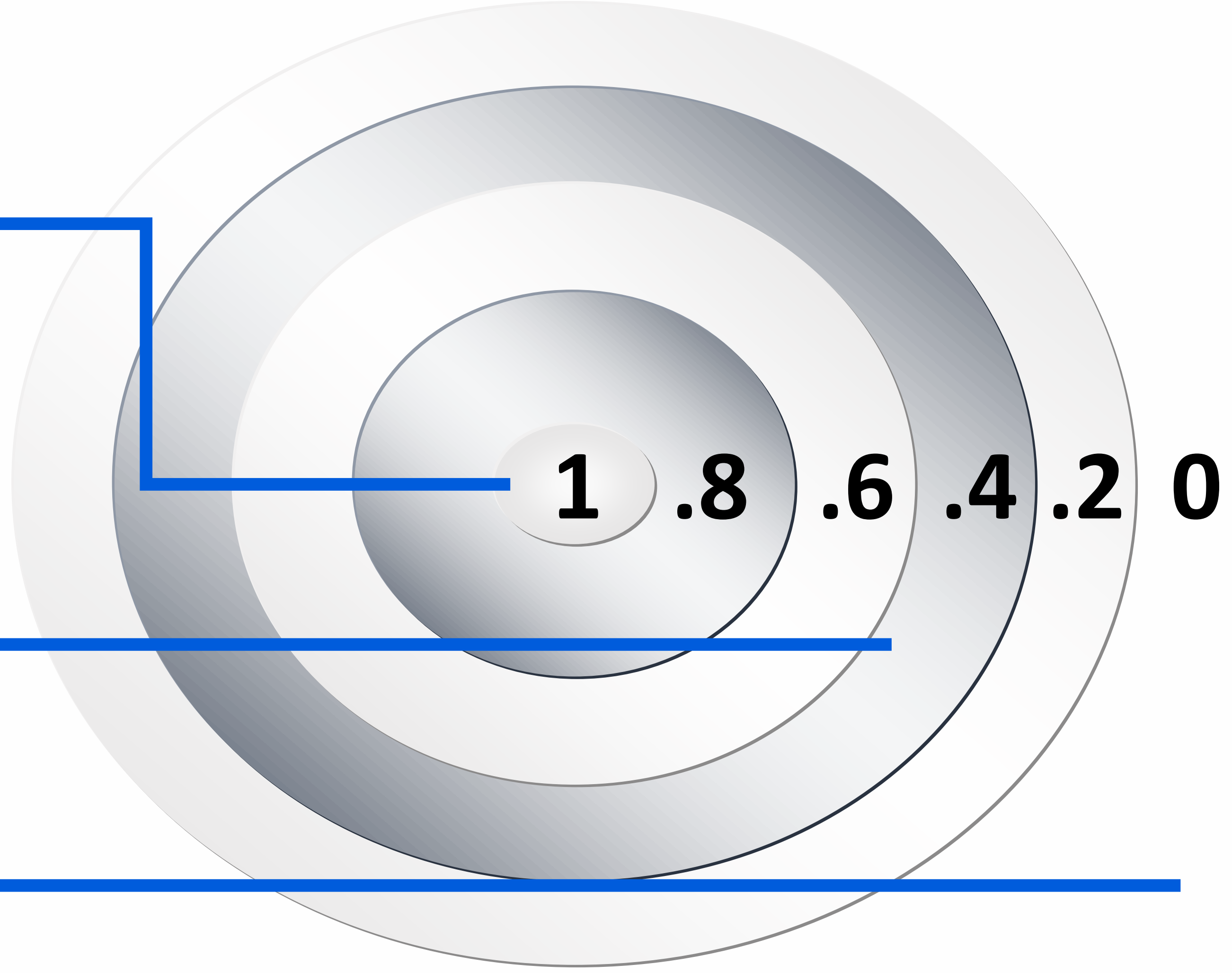
π
$: \Omega \rightarrow [0, 1]$
$\omega \rightarrow \pi_x(\omega)$

The possibility degree that x is ω

Fully possible ($\pi_C(C_2)=1$)

Possible

Totally Impossible ($\pi_C(C_1)=0$)



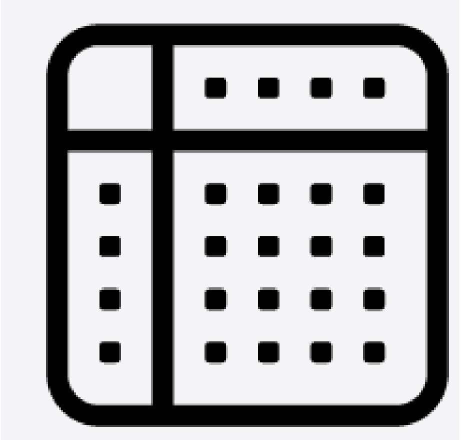
Possibilistic dataset – how to get it?

Option 1: a SME will annotate the dataset with the possibility distributions

[<u>Challenge</u>: SME should understand that a possibility distribution is not a probability distribution…]

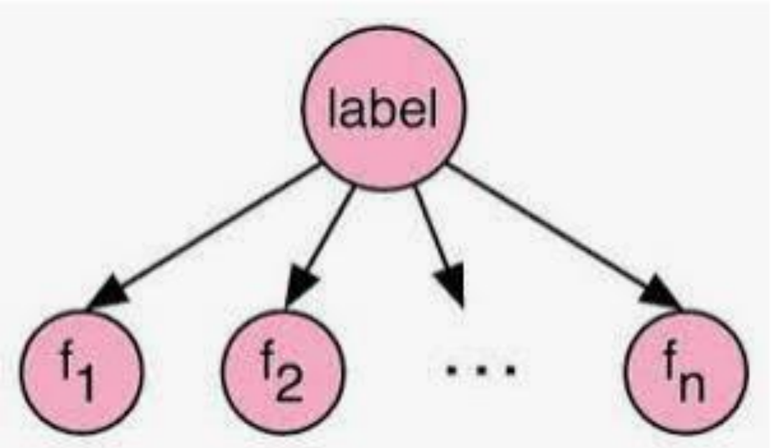
Option 2: Generate the possibilistic dataset from a standard dataset using the following procedure:

	Feature 1	Feature 2	…	Feature m	C_1	C_2	…	C_c
1	23.5	0	…	Low	0	1	…	.4
2	13.75	1	…	Average	1	0	…	0
…	…	…	…	…	…	…	…	…
n	20	1	…	High	1	1	…	0



Standard dataset

1

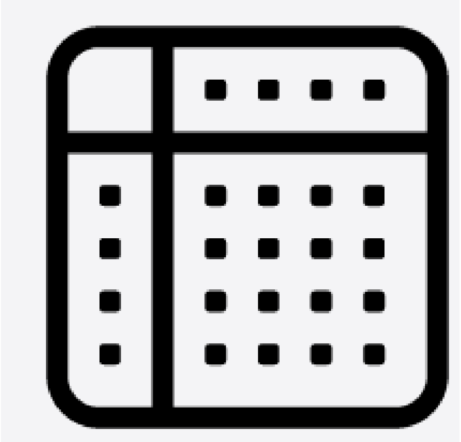


Train a Naïve Bayes model

2

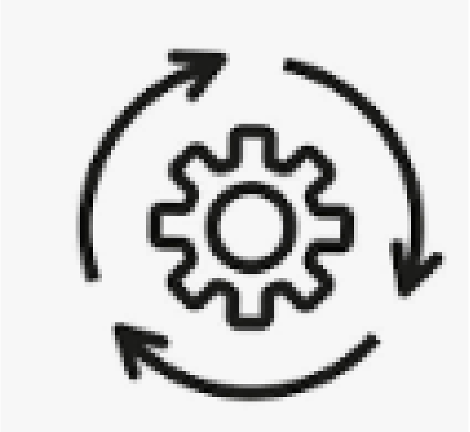
Drop the class labels from the initial standard dataset and feed it to the trained Naïve Bayes model

3



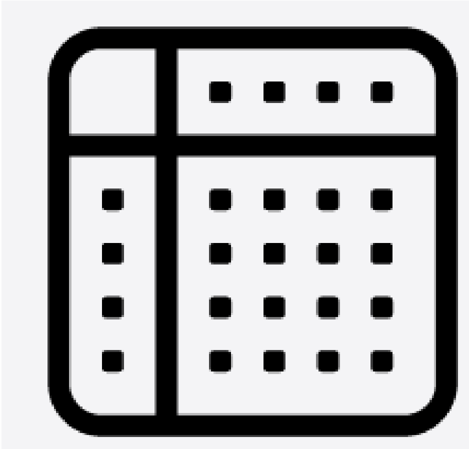
Probabilistic dataset : each label is now a probability distribution

4



Probability - Possibility transformation

5



Possibilistic dataset

- <u>Pros</u>: detects hidden class uncertainty in datasets
- <u>Cons</u>: little information compromise

Other options also exist…

NS-PDT

Building decision trees from training sets with imprecise class labels using the concept of non-specificity

Imprecise Tr

Income	Property	UnCredit	C_1	C_2	C_3
High	Greater	No	1	0.1	0.3
High	Greater	Yes	0.8	1	0.6
High	Greater	No	1	0.5	0.3
High	Less	Yes	0	1	0
Average	Greater	No	1	0	0.4
Average	Greater	Yes	0.7	1	0.2
Average	Less	No	0.7	1	0.7
Average	Less	Yes	0	1	0.3
Low	Less	No	0.5	0.5	1
Low	Less	Yes	0	0.3	1

NS-PDT: attribute selection measure

Using Non-Specificity

Partition 1

[1 0.3 0.6] [0 1 0.7]

[1 0 0] [1 0.3 1]

[0 0.6 1] [0.5 1 0.1]

→ π_{avg}^{1} [0.58 0.53 0.56]

→ π_{rep}^{1} [1 0.91 0.96]

→ $U(\pi_{rep}^{1}) = 1.49$

Partition 2

[1 1 0.3] [0.7 0 1]

[0.2 0.8 1] [1 0.3 1]

[1 0.6 0] [0 1 0]

→ π_{avg}^{2} [0.65 0.61 0.55]

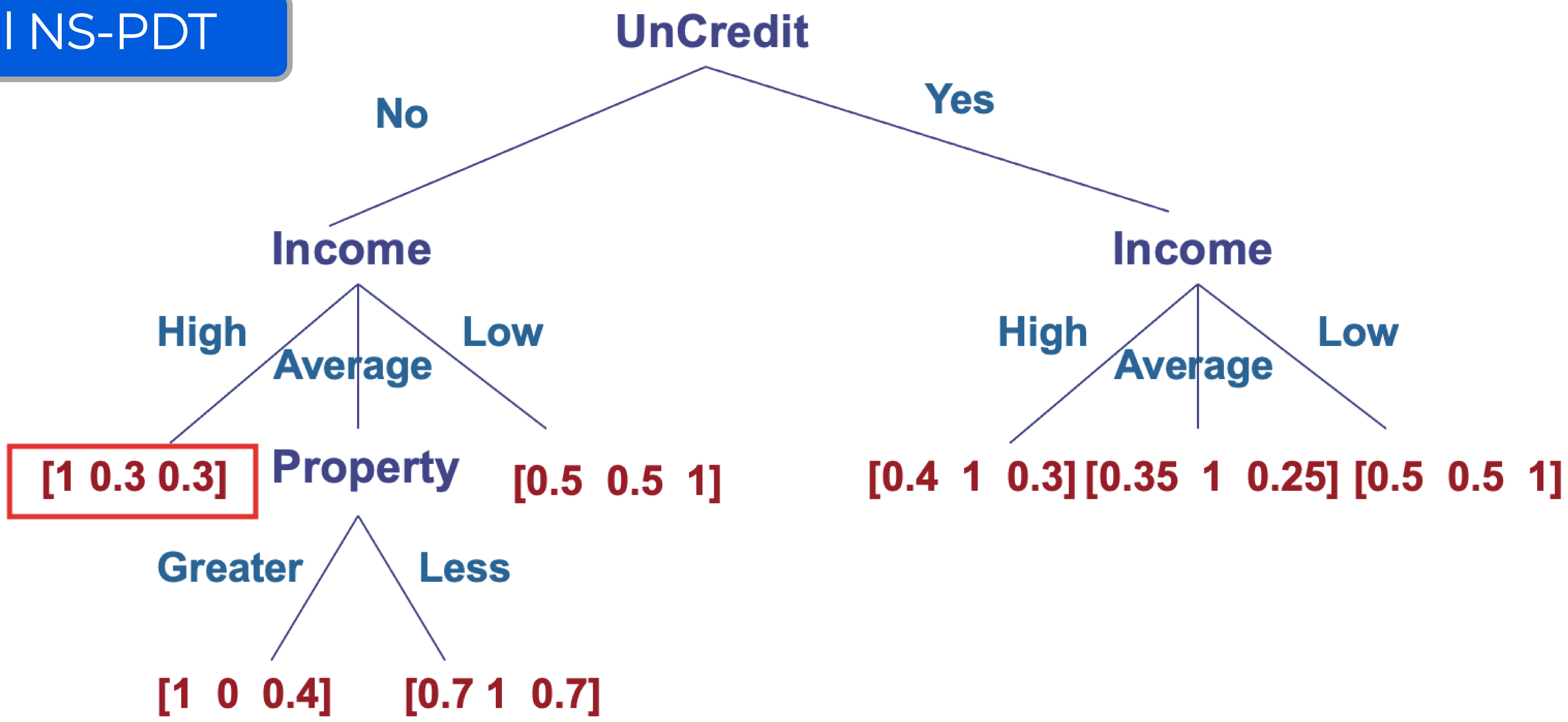
→ π_{rep}^{2} [1 0.93 0.84]

→ $U(\pi_{rep}^{2}) = 1.42$

→ Partition n°2 is more specific

Classification using NS-PDT

→ Final NS-PDT



We can predict the class of the instance: <High, Greater, No>:?

The Non-Specificity based Discretization

Standard Discretization Algorithm [Fayyad and Irani, 93]

	F_i	L
	0.1	O
	0.1	O
	0.1	O
t_1	0.3	X
	0.3	X
	0.4	X
	0.5	X
	0.5	X
t_2	0.5	O
	0.6	O
	0.6	O
	0.7	O
	0.7	O
	0.8	O
t_3	0.9	X
t_4	0.9	O
	0.9	O
t_5	0.9	X
	0.9	X

T_1

T_2

Total: 19 instance, 8: X 11: O

1. Sort instances in ASC order (by F_i)
2. Find cut point *t* that maximizes Gain(T,t)

   t: the average between 2 F_i values around the boundary point (when class label changes).

T: training partition, t: threshold that will split T into 2 sub-partitions:

- T_1 : Instances where $F_i \leq t$
- T_2 : Instances where $F_i > t$

3. Repeat from 2 for each generated sub-partition until stopping criterion is met

Possibilistic Discretization Algorithm

Cut	F_i	$\pi(X)$	$\pi(O)$	Partition
	0.1	1	0.8	T_1
	0.1	0.5	1	
t_1	0.1	0.8	1	
	0.3	1	0.2	T_2
	0.3	1	0.6	
t_2	0.4	1	0	
t_3	0.5	0.1	1	
	0.5	1	0.5	
t_4	0.5	1	0.3	
	0.6	0	1	
t_5	0.6	0.2	1	
	0.7	1	0	
	0.7	1	0.6	
	0.8	0.8	1	
t_6	0.9	1	0.7	
t_7	0.9	0.3	1	
	0.9	1	0.6	
	0.9	1	0.2	
	0.9	1	0.1	

Total: 19 instance

1. Sort instances in ASC order (by F_i)
2. Find cut point *t* that maximizes NSGain(T,t)

   Cut points: when *InfoAff* $(\pi_i, \pi_{i+1}) \leq \eta$ (hyper-parameter, default: 0.7)

   T: training partition

   t: cut point that will split T into 2 sub-partitions:

   - T_1 : Instances where $F_i \leq t$
   - T_2 : Instances where $F_i > t$

3. Repeat from 2 for each generated sub-partition until stopping criterion is met: NSGain ≤0

$$InfoAff([0.8,1],[1,0.2]) = 1 - \frac{\left(\frac{0.2+0.8}{2}\right) + 1 - (\max(\min(0.8,1), \min(1,0.2)))}{2}$$

$$= 1 - \frac{0.5+0.2}{2} = 0.65 \ (\leq 0.7 \text{ so cut point})$$

For t_1: $NSGain(T, t1 = 0.2) = U(\pi_{rep(T)}) - \left(freq_{T_1} * U(\pi_{rep(T_1)}) + freq_{T_2} * U(\pi_{rep(T2)})\right)$

$\pi_{rep}(T)$: max – normalized average possibility distribution representing T

Possibilistic Similarity Measure

Information Affinity: *[Jenhani, Benferhat and Elouedi; ECSQARU'07, IPMU'08, Foundation of Reasoning under Uncertainty, 2010]*

Definition let π_1 and π_2 be two possibility distributions on the same universe of discourse Ω. We define a measure *InfoAff* (π_1, π_2) as follows:

$$InfoAff(\pi_1,\pi_2) = 1 - \frac{d(\pi_1,\pi_2) + Inc(\pi_1 \wedge \pi_2)}{2}$$

Where $d(\pi_1,\pi_2) = \frac{1}{n}\sum_{i=1}^{n}|\pi_1(\omega_i) - \pi_2(\omega_i)|$ represents the Manhattan distance between π_1 and π_2 and $Inc(\pi_1 \wedge \pi_2)$ tells us about the degree of conflict between the two distributions.

$$Inc(\pi) = 1 - \max_{\omega\in\Omega}\{\pi(\omega)\}$$

Non-specificity Measure

U-uncertainty: ***[Klir and Folger, 1988]***

$$U\colon \mathcal{R} \to \mathbb{R}^{+}$$

where $\mathcal{R}$ denotes the set of all finite, ordered, and normal possibility distributions.

Given a possibility distribution

$$\mathrm{r} = (\mathrm{r}_1, \mathrm{r}_2, \ldots, \mathrm{r}_\mathrm{n}) \text{ such that } 1 = \mathrm{r}_1 \geq \mathrm{r}_2 \geq \cdots \geq \mathrm{r}_\mathrm{n}$$

The U-uncertainty of r, U(r), can be expressed by :

$$\mathrm{U}(r) = \sum_{i=2}^{n} (r_i - r_{i+1})\, log_2\ \mathrm{i} = \sum_{i=2}^{n} r_i log_2 \frac{i}{i-1}$$

where $\mathrm{r}_{n+1} = 0$ by convention.

Algorithm: Illustration

F_i	π(X)	π(O)
0.1	1	0.8
0.1	0.5	1
0.1	0.8	1
0.3	1	0.2
0.3	1	0.6
0.4	1	0
0.5	0.1	1
0.5	1	0.5
0.5	1	0.3
0.6	0	1
0.6	0.2	1
0.7	1	0
0.7	1	0.6
0.8	0.8	1
0.9	1	0.7
0.9	0.3	1
0.9	1	0.6
0.9	1	0.2
0.9	1	0.1

T_1, T_2, t_1, t_2, t_3, t_4, t_5, t_6, t_7

19 Total: 19 instance

π_T(X)=(1+0.5+0.8+1+…+1)/19=0.774

π_T(O)=(0.8+1+1+0.2+…+0.1)/19=0.61

$\pi_{rep(T)}$(X)	$\pi_{rep(T)}$(O)
1	0.79

U(π_{rep}(T))=(1-0.79)*$\log_2$(1)+(0.79-0) *$\log_2$(2)=0.79

π_{T2}(X)=(1+1+1+0.1+…+1)/16=0.775

π_{T2}(O)=(1+0.6+0+1+…+0.1)/16=0.55

$\pi_{rep(T2)}$(X)	$\pi_{rep(T2)}$(O)
1	0.7

U(π_{rep}(T_2))=(1-0.7)*$\log_2$(1)+(0.7-0) *$\log_2$(2)=0.7

π_{T1}(X)=(1+0.5+0.8)/3=0.766

π_{T1}(O)=(0.8+1+1)/3=0.933

$\pi_{rep(T1)}$(X)	$\pi_{rep(T1)}$(O)
0.821	1

U(π_{rep}(T1))=(1-0.821)*$\log_2$(1)+(0.821-0) *$\log_2$(2)=0.821

NSGain(T, t_1=0.2)=0.79-[(16/19)*0.7+(3/19)*0.821]=0.07

Similarly, we compute NSGain(T, t_2=0.45), NSGain(T, t_3=0.5), … then select max

The consecutive selected thresholds will form the cutoff points.

Experimental Setup and Results

Datasets [UCI ML Repository]

Dataset	#instances	#classes	#features	#continuous features
Letter recognition	20 000	26	16	16
Dry Bean	13 611	7	16	16
Magic Gamma Telescope	19 020	2	10	10
Occupancy Detection	9 752	2	5	5
Spambase	4 601	2	57	57
Adult	48 842	2	14	6
Bank Marketing	45 211	2	20	10

Possibilistic versions of these datasets have been generated using Option 2 (NB + Proba-Poss transformation)

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Results – Crisp datasets

Dataset	Classifier	Mean Acc. (Non dic.)	Mean Acc. (Std. disc.)	Mean Acc. (NS-disc.)
Letter Recognition	NB	64.01	**73.85**	70.6
	J48	**87.92**	78.75	80.59
	RF	**96.41**	93.41	92.61
	1-NN	**95.96**	91.86	89
	LogReg	91.24	**92.84**	90.14
Dry Bean	NB	89.7	**89.94**	88.5
	J48	**91.03**	90.05	90.25
	RF	**92.5**	91.47	91.14
	1-NN	**90.2**	89.25	90.2
	LogReg	**92.6**	92.3	**92.6**
Magic Gamma Telescope	NB	72.68	**78.25**	75
	J48	**85.05**	84.45	77.57
	RF	**88**	84.04	77.46
	1-NN	80.93	**81.97**	77.42
	LogReg	79.11	**84.68**	77.5
Occupancy Detection	NB	95.34	99.1	**99.33**
	J48	95.86	**99.37**	**99.37**
	RF	**99.4**	**99.4**	99.37
	1-NN	94.99	**99.37**	**99.37**
	LogReg	99.24	**99.35**	**99.35**
Spambase	NB	85.24	**90.19**	85.78
	J48	82.59	**92.82**	91.58
	RF	**95.5**	94.59	93.87
	1-NN	85.28	**93.1**	92.24
	LogReg	92.41	**94.41**	91.58
Adult	NB	83.25	**83.87**	82.35
	J48	86.1	**86.67**	85.45
	RF	85.17	**85.4**	84.75
	1-NN	79.52	83.04	**84.13**
	LogReg	85.09	**87.23**	85.58
Bank Marketing	NB	88	**88.88**	**88.88**
	J48	90.31	**90.32**	88.88
	RF	**90.38**	89.92	88.87
	1-NN	86.96	88.83	**88.87**
	LogReg	90.15	**90.4**	88.87

Crisp dataset

F1	F 2	…	F m	C_1	C_2	…	C_c
23.5	0	…	Low	0	1	0	0
13.75	1	…	Average	1	0	0	0
…	…	…	…	…	…	…	…
20	1	…	High	0	1	0	0

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Results - Possibilistic datasets

Dataset (Discretized)	NS-PDT
Letter recognition	• CMPcc: 60.2% • InfoAffC: 0.871
Dry Bean	• CMPcc: 88.47% • InfoAffC: 0.963
Magic Gamma Telescope	• CMPcc: 81.65% • InfoAffC: 0.836
Occupancy Detection	• CMPcc: 95.9% • InfoAffC: 0.956
Spambase	• CMPcc: 97.9% • InfoAffC: 0.84
Adult	• CMPcc: 96.66% • InfoAffC: 0.96
Bank Marketing	• CMPcc: 86.82% • InfoAffC: 0.882

CMPcc: Cautious Most Plausible-based correct classification

$$CMPcc = \frac{\text{number of correctly classified instances}}{\text{total number of testing instances}} \times 100$$

InfoAffC: Information Affinity Criterion

$$\text{InfoAffC} = \frac{1}{n} \sum_{i=1}^{n} InfoAff\left(\pi_i^{\text{init}}, \pi_i^{\text{pred}}\right)$$

Conclusion and Future work

Conclusion and Future work

- A supervised discretization approach has been proposed for possibilistic (labelled) data
- Non-specificity and Information Affinity measures are used by the main building blocks of the proposed algorithm.
- The proposed pre-processing discretization approach will make it possible to use several possibilistic classifiers which were initially designed to handle categorical data only.
- With crisp data, NS discretization showed competitive results.
- More suitable for possibilistic data

Future work:

- Consider feature dependency during discretization instead of discretizing each feature individually.
- Handle unbalanced feature intervals.

Thank you!

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