Proposition of a semi-automatic possibilistic information scoring process

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Abstract

This paper proposes a semi-automatic three step information scoring process that starts from constructs representing structured pieces of information and a user query. It first identifies the constructs relevant to answer the user question, based on their similarity to the query. The relevant items are then individually scored, taking into account both the reliability of their source and the certainty the latter expresses through its choice of linguistic terms. Lastly, these individual scores are fused, modeling a corroboration process that takes into account information obsolescence and source relations. This procedure is performed in the framework of possibility theory, relying on the definition of the appropriate aggregation operators.

Keywords: information scoring, possibility theory, aggregation operators, fusion

1. Introduction

Information scoring aims at assessing the quality of information, and in particular the confidence that can be placed in it. It constitutes an essential tool for informational watch, especially in the context of the development of so-called open sources: the increased use of the Web makes it possible for everyone to participate in the information spread and to be a source of information. It is thus necessary to dispose of tools for automatically assessing the quality of information collected on the Internet. Their applications include economic and strategic watch, military intelligence, as well as fight against terrorism [1].

Due to this importance, information evaluation has been conceptualised and precisely defined by the NATO standardization agency, initially in the standard agreement STANAG2022 [2]. The latter defines the degree of confidence that can be placed in a piece of information as a two-dimensional variable, distinguishing two components: the reliability of the information source and the credibility of the informational content, understood as its confirmation by other sources.

This initial definition, which has been shown to suffer several theoretical weaknesses [3, 4, 1], has been enriched by other dimensions, defining e.g. the source reliability as deriving from its relevance and its truthfulness [5, 6] or the information plausibility with respect to *a priori* knowledge [4, 7]. Several formalisms have been proposed to model the quality assessment, among which multivalued logic [8] and evidence theory [6, 9, 10].

In this paper we consider the issue of information scoring with the aim of assessing the confidence that can be attached to an event e, based on a set of textual documents: the objective is to answer a question of the type “did e take place?”, enriching the binary answer yes/no with a confidence level.

To that aim, we propose a semi-automatic scoring process illustrated on Figure 1: it starts from structured constructs automatically extracted from textual documents and consists of three main steps. First the relevant constructs, which can contain helpful indications on the answer, are identified. Then each of these relevant constructs is individually scored, to determine the answer it provides to the question and its associated confidence level. For the latter we propose to take into account both the reliability of the source and its own certainty, as expressed by the specific linguistic tags it uses. Lastly, the individual scores of the relevant constructs are aggregated into a final score. In this step we propose to take into account a temporal dimension, to reduce the effect of older, and possibly out-of-date, pieces of information, as well as the relationships between the sources: the latter make it possible to refine the notions of confirmation and invalidation, weighting them according to affinity or hostility relations between sources, e.g. to reduce the confirmation effect if the two sources are known to be friends.

Formally, we propose to represent the confidence level in the framework of possibility theory: the aim is to estimate the possibility distribution associated with the considered event e, more precisely to compute the values of the possibility degrees $\pi(e)$ and $\pi(\neg e)$. Then if $\pi(e) = 1$, the answer is positive, e took place, and the necessity $N(e) = 1 - \pi(\neg e)$ gives the associated certainty, i.e. confidence level. If $\pi(\neg e) = 1$, then the answer is negative, with confidence $1 - \pi(e)$. If both $\pi(e)$ and $\pi(\neg e)$ equal 1, no certitude at all is available, the question can actually not be answered.

The paper is organised as follows: Section 2 gives

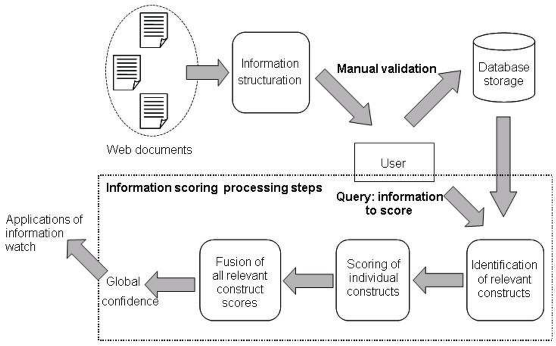

Figure 1: Proposed information scoring process.

a global view on the proposed process, describing its principles, inputs and outputs. The next sections detail the main steps of the proposed process: Section 3 describes the identification of the pieces of information relevant to score the confidence attached to the queried event, Section 4 presents their individual scoring. Lastly Section 5 describes the fusion of the individual scores into a global score.

2. Architecture of the proposed model

In this section, we give a global view on the proposed information scoring model represented on the lower part of Figure 1, whose upper part represents preprocessing steps described in Section 2.2. We first illustrate its expected behaviour with an example and then precisely detail its inputs and outputs.

2.1. Illustrative example

Throughout the paper we consider an example related to the double bomb attack in the Moscow metro on March 29th, 2010. We suppose the user wants to identify the author of these attacks from open-source collected information. More precisely, we consider that the news items summarised in Table 1 were collected: a few hours after the attacks, A. Bortnikov, director of the Russian Federation security agency, mentions the lead of the terrorist organisation called Caucasus Emirates, but on the following day, the leader of this organisation, D. Umarov, denies being responsible for the attacks. Nevertheless, on the day after, the Russian Home Secretary declares that this rebel organisation is involved in the attacks. Beside these pieces of information discussing the authors of the bomb attack, two other news items are available: one states the number of victims, while a fifth one actually is about a different bomb attack.

We then consider that the user asks the question "is the Caucasus Emirate organisation the author of the bomb attacks in Moscow of March 29th, 2010?" and expects a binary answer enriched with a confidence score.

It can be underlined that the previous set of news is representative of the difficulties that can be encountered: although simplified, it contains both a succession of relevant and contradictory assertions, and pieces of information having a similar but useless content.

(i_1) A. Bortnikov, 03/29/10: "The Causasus Emirate rebels could be involved in the Moscow metro bombings of this morning"
(i_2) D. Umarov, 03/30/10: "The Causasus Emirate rebels are not involved in yesterday Moscow bombings"
(i_3) Russian Home Secretary, 03/31/10: "The Causasus Emirate rebels are involved in the Moscow metro bombings of March 29th, 2010"
(i_4) Russian Home Secretary, 03/31/10: "At least 26 people were killed and more than 60 injured in the two suicide bomb attacks on the Moscow metro"
(i_5) F. Shahzad, 06/21/10: "I want to plead guilty 100 times over for the failed Times Square bomb attack on May 1st, 2010 "

Table 1: Illustrative set of news items.

2.2. Inputs

The proposed information scoring process does not directly take into account the textual documents constituting the set of news items. The latter first undergoes a structuration process that extracts constructs as illustrated by Table 2 for the texts mentioned in Table 1: properties of the described event are extracted, depending on its type. In the case of a bomb attack for instance, they can include date, location, author, possibly number of victims; for meetings, they include date, location and involved participants, possibly the duration. It must be noted that for a given structured piece of information, all or only some of the properties may be available.

Furthermore, metadata are extracted from the news items, such as the publication date, the source and the certainty it expressed: sources usually make use of linguistic tags to indicate required caution or confidence in the event they report. These tags for instance include adjectives (such as certain, likely or improbable), modal verbs (e.g. may, might, could, should), adverbs or complex idiomatic structures. Modifiers, such as "very", can be used to reinforce or weaken the previous linguistic tags. The certainty expressed by a source is determined following the approach proposed by [11]: it relies on linguistic patterns whose results are aggregated into a global certainty level that can take 4 values, namely low, moderate, high or absolute.

The inputs of the proposed information scoring process thus include such a list of constructs, as illustrated by Table 2 for the news items given in Table 1. We suppose that these constructs do not contain errors, possibly thanks to a manual valida-

Id	Publication date	Source	Expressed certainty	Event type	Author	Location	Event date
c_1	03/29	A. Bortnikov	Low	Bomb attack	CE	Moscow	03/29
c_2	03/30	D. Umarov	Absolute	Bomb attack	not(CE)	Moscow	03/29
c_3	03/31	Russian Home Secretary	Absolute	Bomb attack	CE	Moscow	03/29
c_4	04/01	Russian Home Secretary	Absolute	Bomb attack	?	Moscow	03/29
c_5	06/21	F. Shahzad	Absolute	Bomb attack	F. Shahzad	New York	05/01
q	07/15	user	-	Bomb attack	CE	Moscow	03/29

Table 2: Example of information constructs and structured query, input of the model. CE denotes Causasus Emirate. All dates refer to 2010, which is omitted in the table.

tion by the user.

As represented on Figure 1, the user also provides his/her question as input. It is formalised in the same form as the construct: the last row of Table 2 shows the structured form of the question introduced in the illustrative example, "is the Caucasus Emirate organisation the author of the bomb attacks in Moscow of March 29th, 2010?", considering the user asks on July 15th. The metadata concerning expressed certainty is left empty, because it does not make sense for the query and would not be useful in the scoring process.

The information scoring then processes these inputs in three steps, as depicted in Figure 1 and described in Sections 3 to 5.

2.3. Output

The system is then expected to answer the question "did the event take place?", enriching the binary yes/no answer with a confidence level. Formally, we denote $\mathbf{e}$ the binary variable that can take its values in the domain $E = \{e, \neg e\}$, with $\mathbf{e} = e$ indicating a positive answer and $\mathbf{e} = \neg e$ a negative answer.

To model the uncertainty associated with $\mathbf{e}$, we propose to consider the framework of possibility theory that offers several advantages: it allows to model ignorance and subjective uncertainty, as opposed to probability that would not be appropriate. It offers a wide range of aggregation operators with increased flexibility as compared to the evidence theory when it comes to fuse several pieces of information. Moreover possibility theory is compatible with the fuzzy set theory that can be usefully exploited in the considered context, in particular to model imprecision occurring in natural languages texts, as discussed in Section 3.1.2.

Quantifying the uncertainty attached to $\mathbf{e}$ defined in the domain $E = \{e, \neg e\}$ then consists in estimating the possibility distribution π defined on E: the information scoring model aims at providing estimates of the values $\pi(e)$ and $\pi(\neg e)$. Then if $\pi(e) = 1$, the answer is positive, and the associated confidence level is computed as the necessity $1 - \pi(\neg e)$. If, on the contrary $\pi(\neg e) = 1$, then the answer is negative, with confidence $1 - \pi(e)$.

3. Semi-automatic identification of relevant constructs

The first step of the proposed information scoring process identifies, from the set of constructs, the ones that are susceptible of providing evidence on the answer and determines whether they answer positively or negatively the user question.

Given the diversity of linguistic forms that may be used to express an information, it is unlikely that all relevant constructs have exactly the same value for the properties of the considered event. Thus a semi-automatic process, as proposed in [12], seems more appropriate than an exact identification. To that aim, as detailed below, we propose to show the user a list of the information elements most similar to his/her query so that he/she can validate the list of selected constructs.

3.1. Similarity computation

3.1.1. Global similarity measure

We propose to define the similarity between constructs to be 0 if their event type is different. Indeed, in such a case, it is certain the constructs deal with different events and they are considered to be of no use to answer the question. Otherwise, the similarity value is computed as the aggregation of elementary similarities assessed for each property. The metadata (publication date, source, expressed certainty) are not taken into account to identify the relevant constructs.

More formally, denoting q the construct corresponding to the query and c the candidate construct, T_q and T_c their respective types, $p(q)$ and $p(c)$ the values they take for property p, S_p the elementary similarity measure associated with p and Agg an aggregation operator, the general form of the similarity measure is

$$S(c, q) = \begin{cases} 0 & \text{if } T_c \neq T_q, \\ Agg(S_p(p(c), p(q))) & \text{otherwise.} \end{cases}$$

It must be underlined that some property fields may be missing, either because they were omitted in the text or because the automatic structuration failed to identify them. In this case, it is not possible to compute the corresponding elementary similarity. The global similarity value must then be weakened:

we propose to weight the above value by multiplying it by the proportion of available properties among all possible properties.

For the definition of the elementary similarity measures S_p, three property types must be distinguished: numerical values, dates and symbolic concepts. To compare numerical values, we simply use a decreasing function of the difference between the two values [13]. We impose it to be normalised so that it is 1 when the two values are equal, and 0 when the difference is above a given threshold. In the following, we detail the definition of the similarity measures for dates and concepts.

3.1.2. Similarity between dates

Dates can be imprecise, i.e. known up to a day, a month or only a year, and it can be necessary to compare dates with different precision levels. Therefore we propose that, before comparison, each date is mapped to a fuzzy subset, triangular for a precise date (known up to the time level) or trapezoidal for imprecise dates. In the following, D_c and D_q denote the fuzzy subsets associated with the dates mentioned in the constructs to be compared.

The similarity measure should not be symmetrical: the query q plays the role of a reference to which c compatibility must be computed, leading us to choose a satisfiability measure [14].

Furthermore to avoid penalising too imprecise dates, which would discard constructs even if all other properties exactly match the requested values, we explicitly take into account the date precision: we define a precision level $pl(D)$ for a date D as 1 if D is only specified as a year, 2 if the month is available, 3 if the day is known and 4 if the time is also given. Denoting M a fuzzy subset measure [14] such as the area, the date similarity is then computed as

$$S_{date}(c,q) = \begin{cases} \frac{M(D_c \cap D_q)}{M(D_c)} & \text{if } pl(D_c) \geq pl(D_q), \\ \frac{M(D_c \cap D_q)}{M(D_q)} \frac{pl(D_c)}{pl(D_q)} & \text{otherwise.} \end{cases}$$

For the considered example, for $j = 1, ..., 4$, $S_{date}(c_j, q) = 1$ because the dates are precise and equal, whereas $S(c_5, q)$ depends on the support definition of the fuzzy subsets representing the dates. Yet, as the dates in c_5 and q differ by more than one month, whereas they are given up to the exact day, it seems sensible to consider that the fuzzy subsets would not intersect. Thus $S_{date}(c_5, q) = 0$.

3.1.3. Similarity between concepts

In order to compare locations and persons or organisations, we consider that they correspond to nodes in an available domain ontology, as illustrated in Figure 2 for geographical knowledge. This hypothesis is reasonable in the context of automatic information structuration, which usually also exploits such an ontology.

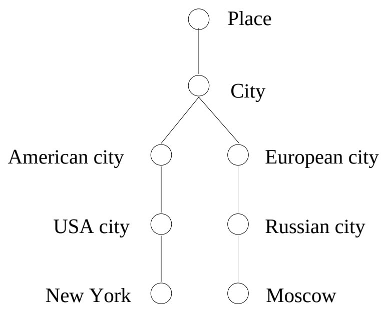

Figure 2: Extract of an ontology for geographical knowledge.

We then propose to use a classic ontology similarity [15]: the similarity between two concepts C_c and C_q depends on the length l of the shortest path between them and on the depth d of the deepest concept generalising both. More precisely it is computed as $S = 2d/(l + 2d)$.

For the considered example, one would then again get $S_{place}(c_j, q) = 1$ for $j = 1, ..., 4$. Comparing New York and Moscow, their shortest path is of length 6, their deepest generalising concept is 'City' with depth 2. Therefore $S_{place}(c_5, q) = 2 \times 2/(6 + 2 \times 2) = 0.4$. The same process must be applied to persons or organisations.

3.2. Manual identification of relevant confirmation and invalidation

The constructs can then be ordered by decreasing similarity with the user query. The user is asked to validate the list of relevant constructs, based on this list. This guarantees the correctness of the identified relevant pieces of information, while alleviating the user workload by the preliminary sorting selection.

The user is also asked to indicate whether the relevant constructs constitute a confirmation or an invalidation to his/her question. Indeed, this step requires a semantic understanding of texts that automatic tools usually fail to provide: negation words (not, never, or verbs such as deny or protest) can be handled, but often, subtle expressions of negation are used that would cheat an algorithm.

For the illustrative example, we suppose that the user would then validate items c_1 to c_3, the second one being an invalidation, the two others confirmations to his/her query. He/she would discard c_4 despite its high similarity score, because it is neither a confirmation nor an invalidation to his/her query, and it is not relevant. Lastly c_5 is not similar enough and thus it is not relevant either.

4. Individual construct scoring

The second step of the proposed information scoring process consists in individually scoring the constructs identified as relevant during the first step. As indicated in Section 2.3, for a given construct c

the expected result formally consists in a possibility distribution on the domain $E = \{e, \neg e\}$, i.e. in computing the values $\pi_c(e)$ and $\pi_c(\neg e)$.

If the construct is marked as confirmation, then $\pi_c(e) = 1$, and only $\pi_c(\neg e)$ is to be determined; if it is an invalidation, then $\pi_c(\neg e) = 1$, and $\pi_c(e)$ must be computed.

The proposed information scoring process exploits two clues: the certainty expressed by the source, and its reliability. Indeed, one tends to be more confident in the realisation of an event if it is reported as certain by a reliable source. Below we formalise this intuitive principle.

4.1. Expressed certainty

The structured news items contain a metadata field encoding the certainty expressed by the source on four levels, namely low, moderate, high and absolute. These values must be translated, we propose to map them to a numeric value γ, respectively $\gamma = 0.3$, 0.5, 0.7 and 1.

The possibility distribution induced in the case of a confirmation from this linguistically based clue is then $\pi_{ling} = (\pi_{ling}(e) \quad \pi_{ling}(\neg e)) = (1 \quad 1-\gamma)$, whereas it is $(1-\gamma \quad 1)$ if the considered construct has been marked as invalidation.

For the illustrative example, these distributions are represented in the third column of Table 3.

4.2. Topic-dependent reliability

The reliability of the source also influences the confidence that can be attached to its assertions. It can be considered as metaknowledge that should be used to correct the confidence the source expresses: even if the source is very confident, if it is not reliable, one should probably not give its assertion too much importance.

We propose to model a topic-dependent reliability, expressing the fact that a source can be competent on a given domain, where it can be trusted, and less competent on other domains, where its assertions should be considered with more caution.

For a given topic T, we thus model the source reliability through a possibility distribution on the universe $R = \{r_T, \neg r_T\}$, where r_T denotes 'reliable for the topic T'. It is usually considered that a source can be reliable with more or less certitude, the possibility distribution is thus of the form $(1 \quad \rho_T)$.

4.3. Combination

From the certainty expressed by the source and its reliability for the topic of the processed construct, the confidence the user gives to the provided piece of information can then be computed.

If the source is perfectly reliable, i.e. with reliability distribution (1 0), then the final confidence equals the certainty expressed by the source itself. On the other hand, if no certainty regarding the reliability is available, modeled by the distribution (1 1), then the assertion should not provide any information, and the confidence should be 0.

Id	Status	π_{ling}	r	π_c
c_1	conf.	$(1 \quad 0.7)$	0.5	$(1 \quad 0.85)$
c_2	inv.	$(0 \quad 1)$	0.3	$(0.7 \quad 1)$
c_3	conf.	$(1 \quad 0)$	0.5	$(1 \quad 0.5)$

Table 3: Individual scoring of the relevant constructs. Status indicates whether the construct was tagged as confirmation (conf.) or invalidation (inv.), π_{ling} gives the possibility distribution derived from the linguistic tags, r the certainty degree on the source reliability and π_c the resulting individual scoring.

Therefore, we propose to aggregate these two possibility distributions using the discounting operation proposed by [16]: denoting $r = 1 - \pi(\rho_T)$ the certainty degree on the source reliability for the topic T addressed by the considered news item, we derive π_c as

$$\begin{aligned}\pi_c(e) &= r\pi_{ling}(e) + 1 - r,\\ \pi_c(\neg e) &= r\pi_{ling}(\neg e) + 1 - r.\end{aligned}$$

The values obtained for the considered examples are shown in Table 3. The certainty degrees on the source reliability are set to 0.5 for A. Bortnikov and the Russian Home Secretary and 0.3 for D. Umarov. These values can be obtained subjectively (considering for instance that if A. Bortnikov is competent to report on the bomb attack, his objectivity may be lower), or automatically from a feedback learning process that *a posteriori* confronts the opinions a source expressed with the reality when the latter becomes known.

It can be observed that in the considered example, due to the lack of reliability of the sources, for each of them, the possibility of the opposite of their statements increases, diminishing the confidence. This in particular holds for D. Umarov statement (c_2): his absolute confidence is transformed into a piece of knowledge with certainty 0.3 only.

5. Fusion of individual scores

The last step of the proposed information scoring process models the corroboration phase, which plays a major role in the initial models [2]. The aim is to aggregate the results obtained by the individual constructs exploiting the mutual confirmation or invalidation to gain global confidence.

Formally, the question is to aggregate the possibility distributions provided by the relevant constructs, π_c. The simplest approach would consist in defining the final distribution as the normalised average of the individual distributions. For the considered example, this leads to the distribution $(1 \quad 0.87)$: the Caucasus Emirate is considered as possible author of the bomb attack, with a very low certitude.

As opposed to this baseline method, we propose to enrich the fusion taking into account additional dimensions to weight the influence of each construct, as detailed below: on one hand, we consider the temporal dimension, to weight down the constructs depending on their possible obsolescence. On the other hand, we propose to take into account possible dependencies between the sources, e.g. to diminish the influence of confirmations provided by sources known to have kinship relations, which are expected to be somehow redundant.

5.1. Temporal weighting

Taking into account temporal dimensions consists in weighting the constructs depending on their publication dates and consequently their possible obsolescence. This is in particular essential in domains where pieces of information follow one another at a high frequency, for instance in the stock market domain: the initial pieces of information soon become out-of-date.

For this weighting, we propose to associate each construct with a *currentness score*: initialised on the day of its publication to a reference value n, it is decremented at each time step. A construct thus becomes invalid after n time steps.

The initial value n must depend on the considered domain: small values are appropriate for dynamic domains that are prone to numerous and frequent updates, whereas higher values are desirable for more stable domains. Lastly, to avoid decrease in periods without information, it seems appropriate that no decrease occurs after the last piece of information has been published.

These weights can then be used in the aggregation process, to adjust the influence of the pieces of information on the final result.

For the considered example, we set the initial currentness score to the low value $n = 5$ to take into account the high frequency of information publications in the context of terrorism. Thus the constructs c_1, c_2 and c_3 get weights 3, 4 and 5 respectively. After normalisation, the result of the weighted mean is then $(1 \quad 0.84)$. This means that the certainty is slightly higher than for an average aggregation: the contradiction by D. Umarov is down weighted and the last construct c_3, supported by the first one, c_1, outweighs it.

5.2. Source network

The relationships between sources also make an essential dimension that must be represented and exploited in the fusion process, more precisely in the corroboration seeking step: it is considered that the trust in a piece of information increases with its confirmations by other pieces of information. Now a confirmation by sources known to be in affinity relation should have a lower influence than a confirmation obtained from independent, not to say hostile, sources. Indeed, friendly sources are expected to be in agreement and to produce somehow redundant information.

It is reasonable to assume that users have knowledge about the source relations: it can be based on general knowledge, e.g. asserting affinity between a president and the Prime minister, or on geopolitical or economical expertise. Therefore we suppose that a source network is available, with two types of relations, affinity and hostility, both considered to be symmetric, and we propose to exploit this graph to aggregate confidence derived from their individual statements. The process is made of two steps: graph partitioning and aggregation.

5.2.1. Partitioning the source network

The first phase aims at decomposing the graph of sources into subgraphs constituting subgroups of allied sources, linked by affinity relations, whereas between the groups, hostility or independence hold.

Formally, denoting $\mathcal{S}$ the set of sources, v and w two sources, vHw (resp. vAw) if they are linked by a hostility (resp. affinity) relation, the aim is to determine a source partition $\mathcal{C} = \{C_1, ..., C_p\}$ such that $\cup_i C_i = \mathcal{S}$ and for all i, j, $C_i \cap C_j = \emptyset$ that minimises the cost function

$$\begin{aligned} f(\mathcal{C}) \quad = \quad & \alpha \sum_{i=1}^{n} \left|\{(v,w) \in C_i^2 | vHw\}\right| \\ & + \beta \sum_{(i,j)|j>i} \left|\{(v,w) \in C_i \times C_j | vAw\}\right| \end{aligned}$$

The first term expresses a consistency constraint: it imposes the minimisation of hostility relations within a source subgraph. The second term represents a separability constraint, imposing the minimisation of affinity relations between sources subgraphs. The parameters α and β are weights controlling the relative importance of the two terms: they allow the user to express whether he/she prefers to ignore affinity or hostility relations when the optimal solution requires to violate some relations. This function can be optimised using for instance the A^* algorithm or meta-heuristics [17].

For the considered example, we suppose the user can tell that A. Bortnikov and the Russian Home Secretary are in affinity relation, and that both of them are hostile to D. Umarov. In this case, the obtained graph decomposition, illustrated on Figure 3, is obvious and leads to the identification of two subgraphs that are indeed consistent and separable. Figure 4 illustrates an example with no perfect solution: the optimal decomposition ignores the affinity relation between sources S_3 and S_5. Therefore its associated cost is $f(\mathcal{C}) = \beta$. It can be underlined that the graph represented in this figure is not complete: some sources are neither in affinity nor

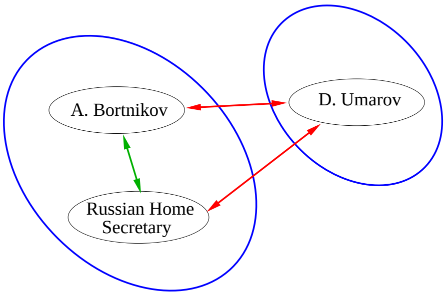

Figure 3: Source network decomposition, with cost $f(\mathcal{C}) = 0$.

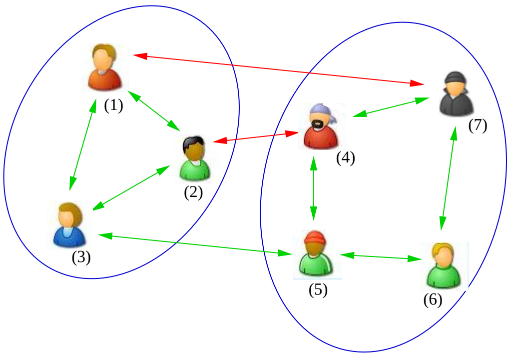

Figure 4: Complex source network decomposition, with cost $f(\mathcal{C}) = \beta$ because of the affinity relation between sources (3) and (5).

hostility relation, which means they are considered as independent.

5.2.2. Partition-based fusion

The fusion based on the source network decomposition is then in turn made of two steps, as detailed below: first a partial fusion within each subgraph, then the fusion of the results obtained for each subgraph. It must be underlined that the provided distribution may need to be normalised so as to guarantee that its maximal value is 1.

The partial fusion, within subgraphs, applies to friendly sources, which are expected to be redundant: unanimity among such sources should not be considered as confirmation and should not reinforce the confidence. Thus we propose to consider trade-off operators that yield an aggregated value intermediary between the individual values: if all sources agree, on a high or on a low confidence, the result belongs to the same range. If the group contains contradictions, i.e. if a source has a value clearly distinct from the others, it can be compensated for by the others.

Another, more severe, possibility, consists in rejecting and penalising such internal contradictions, requiring that friendly sources are consistent before putting confidence in their assertions. In this case, a conjunctive operator can be considered: a single source in disagreement with its group is enough to dramatically decrease the global confidence. This behaviour can be further refined using a weight depending on an affinity degree within the subgraph, computed from connectivity measures applied to the subgraph.

The next step fuses the results provided by the different subgraphs, which are independent or hostile. Thus, redundancy can be seen as reinforcement: if independent or hostile source groups give a high confidence to the same event, this unanimity can be judged significant. The groups then reinforce each other, leading to an even higher global confidence. Likewise, global agreement on a low confidence can lead to an even lower result. Lastly, in the expected case where a disagreement is observed, a simple trade-off behaviour can be considered. These requirements impose that the aggregation operator is conjunctive for low values, disjunctive for high values and trade-off in intermediary cases. Such behaviours are called variable attitude behaviours and said to possess a total reinforcement property [18]. They are illustrated by the symmetric sum [19] for instance, defined as

$$Agg(x, y) = \frac{x \cdot y}{x \cdot y + (1 - x)(1 - y)}$$

Besides, it seems relevant to take into account the subgraphs cardinalities: a bigger source group should play a more important role than a small one, yet without dominating the result. Therefore we propose to associate each source subgraph with a weight depending on its number of elements. To avoid domination, where the smallest groups are ignored in the aggregation, we propose to consider the square root of their number of elements.

5.2.3. Application to the example

For the considered example, the partition-based fusion first aggregates the distributions within each subgraph. A. Bortnikov and the Russian Home Secretary, who are assigned to the same group, provide, as expected, the same information. Thus they are not considered as confirming each other and their confidences are not reinforced. Applying as trade-off operator the average, the obtained possibility distribution is (1 0.68) after normalisation. The second subgraph only contains a single source, corresponding to a single construct, whose possibility distribution remains unchanged, (0.7 1).

Lastly, these two distributions are fused: two hostile groups provide contradictory information, the fusion thus computes a trade-off, weighted by the size of the subgroups. After normalisation, one gets (1 0.92). Thus the uncertainty increases significantly, as compared to the baseline average aggregation. This result comes from the reduced role assigned to the sources in favor of the Caucasus Emirates involvement, because they are considered as too close to each other to provide complementary information.

6. Conclusion

In this paper, we proposed a semi-supervised information scoring process in the possibilistic framework. Starting with structured constructs representing news items, it provides a global confidence, taking into account the source reliabilities, the certainty they express, the publication dates of the news items and the relations between sources. It relies on the proposition of appropriate aggregation operators at each step of the process.

Ongoing works aim at validating experimentally the proposed model, with the difficulty of choosing the quality criterion. The identification module will be tested on real data, through the comparison of the sorted lists it provides and the selection of the user. The evaluation of the individual and fused scoring steps appears to be less obvious: in the case of real data, it is difficult to dispose of an expected result constituting a ground truth to which the computed possibility distributions can be compared. On the other hand, the use of simulated data raises the question on how to control their relevance: it is for instance necessary to ensure that reliable sources do provide information most of the time compatible with the reality. The experimental design is thus a challenging issue as such.

From a theoretical point of view, considered perspectives include the generalisation of the model to deal with the case of successive sources [9] in the possibilistic framework: when a new item actually reports a source reporting an event, the aggregation issues raise new questions, e.g. about chaining effects, questioning the reliability that should be taken into account as well as the way the relations between sources must then be considered.

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