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Dynamic Frames and Semantic Information

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Abstract

The concept of information was introduced in the middle of the last century by Shannon and since then an entire branch of research has been developing into what is called Mathematical Theory of Communication which deals with studying the amount of information exchanged in a communication channel. In this article we want to use the concept of information to analyze the Dynamic Frames developed by Barsalou in Cognitive Science.

Keywords: Semantic Information, Dynamic Frame

1. Introduction

Information is a concept whose meaning we have not recovered from ancient philosophy or Christian theology, but it is a purely modern concept; hence the difficulty in its definition and the multiple meanings that have been assigned to the concept. Shannon for example, highlights this difficulty in the following way: "... *It is hardly to be expected that a single concept of information would satisfactorily account for the numerous possible applications of this general fields.*" [1].

Information is usually associated with something independent of the user, which has semantic content (has a meaning) and which is transmitted through multiple means (texts, websites, maps...).

It is usually conceived in terms of "data + meaning" and Floridi gave a general definition by stating that σ – the basic unit of information (infon) – is an instance of semantic information if it consists of data that is correctly formatted and has meaning [15]. Information is therefore composed of data, but is not determined only by them; so what is their role? To better understand these aspects, let's consider the following simple example: let's examine a page of a book written in an unknown language and notice that we are in possession of some data without meaning; if we delete half the page, we will have half the amount of data but still no meaning; even if we leave just one symbol on the page, we still have data – a small amount – and always no meaning. In these three cases we are in possession of data that is not significant and therefore we have no information. If we now delete the last symbol and leave the page completely blank, we are in the presence of data (the empty page), but with a meaning (the page has no semantic content); the latter case provides us with some information even if it seems like we don't have any data available. Information is therefore not linked only to the presence of data, but is rather conceived as a lack of uniformity, as Bateson reminds us when he asserts "*In fact, what we mean by information ... is a difference which makes a difference*" [3].

1.1 Semantic Information

When it comes to the concept of information, we are usually dealing with the Statistical Theory of Information proposed by Shannon, but it – as its name states – has to do with the statistical properties of the information transmitted in a communication channel. Shannon's theory does not deal with the most significant aspect of the term information, namely its semantic content [2]. The first to address the problem from this point of view were Carnap and Bar-Hillel and since then the theory they developed has been called semantic theory of information[1]. In both theories information is defined in terms of a certain concept of probability:

$$\inf(\sigma) = -\log\big(p(\sigma)\big)$$

where σ[2] represents the probability of the infon and from it, it is possible to obtain the concept of entropy associated with information:

[1]The Carnap and Bar-Hillel Theory is defined by Floridi as Weak Semantic Theory of Information in contrast to the Strong Semantic Theory of Information proposed by Floridi himself.

[2]σ represents an instance of information such as a symbol, a proposition or an event.

$$H = -\sum_{\sigma} p(\sigma) inf(\sigma)$$

where the summation is done on each individual infon. Although the two theories use the same mathematical structure, the concept of probability on which they are based is different: in statistical theory – where we are interested in repeatable situations in the long term – a frequentist interpretation of probability is presupposed, while in semantic theory – in which we are interested in the different alternatives that are made available to us by language – we use a logical interpretation of probability.[3] [4]. To assign probability to the different alternatives made available in a certain linguistic context it is necessary to identify some principle that facilitates us in this task; from a heuristic point of view, it can be stated that the more precise a proposition is, i.e. it eliminates any other possibilities, and the greater the information it conveys. This consideration is formalized in the Inverse Relationship Principle, which states that "*the amount of information associated with a proposition is inversely related to the probability of that proposition*". Based on this principle it is possible to define the content of information as:

$$cont(\sigma) = 1 - p(\sigma)$$

which can be easily traced back to the amount of information (inf) introduced previously, with the equation:

$$inf(\sigma) = \log\frac{1}{1 - cont(\sigma)}$$

Carnap and Bar-Hillel's semantic theory is based on the principle just described and is developed for monadic first-order logic. In this regard, consider a class of languages, each of which is made up of a finite series of monadic predicates (naming properties), which apply to an equally finite number of individual constants (naming individual) and which can be composed with the usual logical connectors. From a formal point of view, a language is defined as a set $L_m^n = (\{c_1 \dots c_n\}, \{P_1 \dots P_m\})$ made up of n individual constants c_i and m predicates P_j. The propositions $P_j\, c_i$ is an atomic sentence and indicates that the constant c_i has the property P_j. It is possible to construct an arbitrary number of other propositions, based on the atomic ones and using logical connectors. Of particular importance are those combinations that involve the conjunction of predicates (negated or non-negated) applied to all individual constants in such a way that each constant appears only once in the proposition: such propositions are called state-descriptions (they are usually represented with the letter *w*). The set of state descriptions constitutes the logical space and each state description represents a possible state of the world. On the logical space it is possible to define one or more probability measures *m*(-)[4] which are associated with the corresponding confirmation function:

$$c(\sigma, e) = \frac{m(\sigma \wedge e)}{m(e)}$$

where e represents the empirical evidence with respect to σ[5]

To give a concrete example, let's examine a language made up of 3 individual constants and a single predicate, the formalization of which is $L_1^3 = (\{a,b,c\},\{F\})$: the logical space generated by this language is made up of 8 state descriptions and it is proposed in the following table:

State	Propositions	m	cont	inf	State	Propositions	m	cont	inf
w_1	$Fa \wedge Fb \wedge Fc$	0.125	0.875	3.0	w_5	$\neg Fa \wedge \neg Fb \wedge Fc$	0.125	0.875	3.0
w_2	$\neg Fa \wedge Fb \wedge Fc$	0.125	0.875	3.0	w_6	$\neg Fa \wedge Fb \wedge \neg Fc$	0.125	0.875	3.0
w_3	$Fa \wedge \neg Fb \wedge Fc$	0.125	0.875	3.0	w_7	$Fa \wedge \neg Fb \wedge \neg Fc$	0.125	0.875	3.0
w_4	$Fa \wedge Fb \wedge \neg Fc$	0.125	0.875	3.0	w_8	$\neg Fa \wedge \neg Fb \wedge \neg Fc$	0.125	0.875	3.0

Table 1: Example of a Language L_1^3

[3]Carnap reported the difference in two disjoint concepts of probability: propability[1] for the statistical interpretation and probability[2] for the logical interpretation (degree of confirmation: a quantitative concept representing the degree to which the assumption of the hypothesis h is supported by the evidence e.)

[4]The choice of the probability measure is determined for example by the symmetric structures that are identified in the logical space (consider for example Carnap's m* function).

[5]From now on we will replace the generic infon σ with a proposition/hypothesis h linked to the linguistic context being considered.

We can underline that each state is equiprobable – $m(w_i) = 0.125$ – and need 3 bits of information in order to be defined – $inf(w_i) = 3$ bit.

2. Dynamic Frame

The concept of dynamic frame was introduced into cognitive psychology by Barsalou and represents a cognitive structure in which conceptual and empirical information are represented in a precise and determined manner [5,6]. Dynamic frames have been used profitably in the Philosophy of Science to analyze scientific concepts [7] and conceptual change [8, 14] but also in the history of science [9,10].

In short, a frame is an attribute-value matrix that has the task of representing how some characteristics (the values) are the instance of other properties (the attributes). The typical example used to illustrate what a dynamic frame consists of is the one associated with the concept of 'bird', the graphic representation of which is shown in Fig.1. The leftmost element is the concept bird which is called "*superordinate concept*"; in the central box there are the attributes {beak, foot} and the values associated with them[6]. The last column of the diagram corresponds to "*subordinate concepts*" – or derived concepts which are a specialization of the main concept and activate only certain values[7]. The red arrow instead represents a constraint that exists between the 'beak' attribute and the 'foot' attribute. The constraints are links that intervene between attributes or between values and the most significant ones are the constraints that exist between values [8].

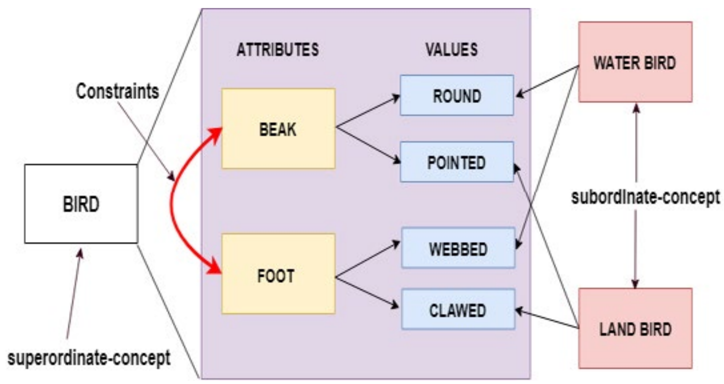

Figure 1: Dynamic Frame of 'Bird' Concept

In the following, we will only consider constraints between values. To better understand the nature of constraints, let us examine the contribution offered by Strößner, who proposed a probabilistic extension of frames in which the values assumed by the attributes and their constraints are associated with a probability distribution [11]. If we take the classic example of the concept of bird, we know that the structure of the foot (clawed, webbed) determines the different modes of locomotion (flying, swimming and walking); so for example a 'flying bird' typically has 'clawed feet'. These correlations (the constraints in Barsalou's terms) are described by conditional probabilities which are reported in the following summary table [12].

		P(fly)	P(swim)	P(walk)
		0.75	0.15	0.10
		Joint probability distribution		
P(clawed)	0.80	0.72	0.00	0.08
P(webbed)	0.20	0.03	0.15	0.02
		Conditional probability		
P(… | clawed)		0.90	0.00	0.10
P(… | webbed)		0.15	0.75	0.10

Table 2: Probability Distribution of Bird Concept

[6]E.g. the beak attribute has the values {round, pointed}.
[7]E.g. subordinate concepts are "water bird" and "land bird".
[8]E.g. in the case of the subordinate concept 'water bird' there is the constraint that the webbed feet (foot = WEBBED) always correspond to the rounded beaks (beak = ROUND).

The second row shows the marginal probabilities of the values assumed by the 'Locomotion' attribute, while the second column shows the marginal probabilities associated with the values of the 'Foot' attribute. In the central part of the table, you have the joint probabilities of the various attributes; so for example we have that $P(foot = clawed, loc = fly) = 0.72$. Finally, at the bottom of the table, you have the conditional probabilities based on the 'Foot' attribute; for example, $P(loc = fly \mid foot = clawed)=0.90$. Note that $P(swim \mid clawed)=0$ represents a 'deterministic' constraint since a 'bird' is never observed that has swimming locomotion and 'clawed' legs.

We can report the data of Table 2 in the following probabilistic dynamic frame:

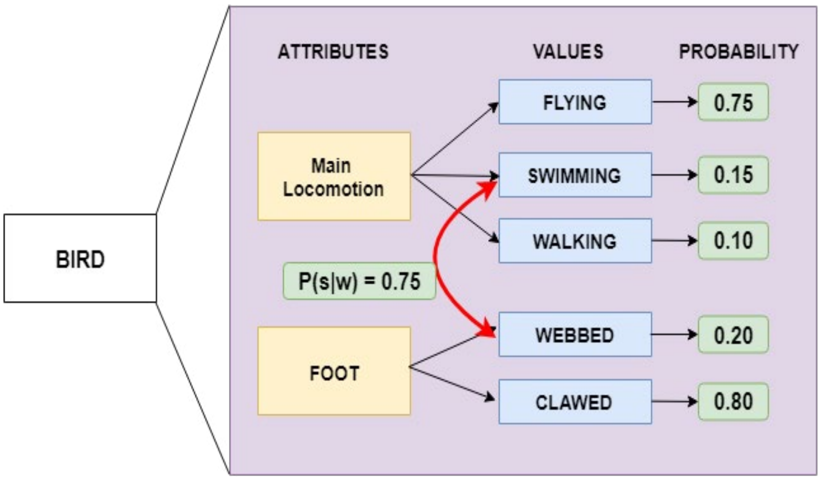

Figure 2: Probabilistic Dynamic Frame of 'Bird' Concept

Where a column on the right has been added to show the probability of each value and the constraint between the webbed and swimming values has been specified through a conditional probability. Note however that in this case the constraint is defined between the ‘Foot’ attribute and the ‘Main locomotion’ attribute as the conditional probability is specified for each value, as highlighted in Table 2.

But what is the effect of a constraint in these probabilistic frames? When the concept specializes, that is, when an attribute assumes a certain value belonging to a constraint, the probability of the constrained value is equal to the conditional probability; in our example we have

$$\text{foot} = \text{webbed} \rightarrow \mathrm{P}(\text{webbed}) = 1; \mathrm{P}(\text{swimming}) = \mathrm{P}(\text{swimming}|\text{webbed}) = 0.75$$

The constraint also modifies the probabilities of the other values according to a weighted formula. If we indicate with $\{W_i\}$ and $\{V_j\}$ the values assumed by the two attributes W and V and suppose that there is a constraint between V_1 and W_1 represented by the conditional probability $P(W_1 \mid V_1)$ the probabilities of the values W_i – with $W_i \neq W_1$ – are changed according to the following formula:

$$\mathrm{P}'(\mathrm{W_i}) = \mathrm{P}(W_i)\frac{1 - P(W_1|V_1)}{1 - P(W_1)}$$

If we now consider the composite concept ‘foot-webbed-bird’ that is obtained when the foot attribute takes the value webbed and the locomotion values are modified according to the previous formula, we have a new probabilistic dynamic frame:

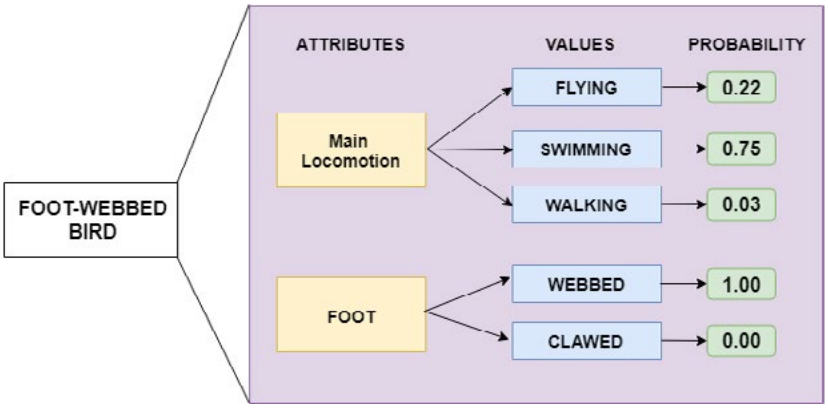

Figure 3: Probabilistic dynamic frame of 'foot-webbed bird' concept

where it is observed that the attribute foot has assumed the value 'webbed' (probability = 1) and the probability distribution linked to the attribute 'Main Locomotion' has changed according to the formula.

The changes of the probability distribution of an attribute's values by a constraint, highlights that in the probabilistic approach the constraints are a global characteristic; this aspect is highlighted further if we observe that the link between two values V_1 and W_1 is bidirectional as can be seen using Bayes' theorem:

$$P(V_1|W_1) = \frac{P(W_1|V_1) \cdot P(V_1)}{P(W_1)}$$

In our example we can calculate $P\,(webbed \,|\, swimming)$ that have the value:

$$P(\text{webbed}|\text{swimming}) = \frac{P(swimming|webbed) \cdot P(webbed)}{P(swimming)} = \frac{0.75 \cdot 0.20}{0.15} = 1.0$$

which shows how the constraint on the foot structure imposes another constraint that determines how swimming birds have a webbed foot structure. We also have a derived constraint on 'clawed-footed bird', because this subtype of bird does not use swimming as main locomotion; in formula we have:

$$P(clawed|swimming) = 0 \text{ and so } P(swimming|clawed) = 0.$$

3. Semantic Information of a Dynamic Frame

Dynamic frames are a structure that can be represented with a first-order formulas and therefore the question of associating a quantity of information to the frame arises spontaneously based on the semantic theory of Carnap and Bar-Hillel [13]. The starting point is to show how an attribute of a frame can be represented by a language composed of monadic predicates and individual constants. To do this, consider an attribute $A = (a, \{V_1^a \ldots V_m^a\})$ and note that it can be related to a language L_m^1 composed of a single individual constant a – the attribute itself – and by m predicates, corresponding to the possible values assumed by the attribute. If attribute a has the value V_1 there is a proposition $V_1^a a$. which describes its state. The state descriptions that can be obtained by combining the predicates and the single individual constant with the usual logical connectors are $2^{n.m} = 2^m$. However, note that an attribute can take on one value at a time and this limits the number of state descriptions admissible to m; such states are called base-state description and are formally defined as:

$$b_i^a = V_i\left(\bigwedge_{j\neq i} \neg V_j\right)\text{a} = \neg V_1\text{a} \wedge \ldots \wedge \neg V_{\text{i}-1}\text{a} \wedge V_\text{i}\text{a} \wedge \neg V_{\text{i}+1}\text{a} \ldots \wedge \neg V_\text{m}\text{a}$$

Therefore, for an attribute we have the relation:

$$A = (a, \{V_1^a \ldots V_m^a\}) \Longrightarrow L_m^1 \Longrightarrow \{b_1^a \ldots b_m^a\}$$

Finally, if we consider the fact that a frame is a set of attributes, we will have:

$$\text{F} = (A_1 \ldots A_n) = \left(a_1, \{V_1^{a_1} \ldots V_m^{a_1}\}\right) \ldots \left(a_n, \{V_1^{a_n} \ldots V_r^{a_n}\}\right) \Longrightarrow \left(L_m^{a_1} \ldots L_r^{a_n}\right)$$
$$\Longrightarrow \left(\{b_1^{a_1} \ldots b_m^{a_1}\} \ldots \{b_1^{a_n} \ldots b_r^{a_n}\}\right)$$

The state descriptions of the dynamic frame will be the conjunction of the various base-state descriptions of the individual attributes. For example, if we have *n* attributes, each of which takes on certain values, the generic state description is given by the following formula:

$$w_{V_i^1 \ldots V_k^n} = b_i^{a_1} \wedge \ldots \wedge b_k^{a_n}$$

The set of all state descriptions generates the logical space associated with the dynamic frame. Once the logical space is known, it is necessary to define a probability measure on it. If the constraints between the values are not considered, the state descriptions are equally probable and therefore we have for a generic state $m(w_{V_i^1 \ldots V_k^n}) = 1/n$. However, if we consider the constraints between the values we can use the confirmation function equation – introduced previously – to impose restrictions on the probability measure. A constraint corresponds to stating that in the face of evidence in which a certain attribute takes on a certain value ($V_j\, b$), the hypothesis that another attribute takes on a certain other value ($V_i\, a$) is certain: in formulas we have[9]

$$h = V_i a\,,\; e = V_j b \Longrightarrow c(h, e) = \frac{m(h \wedge e)}{m(e)} = \frac{m(V_i a \wedge V_j b)}{m(V_j b)} = 1.0$$

Once the probability measure on the logical space has been determined we can calculate the amount of information of a state-description as $\inf(w_i) = -\log(m(w_i))$ and hence the amount of information in the entire frame:

$$inf(F) = \sum_i m(w_i) \cdot inf\big(m(w_i)\big)$$

where index i run on the state-descriptions of the logical space associated with the dynamic frame.
To make the formulation developed so far clearer, let's consider our example of the dynamic frame of the concept 'bird', limiting ourselves to the attribute's 'beak' and 'foot' (see Fig.1).

The frame is represented by:

$$bird = (beak, foot) = \big((beak, \{Round, Pointed\}), (foot, \{Webbed, Clawed\})\big)$$
$$= \big((b, \{R, P\}), (f, \{W, C\})\big)$$

and the logical space is reported in the following table:

State	Propositions	Sub-concept	m	inf
w_1	$(R \wedge \neg P)b \wedge (W \wedge \neg C)f$	water-bird	0.5	1.0
w_2	$(R \wedge \neg P)b \wedge (\neg W \wedge C)f$	-	0.0	0.0
w_3	$(\neg R \wedge P)b \wedge (W \wedge \neg C)f$	-	0.0	0.0
w_4	$(\neg R \wedge P)b \wedge (\neg W \wedge C)f$	land-bird	0.5	1.0

Table 3: Logical Space of Bird Concept

Note how the state descriptions w_1 and w_2 correspond to the sub-concepts of the frame. To calculate the probability measure, constraints have been used; for example, if we impose the constraint *foot = webbed → beak = round,* where evidence *e* : *foot = webbed* confirms hypothesis *h* : *beak = round* we have the equation:

$$c(h, e) = \frac{m(Rb \wedge Wf)}{m(Wf)} = \frac{m(w_1)}{m(w_1) + m(w_3)} = 1 \Longrightarrow m(w_3) = 0$$

[9]The formula is also valid in the case in which for a given piece of evidence the probability of a certain hypothesis is zero.

Note also that the amount of information in the individual state descriptions with non-zero probability is equal to 1 bit; which is expected since a single data is sufficient to determine the state. Finally, the amount of information of the entire frame is:

$$inf(bird) = \sum_i m(w_i) \cdot inf\big(m(w_i)\big) = 0.5 \cdot 1.0 + 0.5 \cdot 1.0 = 1$$

In order to have the concept of bird completely determined we need the same amount of information as its subordinate concepts; this strange behaviour is due to the fact that the state descriptions are equiprobable.

So far, we have used deterministic constraints – where the conditional probability is 1/0 depending on the case – to determine the probabilities of the state descriptions in order to derive the amount of information; this strategy becomes difficult once the structure of the frames becomes complex. To overcome the difficulty, we can use the probabilistic dynamic frames introduced by Strößner and focus our attention on the bird concept of Fig. 2 and Fig. 3 which have a non-deterministic constraint.
The frame is represented as:

$$bird = (foot, motion) = \big((foot, \{Webbed, Clawed\}), (motion, \{Fly, Swim, Walk\})\big)$$
$$= \big((f, \{W, C\}), (m, \{F, S, K\}),\big)$$

We can consider three types of probabilistic dynamic frames, modifying the conditional probability distribution each time. Let us start by considering the case – which we call $bird_1$ – where the attributes of the concept are independent on each other, that is, let us suppose that the marginal probabilities expressed in Table 2 are associated to independent random variables. Then we can propose the example – that we call $bird_2$ – where we use the joint probability distribution of Table 2 and finally, we consider the distribution probability of 'foot-webbed-bird' – $bird_3$.

The logical space that we construct is described in the following table:

State	Propositions	p_1	Inf_1	p_2	Inf_2	p_3	Inf_3
w_1	$(W \wedge \neg C)f \wedge (\mathrm{F} \wedge \neg S \wedge \neg K)\mathrm{m}$	0.15	2.73	0.03	5.05	0.22	2.18
w_2	$(W \wedge \neg C)f \wedge (\neg\mathrm{F} \wedge S \wedge \neg K)\mathrm{m}$	0.03	5.05	0.15	2.73	0.75	0.41
w_3	$(W \wedge \neg C)f \wedge (\neg\mathrm{F} \wedge \neg S \wedge K)\mathrm{m}$	0.02	5.64	0.02	5.64	0.03	5.05
w_4	$(\neg W \wedge C)f \wedge (\mathrm{F} \wedge \neg S \wedge \neg K)\mathrm{m}$	0.60	0.73	0.72	0.47	0	0
w_5	$(\neg W \wedge C)f \wedge (\neg\mathrm{F} \wedge S \wedge \neg K)\mathrm{m}$	0.12	3.05	0	0	0	0
w_6	$(\neg W \wedge C)f \wedge (\neg\mathrm{F} \wedge \neg S \wedge K)\mathrm{m}$	0.08	3.64	0.08	3.64	0	0

Table 4: Logical Space of $bird_i$

The columns p_i and Inf_i are related to the corresponding concepts $bird_i$. If we consider the quantity Inf_i of state descriptions – which correspond to the various sub concepts – we note that some of them require a significantly greater amount of information than others; this behaviour also allows us to define a ranking among the sub concepts to identify the most common ones from those that occur more rarely. So, for example we note how the state w_4 of the second dynamic frame is by far the most common; in fact – as we expect – it corresponds to a bird that has clawed feet and that moves by flying.

We can finally calculate the amount of information for the three examples:

$$inf(bird_1) = 1.738 > inf(bird_2) = 1.303 > inf(bird_3) = 0.938$$

From which it is easy to deduce that the stronger the constraints of the dynamic frame are, the smaller the amount of information needed to define them; in fact in the example $bird_1$ there are no constraints between values/attributes, in $bird_2$ there are constraints that connect the values of the attribute 'foot' to the values of the attribute 'locomotion' expressed by a conditional probability distribution and finally in in $bird_3$ – which represents a composite concept – there is a deterministic constraint.

4. Conclusion

In this article we presented a formalism that allows us to associate a quantity of semantic information with a dynamic frame and observed how the elimination of constraints between values determines a greater quantity of information necessary to define the frame. In order to obtain this result, we also use the probabilistic dynamic frame introduced by Strößner, that associate a probability distribution to each value of the frame and to their constraints.

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