A Qualitative Ranking Method for Logical Information Retrieval Models ‡

Theo Huibers§ Nathalie Denos¶

1 Introduction

Information retrieval is the problem of retrieving those documents that are *likely* to be relevant to a certain information need. In 1971, Cooper introduced an objective notion of relevance termed *logical relevance*. Logical models in information retrieval aim to take into account such a logical relation involved in the core notion of relevance. Following [1], we shall call this logical relevance relation *"aboutness"* (represented by the symbol $\mid\!\leadsto$). In logical models, the aboutness derivation is strict: either one can derive the query Q from the document D, or not. Therefore aboutness has no degrees, and documents are not classified with respect to the strength of their aboutness to the query; the user may be overwhelmed by documents.

Pointing to this problem van Rijsbergen proposed the *Logical Uncertainty Principle* in 1986 [2]:

> "Given any two sentences x and y; a measure of the uncertainty of $y \mid\!\leadsto x$ related to a given data is determined by the minimal extent to which we have to add information to the data set, to establish the truth of $y \mid\!\leadsto x$."

This means that, if a system cannot logically determine that a document D is about a query Q, we have to add information to the data set until we can determine it. The strength of aboutness can be modelled by a measure of this extra information.

1.1 Probabilistic extensions of logical IR models

Following these guidelines, some logical models have been extended in order to measure this information. The first approach has been to choose an uncertainty handling model, and work it out on top of the existing logical semantics for aboutness (see for examples the models described in [3],[4],[5],[6]).

All these logical models allow defining a clear and explicit semantics for aboutness, based on the choice of the desirable properties for aboutness. But the handling of uncertainty is no longer explicitly involving aboutness properties. Therefore, the numbers obtained as relevance degrees can hardly be analyzed in terms of their relation to aboutness properties ([7]).

The main problem we see in probabilistic extensions of logical models, is that the aboutness computation is disconnected from the ranking of documents. Nie [8] proposed a ranking of documents following very closely Van Rijsbergen's uncertainty logical principle. He computes how much the information present in query Q, is altered in document D. He does so by aggregating elementary alterations occurring at each step of the inference mechanism that leads from D to Q.

In this case, the inference steps are quantified with respect to how far is the conclusion's information content from the premise's information content. The question then is to know how to formalize such a notion of distance between information contents based on inference.

‡This research was partially supported by the Esprit Network of Excellence No.6606 (IDOMENEUS Research Exchange Program), and by CNET with contract No.94-1B034

§Dept. of Computer Science, Utrecht University, The Netherlands, theo@cs.ruu.nl

¶LGI(CLIPS)-IMAG, Grenoble, France, Nathalie.Denos@imag.fr

1.2 Our purpose

This work is motivated by our claim that:

> *Part of the relevance degrees' rationale rest on users' preferences on aboutness properties*

In previous work, Huibers & Bruza [9, 10] showed that aboutness properties can be expressed as postulates (axioms and deduction rules). Following this approach, we propose to *model relevance degrees at the deduction level* of the logic in order to have them explicitly rest on these preferential grounds.

Our contention is that the inference distance between two pieces of information (how much different they are) is strongly *dependent on the user*, and on parameters which are not part of a general normative view. Moreover, this notion of inference distance between information contents is *not related to a real-numbered scale* in a natural and intuitive way. A user is more inclined to expressing and accepting *ordinal preferences* than numerical ordering. Meanwhile, in most logical models, relevance degrees are usually provided by numbers obtained from certain number combinations which semantics does not show any evidence to be reflecting the desired properties of relevance ranking.

Lastly, we claim that user preferences on documents rest on *preferences among aboutness properties*: while making his choice the user takes for granted certain assumptions on aboutness, and also certain preferences on these assumptions. We cannot prove that, but we can show that if a system can make explicit these possible aboutness assumptions, and draw relevance degrees out of preferences on these assumptions, that system can mimick different kinds of users' relevance judgements.

1.3 Notations

We use a simple formalism representing documents as sets of elementary information carriers.

Moreover, we will use two relational signs between elementary information items : $\rightarrow$ and $\perp$. They allow to express thesaural-knowledge related conditions on elementary information items.

- $i \rightarrow j$ means that the information carried by i is also carried by j (this relation can be seen as the *"isa-relationship"*)
- $i \perp j$ means that the information carried by i and the information carried by j preclude each other (this can be seen as the *"antonym relationship"*)

2 Axiomatic analysis of aboutness

From our point of view, an IR model for relevance allows inferring whether a document is *about* the query. As mentioned in the introduction, we represent the aboutness relation with the symbol $\mid\!\leadsto$. Aboutness is treated as a fundamental notion with regard to information. This differs from other approaches, in which aboutness can only be expressed in terms of so called information containment.

One of the advances of logical information retrieval models[1] is that the derivation steps proposed by the model are explicitly available. For instance the Boolean model uses propositional logic's deduction steps (often in addition with the Closed World Assumption). Studying these logical models, we can recognize different types of derivation arguments useful for determination of aboutness. The first type are the *axioms*, specific like $\{\text{“holland”}\} \mid\!\leadsto \{\text{“mills”}\}$, or, general like $S \mid\!\leadsto S$. They describe the way things are in the "world" where the inference takes place. The second type are the *deduction rules*. They describe the properties of operators, in our simple case the aboutness symbol $\mid\!\leadsto$.

[1] At least if these models are based on a formal description of a logic which can be axiomatized.

2.1 Strict aboutness properties for IR

We interpret the left side of $\mathrel{|\!\!\rightsquigarrow}$ as the document side, and the right side as the query side. We are able to shift the focus on the left or right side of the aboutness symbol.

The first alterations are made starting on the formulae given by the axioms. In our case, we have to give the properties of the aboutness relation with respect to the set-union operator. If we have deduced that the information in S is about the information in T ($S \mathrel{|\!\!\rightsquigarrow} T$), what will be the result of adding information to S? Is $S \cup \{i\}$ still about T?

If aboutness is preserved under addition of information to S without any requirement about what kind of information we may add to S, then we call this kind of rule *monotonic*. An example of such a monotonic rule can be found in the classical logical derivation system, in which the conclusion $p \wedge r \supset q$ is allowed if we can infer that $p \supset q$. Taking $\supset$ as being the aboutness relation $\mathrel{|\!\!\rightsquigarrow}$, and $\wedge$ as being approximately semantically equivalent to our set-union operator $\cup$, the equivalent formulation of this property in our background is :

$$\boxed{\dfrac{S \mathrel{|\!\!\rightsquigarrow} T}{S \cup U \mathrel{|\!\!\rightsquigarrow} T}}$$

This property can be an undesirable one, for aboutness derivation. For instance consider that we can determine that $\{\text{“holland”}\} \mathrel{|\!\!\rightsquigarrow} \{\text{“mills”}\}$. Then suppose we add to the left side information about the “drugs policy”. Then suddenly it is not about “mills” anymore !

$$\{\text{“holland”}, \text{“drugs policy”}\} \mathrel{|\!\!\not\rightsquigarrow} \{\text{“mills”}\}$$

Often user preference plays an important role in the way the addition of information preserves the aboutness relation with the query. The acceptability of a deduction step depends on what the user had in mind. In [11], the authors gave the following example: a user is interested in “bird migration” and gives the query “migration”, then we can assume that with respect to this particular information need, “spring migration” is about “migration” ; nonetheless, the conclusion that “salmon migration” is about “migration” is not allowed. These kinds of user preferences and their non-monotonic behaviour can hardly be generalized. What we can do is to formulate some general requirements in the form:

$$\boxed{\dfrac{S \mathrel{|\!\!\rightsquigarrow} T \quad \textit{Requirement}}{S \cup U \mathrel{|\!\!\rightsquigarrow} T}}$$

This is the general formulation of what we call *left-union rules*. *Requirement* is to be replaced by a constraint on what is added to S.

The skeleton of derivation introduced so far provides the aboutness relation with its fundamental properties, those resting on the commonly agreed part of what “about” means, i.e.

Assumption 1 Specific information is about its generalization.

We shall refer to these derivations as to *strict* or *certain* aboutness derivations.

2.2 Uncertain aboutness properties for IR

Usually, if we cannot strictly deduce aboutness (or, if aboutness is not valid) in the original logical model, then the aboutness relation is extended (for instance by use of an extension to probability) in order to implement a looser definition for aboutness.

The model calculates how much generalization is needed at the left side to make the proof possible. This loosening of the aboutness notion corresponds, in our framework, with additional postulates allowing more derivations ; we call this kind of derivations *plausible aboutness derivations*. Their general formulation as postulates is the following :

$$\boxed{\dfrac{S \cup T \mathrel{|\!\!\rightsquigarrow} U \quad \textit{Requirement}}{S \mathrel{|\!\!\rightsquigarrow} U}}$$

So, if {"holland", "mills"} is about {"holland", "mills"}, then applying this rule leads to the conclusion that {"holland"} is about {"holland", "mills"} if the requirement is validated. With this new rule we have the implicit assumption that general information is about its specialization. The example *"All cows are animals but not all animals are cows"* shows that this assumption sometimes does not guarantee aboutness at all.

In this particular rule, requirements play a pivotal role. Is it allowed to withdraw any information item of the left side? In the previous example we can see that withdrawing "france" from the information {"holland", "france"} does not lead to uncertainty. So, for instance we can adopt the requirement if $T \not\mid\!\leadsto U$ and $S \cup T \mid\!\leadsto U$ then we can draw the conclusion $S \mid\!\leadsto U$.

3 Logical ranking method

We showed previously how aboutness properties can be formulated as derivation rules. In our approach we propose to order these rules with respect to their creditability or their usefulness in order to obtain a logical ranking of documents based on preferences on aboutness properties.

3.1 Ordered derivation system and definitions

In order to define an ordered derivation system, let us start with a definition of a derivation system in general, as introduced in [12]:

Definition 3.1 (Derivation System) An IR *derivation system* $\mathcal{A}$ is a pair of the form $(Ax, Rule)$ with Ax a set of axioms and $Rule$ a set of rules of the form $R(S_1, \ldots, S_k, S_{k+1})$. $S_1, \ldots, S_k$ are the premises of the rule and S_{k+1} is the conclusion.

What we call *postulate* is either an axiom or a rule. All deductions must be of the form: $S \mid\!\leadsto T$, and we restrict to those S which correspond to an actual document of the corpus.

We now give a few definitions needed to describe the ranking mechanism on aboutness deductions that we propose, and to specify the assumptions under which we are working.

Definition 3.2 (Ordered derivation system) An *ordered derivation* system $\mathcal{O}$ on a derivation system $\mathcal{A}$ is the result $\mathcal{O} = o(\mathcal{A})$ of adding a strict order on $\mathcal{A}$'s postulates by applying function o.

Given a strictly ordered list of postulates, we can determine a whole range of derivation systems, starting with a simple one, based on the single first postulate, and then the next one made of the first two postulates, etc. until the very last system which is the set of all the postulates of $\mathcal{A}$ (and therefore is $\mathcal{A}$ itself).

Definition 3.3 (Embedded subsystems, $Sub(\mathcal{A})$) The list of *embedded subsystems* of an ordered derivation system $\mathcal{O} = [p_i]_{i=1..n}$ is the following strictly ordered list of derivation systems

$$Sub(\mathcal{O}) = [Sub_k(\mathcal{O})]_{k=1..n}$$

with $Sub_k(\mathcal{O}) = \{p_j \mid 1 \leq j \leq k\}$

This list is ordered by increasing cardinality of the embedded subsystems.

As mentioned in the previous section the property of *monotonicity* plays a role in our derivation rules. We have to be careful in ordering non-monotonic rules, for theorems of $[p_1, .., p_n]$ may not be theorems of $[p_1, .., p_{n+1}]$.

For the sake of simplicity we limit ourselves to only monotonic ordered derivation systems, which can be defined as follows:

Definition 3.4 (Monotonic ordered derivation system) An ordered derivation system $\mathcal{O} = [p_i]_{i=1..n}$ is called *monotonic* if and only if

$$\forall k, 1 \leq k \leq n-1, theorems(Sub_k(\mathcal{O})) \subseteq theorems(Sub_{k+1}(\mathcal{O}))$$

where *theorems* is the function which maps the set of theorems provable in the derivation system given as a parameter.

Thus we take as a working assumption that none of the sub-derivation systems contains non-monotonic rules.

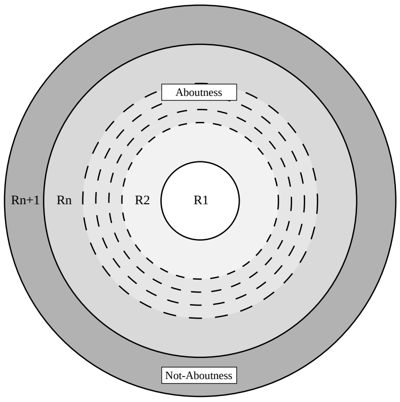
3.2 Modelling IR relevance degrees

Using an ordering of the postulates of a derivation system, we can get a ranked classification on aboutness formulae deducible in this system.

$answer_{(Q,\mathcal{C})}$ maps a derivation system $\mathcal{A}$ into the set of documents based on a corpus $\mathcal{C}$ such that, $answer_{(Q,\mathcal{C})}(\mathcal{A}) = \{D \in \mathcal{C} \mid \vdash_{\mathcal{A}} D \ \mid\!\leadsto\ Q\}$ where D is the representation of a document, and Q the representation of an information need. When the corpus $\mathcal{C}$ is understood, we shall refer to these functions as $answer_Q(\mathcal{A})$ rather than $answer_{(Q,\mathcal{C})}(\mathcal{A})$.

Then we get the following ranked classification of aboutness formulae:

$$\begin{aligned} R_1 &= answer_Q(Sub_1(\mathcal{O})) \\ &\vdots \\ R_k &= answer_Q(Sub_k(\mathcal{O})) \setminus R_{k-1} \\ &\vdots \\ R_{n+1} &= \text{Corpus } \mathcal{C} \setminus answer_Q(\mathcal{A}) \end{aligned}$$



Property 1 A monotonic ordered derivation system $\mathcal{O} = [p_i]_{i=1..n}$, provides a ranked classification with $n+1$ classes, some of these classes could be empty.

Our contention is that this ranked classification nicely fits with the notion of relevance degrees : R_1's members are the aboutness assertions pointing at the most relevant documents *with respect to $\mathcal{O}$'s preference setting on aboutness properties.* This relevance degree decreases with the next R_is, until R_{n+1} which aboutness assertions point at the non-relevant documents.

Therefore, a relevance IR model is an ordered derivation system, and borrowing from [13], we define relevance degrees in terms of preference as follows:

Definition 3.5 (Preference) *Given an ordered derivation system $\mathcal{A}$, d_i is preferred over d_j with respect to query q (denoted as $Pref_{(\mathcal{A},q)}(d_i, d_j)$) if and only if $d_i \in R_k$ and $d_j \in R_l$ with $k < l$.*

As we will see in the next section, the precision of the ranking classification is tunable in this postulate-based modelling context. It can be used, for example, to tune a model as referring to a test collection.

4 Expanding Aboutness Derivation Systems

Referring to the analysis of aboutness properties we gave in section 2, we show here how the two kinds of aboutness derivation rules ("strict" and "plausible"), may be used in the context of our logical ranking model based on postulates ordering. We give here two techniques, and our intuitions about what it can be used for, but more work is needed to have these ideas validated.

4.1 Ordering postulates

First, a relevance model for IR is a derivation system DS. The first parameter is a *preferential* parameter: choose which order to apply on DS's postulates. This choice is limited by the condition that the ordered derivation system ODS obtained be monotonic (at least in the scope of this study).

This tuning is to be done before starting a retrieval session. It is meant to define a general retrieval strategy. It might be set once for all in the case of specialized IR systems, where users share the same retrieval situation: same profile (knowledge of the domain and of the system), and same type of information need. On the opposite, for a non-specialized IR system, different orderings of DS may be available for different types of users and/or different types of information needs.

The *ranking's granularity* is the number of ranked classes of documents one gets out of an IR system. It is directly linked to the number of postulates present in the ordered derivation system (see property 1). We use this property in order to design two tuning techniques for our ranking IR model.

To describe these techniques, we work them on the following example.

We saw in section 2, that in the context of our limited and underspecified, representation model of information, we can draw one axiom (*Reflexivity* $S \mid\!\leadsto S$) and two gross rules:
R_1: $\dfrac{S \mid\!\leadsto T}{S \cup U \mid\!\leadsto T}$ and R_2: $\dfrac{S \mid\!\leadsto T \cup U}{S \mid\!\leadsto T}$

The derivation systems $S_1 = \{Reflexivity, R_1\}$ and $S_2 = \{Reflexivity, R_2\}$ are equivalent in the sense that they allow the derivation of exactly the same formulae. We base our example on system S_1

However, we may not be satisfied with a threefold document ranking (see property 1)!

4.2 Internal Expansion

At the first step of the iterative retrieval for a given information need, the ranked classification obtained with the initial ODS is a gross one, only (the number of ODS's postulates $+1$) classes. Some classes corresponding to a subsystem may consist of a large set of documents, intuitively not all at the same level of relevance. The user can ask for a more detailed ranking of one or several classes of documents. In response to this feedback, the corresponding postulates are internally expanded, so that the next retrieval step takes place in an expanded version of ODS, and provides the user with a more detailed ranking.

Definition 4.1 (Internal expansion of a postulate in an ODS) An *internal expansion* of a derivation rule P_i in an ordered derivation system $\mathcal{O} = [P_1, \ldots, P_{i-1}, P_i, \ldots, P_n]$, consists of replacing P_i by an ordered derivation system $[P_{i_1}, \ldots, P_{i_k}, P_i]$. We obtain another ordered derivation system $\mathcal{EO} = [P_1, \ldots, P_{i-1}, P_{i_1}, \ldots, P_{i_k}, P_i, \ldots, P_n]$.

Let R_i correspond to the class of documents obtained with the subsystem $\{P_1, \ldots, P_i\}$. A desired property of the new proposed ODS is:

If $Pref_{([P_1,\ldots,P_{i-1},P_i,\ldots,P_n],q)}(d_i, d_j)$ then $Pref_{([P_1,\ldots,P_{i-1},P_{i_1},\ldots,P_{i_k},P_i,\ldots,P_n],q)}(d_i, d_j)$

Therefore,the following requirements are needed:

1. No postulate involves the absence of an aboutness relation.
   As mentioned previously, we restrict to monotonic properties.
2. For all Q,
   for $1 \leq j \leq k$ $answer_Q(\{P_1, \ldots, P_{i-1}, P_{i_1}, \ldots, P_{i_j}\}) \subseteq answer_Q(\{P_1, \ldots, P_{i-1}, P_i\})$, i.e. $answer_Q(Sub_{i_j}(\mathcal{EO})) \subseteq answer_Q(Sub_i(\mathcal{O}))$
   The documents retrieved with the new properties must be members of those documents already retrieved with properties $P_1, \ldots, P_i$ in the original system.
3. For all Q,
   for $i \leq l \leq n$ $answer_Q(Sub_l(\mathcal{EO})) = answer_Q(Sub_l(\mathcal{O}))$
   The addition of new properties before relevance degree i must *only* modify the class of documents which has been splitted.

Example 4.1 Given an ODS $\mathcal{A}$ described by $[Reflexivity, R_1]$ with the rule R_1 as $\dfrac{S \mid\!\leadsto T}{S \cup U \mid\!\leadsto T}$, the ODS can be internally expanded into $[Reflexivity, R_{1_1}, R_1]$ with rule R_{1_1} as $\dfrac{S \mid\!\leadsto T \quad U \mid\!\leadsto T}{S \cup U \mid\!\leadsto T}$. This is an internal expansion of the rule R_1.

This tuning allows taking into account the users doubts about the adequacy of some aboutness properties built into ODS, and which he thinks do not fit well with his notion of relevance. This tuning can also be seen in a more simple way: asking a more detailed ranking of a class of relevant documents.

4.3 External Expansion

In the last class of documents provided by an ODS for a given query Q, are the documents which are not member of $answer_Q(\mathcal{A})$, i.e. not about the query with respect to the logical model. Often logical models are precision-oriented models. As a result, this last class is very large. In order to rank this class we need some extra postulates, often referred to as *plausible* postulates.

Definition 4.2 (External expansion of an ODS) An *external expansion* of an ODS $\mathcal{O} = [P_1, \ldots, P_n]$ with a postulate P_{n+1}, is an ordered derivation system $[P_1, \ldots, P_n, P_{n+1}]$.

As usual, in order to keep the derivation system monotonic, P_{n+1} has to be a monotonic postulate.

Example 4.2 Given the ODS $\mathcal{A}$ of the previous example, described by $[Reflexivity, R_{1_1}, R_1]$, the ODS can be externally expanded with the rule $R_2\ \dfrac{S \mid\!\leadsto T}{S \mid\!\leadsto T \cup U}$. This leads to a subclassification of the last class of $\mathcal{A}$.

These new rules allow ranking documents which were considered as non-relevant in the original ODS. Moreover, the second tyrderings of DS may be available for different types of users and/or different types of information needs.

5 Concluding Remarks

This article sets up a method for ranking documents in the context of logical information retrieval models, based on qualitative grounds. The ranked classes of documents are produced without using any quantitative uncertainty function. These classes are meant to contain documents which stand on the same level of relatedness to the query, with respect to the aboutness properties involved in the deduction.

After using our method, it is still possible to rank the classes again, by using quantitative functions. We expect that some of the obstacles met by quantitative handling of uncertainty –like considering all kinds of evidence for aboutness on the same level, are smoother within the scope of one such class of documents; indeed, these functions would then deal with homogeneous sets of documents with respect to the kind of relation they have to the query. Thus these classes could constitute a "normalized" ground for numerical calculation.

Although the method has been demonstrated with an extended example, we still have not paid attention to implementation aspects. We are planning to do experiments.

Another area remaining to be explored, is the involvement of the user in this new sort of ranking method. In our approach relevance feedback should not only concern *"how relevant the documents are for the user"* but also *"what the user thinks of the preferences suggested by the system between documents"*. This type of feedback might involve the user not only directly but also indirectly as it is not possible to directly ask a user for an ordering of postulates !

Extending the method with approaches for this sort of feedback is in the scope of our future work.

Another kind of extension lies in the addition of more relation types between information items which can be used as requirements for an inner expansion of certain rules. One may think of subjective and/or connotative relations like "Alaska" and "Cold", or like "Fire" and "Smoke". These kinds of relations are especially important regarding to non-textual objects, like sounds and pictures.

Finally on the theoretical side, the limitation to only monotonic rules may be undesirable. Also, the *strict* ordering of postulates may not always be relevant in practise. More work is needed to see whether the bulk of this method can still be used after withdrawing these working assumptions.

Acknowledgment

This paper was written while Theo Huibers was visiting the Laboratoire de Génie Informatique in Grenoble, France partly supported by the Esprit Network of Excellence No.6606 (IDOMENEUS Research Exchange Program), which is gratefully acknowledged. He would like to thank the people of the LGI for their kind hospitality. Our appreciation also goes to Alan Smeaton for correcting the english of an earlier draft. Furthermore we would like to thank Catherine Berrut and Yves Chiaramella for suggesting our cooperation in writing this paper.

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