ESSIR '03

Logical Models of Information Retrieval

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Outline

- Why logical models?
- Limitations of classical logic
- IR as uncertain inference
- The Logical Uncertainty Principle (LUP)
- Logical and logical-uncertainty models
- Examples of "LUP based" models
- Current and future work
- References

Why logic in IR? Motivations

- Classical IR models seem to have reached their maximal potential
- Most classical IR models are parametric
- The nature of information is not well captured in classical IR models
- Classic IR models are not flexible enough for heterogeneous or structured information items

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Why logic in IR? Objectives (1)

- Formally capture different aspects of information
  - Document and query representation
  - Matching process (notion of "relevance")
  - Thesaural and ontological information
  - User knowledge
  - Contextual information
  - Combination of information sources
  - Heterogeneity and structure of information items

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Why logic in IR? Objectives (2)

- Represent information
  - Knowledge representation (semantics, soundness, completeness, reasoning)
  - Medium-independent (e.g., FERMI model)
- Theoretical study of IR
  - Formal study of the properties of models and systems (meta-models)
  - Study of the concept of “aboutness”

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A logical framework

- Logic: L
- Document representation: $d \in L$
- Query representation: $q \in L$
- Estimation of “relevance”: ???

- We can attempt to represent other elements of the IR task in L: user knowledge, context, domain knowledge, etc.

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How do we estimate relevance?

- It all depends on the logic used and the semantic associated to "relevance"
- Classical approach
  - Relevance: $d \rightarrow q$
  - Used for long time in Boolean systems
- Non-classical approach
  - Relevance: Strength($d \rightarrow q$)
  - Enables to evaluate partial relevance

Classical logic for IR

- Relevance as: validity of $d \rightarrow q$
  - Inference system: $d \vdash q$ $(\vdash d \rightarrow q)$

    Find finite sequence of inference rules (e.g. Modus Ponens) that leads d to q

  - Model system: $d \models q$ $(\models d \rightarrow q)$

    q is a logical entailment of d if q is true in every model (interpretation) of d

Example (model system)

Propositions {t1, t2, t3} Document d = t1 $\wedge$ t2

Queries:			q1 = t1	q2 = t3	q3 = t1 Ù t3	q4 = t1 Ú t3	q5 = t1 Ù t2
t1	t2	t3	d $\rightarrow$ q1	d $\rightarrow$ q2	d $\rightarrow$ q3	d $\rightarrow$ q4	d $\rightarrow$ q5
1	1	0	1	0	0	1	1

- d \|= q1 d $\not\models$ q2 ok
- d $\not\models$ q2 d $\not\models$ q3 *partial relevance*
- d \|= q4 d \|= q5 *degree of relevance*
- d \|= q1 d \|= q5 *specificity*

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Limitations of classical logic

- Classical logic cannot cope with:
  - Partial relevance
  - Degree of relevance
  - Specificity and exhaustivity
- We need to be able to measure the “strength” of the implication: Strength (d $\rightarrow$ q)
  - One way is to measure the uncertainty of the implication, i.e. Pr(d $\rightarrow$ q), the probability of d $\rightarrow$ q
  - So: IR is a process of uncertain inference

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IR as uncertain inference

- Why inference?

  Inference principle: a document is estimated to be relevant to a query if it logical implies the query: $d \rightarrow q$
- Why uncertain inference?

  Uncertainty inference principle: both document and query representation do not fully capture the informative content of document and query, so there is a measure of uncertainty associated with the implication:

  $Rel_q(d1) > Rel_q(d2)$ if $Pr(d1 \rightarrow q) > Pr(d2 \rightarrow q)$
- How do we evaluate $Pr(d \rightarrow q)$?

  A large number of models have been proposed based on different perspectives and logics

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Uncertain inference and IR

- Various researchers demonstrated that all models of IR can interpreted as uncertain inference
- They take the view that $Pr(d \rightarrow q) = Pr(q|d)$
- They relate the probability of relevance $Pr(R|q,d)$ to $Pr(d \rightarrow q)$ as: $Pr(R|q,d) = f(Pr(d \rightarrow q), Pr(d \rightarrow q))$
- Standard propositional logic and different interpretations of the semantic of probability (aleatory vs. epistemological view) can be used to define all classical models of IR
- Here we take a different view of $Pr(d \rightarrow q)$

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The Logical Uncertainty Principle

- Some models that consider IR as uncertain inference are based on the Logical Uncertainty Principle (LUP):

"Given two sentences x and y; a measure of the uncertainty of $y \rightarrow x$ relative to a given data set, is determined by the minimal extent to which we have to add information to the data set, to establish the truth of $y \rightarrow x$"

Van Rijsbergen, 1986

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Attempts of using LUP in IR

- LUP was one of first attempts to make an explicit connection between non-classical logic and uncertainty modelling in IR
- LUP does not say which logic and uncertainty theory one should use!
- LUP has stimulated a lot of research into the use of logic and uncertainty theory in IR and a number of models have been proposed

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Two different approaches

- Logical Models

  Models capturing the uncertainty mainly in two ways: qualitatively by the logic itself (e.g., via default rules, non-monotonicity, or background conditions), or quantitatively by adding an uncertainty theory to the logic (e.g.,fuzzy logic)

- Logical-Uncertainty Models

  Models based on an uncertainty theory (e.g., probability theory, semantic theory, belief revision, imaging) that is defined on a logical basis

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Logical models

- Many models have been proposed, based on, for example:
  - Fuzzy logic
  - Conceptual graph
  - Situation theory and channel theory
  - Default logic
  - Abductive logic
  - Description logic
  - Belief revision
- As an example I will present some models of IR based on probabilistic argumentation systems and modal logic

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Probabilistic argumentation sys.

- Classical example of logical models
  - Probabilistic Argumentation System (PAS) = Propositional argumentation system + probability theory
  - Clear division of tasks: the propositional argumentation system handles the qualitative aspects of the uncertainty, probability theory handles the quantitative aspects
- PAS enables to apply the LUP to IR

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Propositional argumentation sys.

- Representing uncertain facts and rules

Knowledge	Representation	Natural language
Fact	P_1	P_1 is true
Simple rule	$P_1 \rightarrow P_2$	P_1 implies P_1
Uncertain fact	$a_1 \rightarrow P_1$	P_1 is true under a_1
Uncertain simple rule	$a_{12} \rightarrow (P_1 \rightarrow P2) \Leftrightarrow P_1 \wedge a_{12} \rightarrow P_2$	P_1 implies P_2 under a_{12}

- Prop. AS = (P,A,S), where A is a set of arguments (or assumptions) and S is called knowledge base

Add probability

- Probabilistic AS (PAS) is a (P,A,S,X), where X is set of probabilities on A
  - An hypothesis h is a logical formula in $A \cup P$
  - a is a minimal supporting argument for h if there is no a' such that a is also a argument for h and a |= a'
  - A quasi support for h is the disjunction of all minimal supporting arguments for h (some arguments might be in contradiction with S)
  - A support for h excludes from the quasi support arguments that are in contradition with S
  - PAS can be used to evaluate the degree of support for h (basically the probability of the quasi support conditioned on the fact that S is satisfiable, i.e. non contradictory)

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Example

Consider a PAS with the following S

$S_1 = D \wedge a_1 \rightarrow T_1$

$S_2 = D \wedge a_2 \rightarrow T_2$

$S_3 = T_1 \wedge c_1 \rightarrow Q$

$S_4 = T_3 \wedge c_3 \rightarrow Q$

$S_5 = T_4 \wedge c_4 \rightarrow \neg Q$

$S_6 = T_2 \wedge t_{23} \rightarrow T_3$

$S_7 = T_1 \wedge t_{14} \rightarrow T_4$

With: $X = \{P(a_1)=0.7, P(a_2)=0.8, P(c_1)=0.7, P(c_3)=0.7, P(c_4)=0.6, P(t_{23})=0.6, P(t_{14})=0.4\}$

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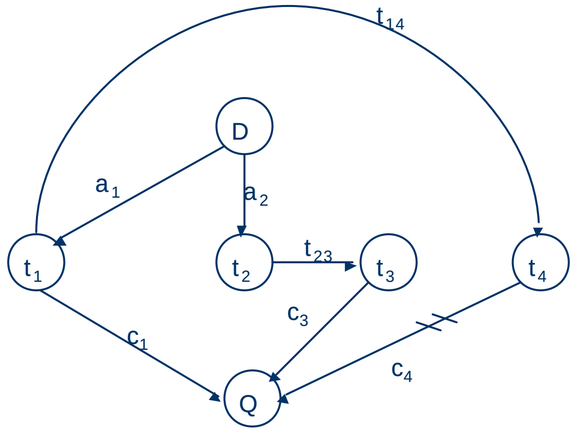
Graphical representation



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PAS and IR

- Here is how Picard and Savoy use PAS in IR
  - D is retrieved if D $\rightarrow$ Q
  - We need to add (S_8= D) to S (D is observed) and the evaluate the hypothesis Q, this can be done by finding all supporting and all refuting evidence for Q
  - Finding arguments can be done resolution (as in propositional logic)
  - Find the support for Q, excluding contradictory evidence
  - Find probabilities associated to arguments (can be done in different ways)
  - Evaluate the degree of support for Q, which is a measure of the strength of D $\rightarrow$ Q

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PAS and LUP

- It has been proved that
  - The symbolic support for h, given S, is the minimal amount of information that must be added to S, sufficient to prove h
  - The degree of support for h is a way to measure how different symbolic support compare to each other and can be used to compare, for example, $D_1 \rightarrow Q$ vs $D_2 \rightarrow Q$
- Notice that the qualitative measure is independent of the probabilities given to the arguments

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Strengths

- S enables to model different types of knowledge
  - Thesaural, structural, inter-document relationships, context, etc.
- The qualitative aspect (based on propositional logic) is independent from the quantitative aspect
  - Different approaches can be used to deal with the quantitative aspects (different way of evaluating the probabilities)
- PAS enable to model some important formal characteristics of IR models
  - Information containment, intentionality, partiality and flow of information, “uncertainty in IR is everywhere”, etc.

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Limitations

- The major problem is the computation of the probabilities, to which the quantitative aspect of PAS is completely dependent
  - Estimate “a priori” support to arguments
  - Estimate probabilities of link arguments
- The tractability of the qualitative aspect might explode in large S
  - It might not be feasible to use PAS for large collections or for complex contexts, document structures, etc.

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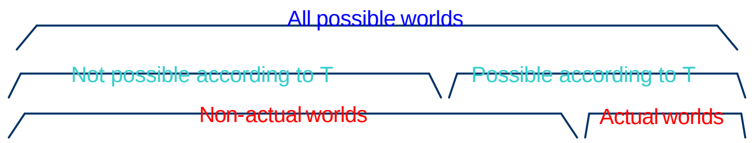
Possible World Semantics

- Possible World Semantics (PWS)
  - Proposed by Kripke in 1971
  - According to PWS the truth value of a sentence is evaluated in the context of a world
  - There are different worlds: possible worlds, actual worlds and non-actual worlds
  - Note: ask a logician how to use PWS, not what it actually means ...



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PWS and modal logic

- PWS has been used in Modal Logic to give a semantic for "Necessity" (L) and "Possibility" (M)
- Basically, given a sentence A:
  - LA is true, iff A is true in all possible worlds
  - MA is true, iff A is true in some worlds
- A number of researchers have tried to apply Modal Logic in IR (see list of references)
- Modal Logic has also been used to implement the LUP
  - Now I will present the work of Nie

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PWS and LUP

- Nie proposed to interpret x and y of LUP as d and q, so: $Pr(d \rightarrow q)$
- Using PWS it is possible to move away from the classical interpretation of: $Pr(d \rightarrow q) = Pr(q|d)$
- Using PWS we can implement LUP to evaluate $Pr(d \rightarrow q)$ in a particular data set K
  - The data sets could include everything: user knowledge, term space, external knowledge, etc.

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Evaluation of Pr(d ®q) using PWS

- This can be done in 3 ways: modify any of the following until the implication d→q holds
  - the data set (so a world is a data set)
  - the document (so a world is a document)
  - the query (so a world is a query)
- Measuring the extent of these modification enable to estimate relevance
- But modifications add uncertainty ...

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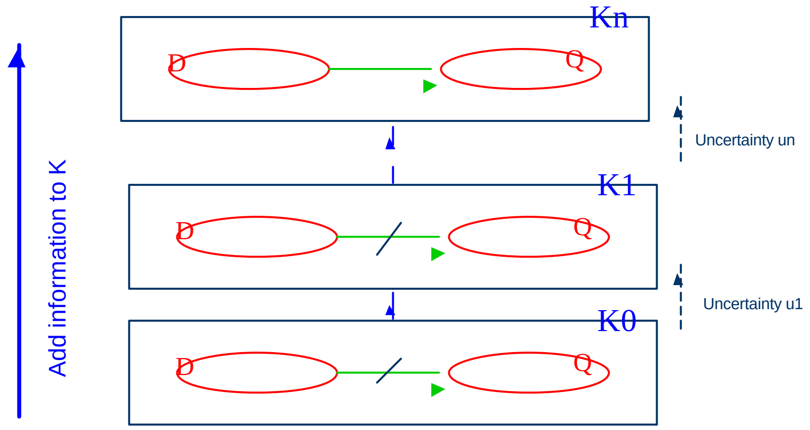
Modification of the data set



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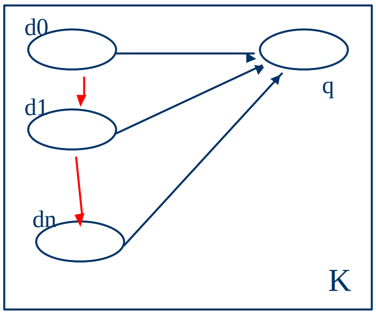
Modification of the document

Given any two sets of information q and d, a measure of the uncertainty of d $\rightarrow$ q relative to a given knowledge is determined by the minimal extent to which we have to add information to d for it to become d' to establish the truth of d' $\rightarrow$ q.



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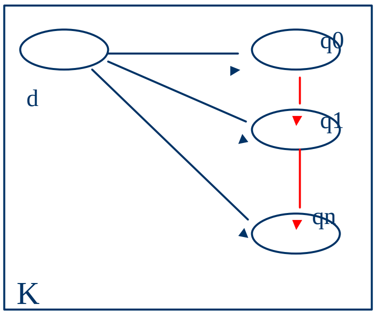
Modification of the query

Given any two sets of information q and d, a measure of the uncertainty of d $\rightarrow$ q relative to a given knowledge is determined by the minimal reduction from q to q', to establish the truth of d $\rightarrow$ q'.



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Example

- Here is an example of document modification:
  - Starts with:

    d={sea,boat}, q={swimming},

    K={sea related to swimming,…}
  - Modify d to d':

    d'={sea,boat,swimming}
  - Now: d' $\rightarrow$ q holds, but we have to consider the uncertainty associated to "sea related to swimming" and the modification carried out
- Problem:
  - What if we started with d={sea,boat,fishing,storm}?

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Generalisation of the LUP

- Nie proposed some extensions of these ideas:
  - Not simply addition to K but transformation: addition, deletion and modification
  - Transformation of documents and queries as well as the data set at the same time
- Generalised Logical Uncertainty Principle (1989)

  $K \mid R(d, q) = F [Pr(K \mid d \rightarrow q), Pr'(K \mid q \rightarrow d)]$

  where: Pr and Pr' are functions of the implication strength

  F: co-ordination function between the two implications

  K: knowledge base or user knowledge (data set)
- This enables to evaluated the exhaustivity and specificity of the document to the query

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Exhaustivity and Specificity

- Consider:

  $d=\{sea,boat\}$, $q_1=\{sea\}$, $q_2=\{sea,boat,fishing,storm\}$
- Document d exhaustive to q_1 ($d \rightarrow q_1$)
  - Indicates how much of the query content is contained in the document content
  - ($d \rightarrow q \equiv d \supseteq q$)
- Document d specific to q_2 ($q_2 \rightarrow d$)
  - Indicates how much of the document content is specific to the query content
  - ($q \rightarrow d \equiv q \supseteq d$)

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Strengths and limitations

- This model suffered from a few limitations:
  - The model was implemented in simplistic terms without considering efficiency
  - The model proved successful with small collections (as effective as current standard models), but experimentation with larger collections proved difficult
- But:
  - This work started a line of research on how to use PWS in IR and how to model revision (additions, contractions, modifications) of q, d and data set
  - Nie extended this work in subsequent papers to better implement and measure the modification of q, d, and K using counterfactuals

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Other logical models of IR

- Other logical models have tried to capture with different logics the modification of d and q
  - Situation theory and channel theory
  - Fuzzy logic
- Other logics capture better K and are able to measure in a better way the modification of K
  - Description logic (e.g. MIRLOG)
  - Belief revision
- Efficient implementation and experimentation of these models have always been the major problems

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The Logical-Uncertainty approach

- Logical-Uncertainty Models of Information Retrieval
  - Models based on an uncertainty theory (e.g., probability theory, semantic theory, belief revision, imaging) that is defined on a logical basis
- These models start from a different perspective

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Logical-Uncertainty models

- Many models have been proposed, based on:
  - Probability theory
  - Bayesian inference networks
  - Semantic information theory
  - Probabilistic Datalog
  - Logical imaging
  - Rough sets
  - Probabilistic argumentation systems
- As an example I will present the models based on belief revision and logical imaging

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Belief revision by logical imaging

- Logical imaging (LI) is a process developed in the framework of belief revision
- LI enables the evaluation of a conditional sentence without explicitly defining the operator "$\rightarrow$"
- What is required is a clustering on the space of events (accessibility relation)
- PWS can be used to define the accessibility relation that LI requires

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PWS and LI

- LI states that:

  "the truth value of a conditional $y \rightarrow x$ in a world w (actual) is equivalent to the truth value of the consequent x in the closest possible world w_y where the antecedent y is true"

- Interpretation:
  - The passage from a world to another world can be interpreted as belief revision, and the passage from a world to its closest is equivalent to the least drastic revision of one's belief
- Logical imaging is a powerful tool to implement the LUP

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LI in IR

- Following Van Rijsbergen's suggestion (1986) a number of approaches to the use of LI in IR have been proposed
- The main problem is the mapping of PWS and LI to the IR problem
  - What is a world and what makes a world actual or possible?
  - What is an accessibility relation?
  - What is a "practical" and "feasible" implementation of LI?
- This is not trivial …

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What is a world in IR?

- Three different interpretations:
  - A world is a document and accessibility is clustering in the document space
  - A world is a state of knowledge, and accessibly is a metric in the space of states of knowledge
  - A world is a term and accessibility is clustering in the probabilistic term space
- Let us see this last interpretation, by Crestani

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Duality view of the term space

- In IR a document collection is often represented by a occurrence matrix, where a document is represented using terms:

	t1	t2	t3	...	tn
d1	1	0	1	...	0
d2	1	0	0	...	1
d3	0	1	1	...	1
...	...	...	...	...	...
dk	1	1	0	...	1

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A world is a term

- By inverting the point of view, we can represent the semantic of a term using documents, so PWS tells us that a document (or query) is true in the context of a term if the term occurs in its interpretation

	d1	d2	d3	...	dn
t1	1	1	0	...	1
t2	0	0	1	...	1
t3	1	0	1	...	0
...	...	...	...	...	...
tk	0	1	1	...	1

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The probabilistic term space T

- To be able to use logical imaging (LI) we need to associate a prior probability Pr(t) to the term space, indicating the importance of the term t, before any query has actually been considered
- Assuming that $\Sigma_T \Pr(t) = 1$, the probability of a document d is equal to the sum of the probability of the terms in it: $\Pr(d) = \Sigma_t \Pr_{d\in d}(t)$

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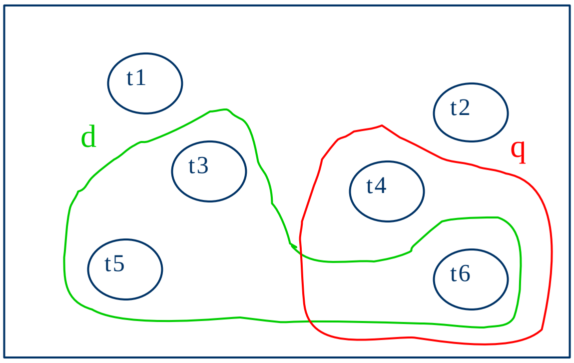
Graphical representation of T



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The LI process in T (1)

- We can estimate $Pr(d \rightarrow q)$ as:

$$Pr(d \rightarrow q) = Pr_d(q)$$

where:

$$Pr_d(q) = \Sigma_t \, Pr_d(t)$$

$Pr_d(t)$ is evaluated by revising the original probability distribution Pr over T (the set of possible words) by imaging on d

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The LI process in T (2)

- In other words:

$$Pr_d(t_j) = \Sigma_{t\ j} Pr(t_j)\ I(t_{ii}, t_j^d)$$

with:

$$I(t_i,t_j^d)=\{1 \text{ if } t_i \text{ is true at } t_j^d;\ 0 \text{ otherwise}\}$$

where t_j^d is the term most similar to t_i appearing in the document d

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LI in plain English

- The prior probability distribution Pr is modified so that all the index terms not occurring in the document transfer their probability to index term occurring in the document, according to their similarity values
- The probability is not destroyed, but only transferred: we have now a new probability distribution
- We obtain the minimal revision of the term space (in term of movement of probabilities) to make the antecedent true and evaluate the probability of the consequent in this new term space
- More complex forms of LI have also been proposed: e.g. Generalised LI, Proportional LI, etc.

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LI and IR

- Important questions:
  - How do we use LI in IR?
  - How can we use LI to implement the LUP?
  - Can we implement it in a efficient and effective way?
  - How does this model compare (analytically, to
- Lots of work was devoted to these solve questions

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Requirements for LI

- The evaluation of Pr(d→q) by LI requires:
  1. a probability distribution over T
  2. a similarity measure S so that for each index term we can determine the t_d
- We can use:
  1. some term weighting function (e.g., idf, tf-idf)
  2. some clustering function of the term space employing a similarity measure (e.g., EMIM), alternatively a thesaurus
- More complex forms of imaging require additional information

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An example of IR by LI (or RbLI)

- Here is a simple example:
  - Suppose we have:

    d = {t1, t5, t6}   and   q = {t1, t4, t6}
  - Suppose also that we have a measure of similarity Sim over T = {t1,..t6} that tell us value s = Sim(ti, tj) for each pair of terms
  - The above requirements on Sim can be relaxed to consider only the terms that are most similar

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RbLI on the document d

Here is the evaluation of Pr(d→q) by imaging on d:

t	Pr(t)	I(t,d)	t_d	$Pr_d(t)$	I(t,q)	$Pr_d(t)$ I(t,q)
1	0.2	1	1	0.3	1	0.3
2	0.1	0	1	0	0	0
3	0.05	0	5	0	0	0
4	0.2	0	5	0	1	0
5	0.3	1	5	0.55	0	0
6	0.15	1	6	0.15	1	0.15
Sum	**1.0**			**1.0**		**0.45**

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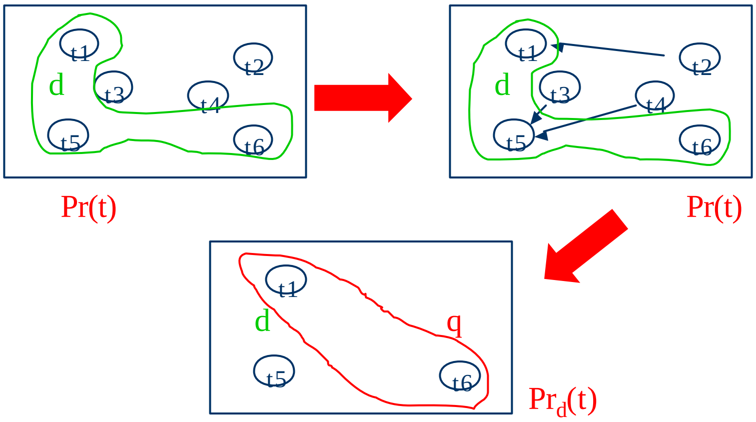
Interpretation of RbLI on d



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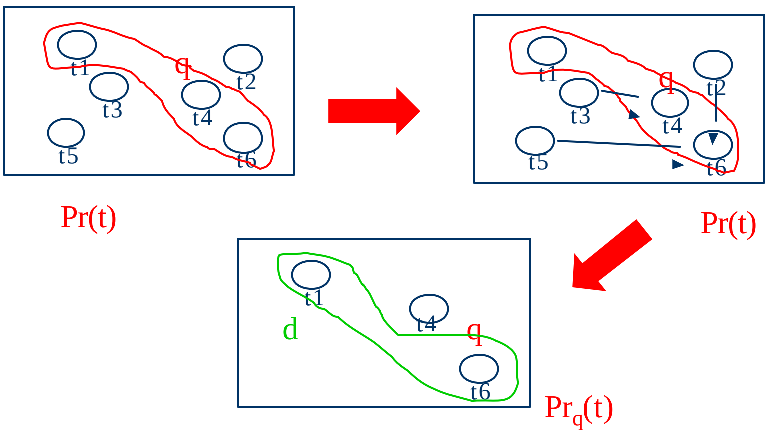
RbLI on the query q

- Li on q can be done in a almost identical way:



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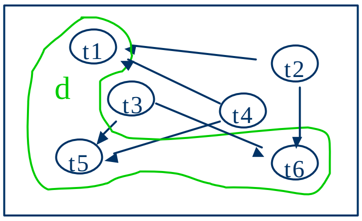
General imaging and RbGLI

- General imaging is an extension of logical imaging proposed by Gardenfors in 1988
  - It enables a better redistribution of probability by imaging based on a “opinionated distribution function”, causing a less drastic movement of probabilities
  - It has been applied to IR in a similar way to RbLI



Pr(t)

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Strengths and limitations

- LI has proved useful for studying the kinematics of probabilities in IR. Comparing:
  - models based on retrieval by joint probability:
    - RbJP: Pr(R |q, d) = Pr(d,q)
  - models based on retrieval by conditional probability:
    - RbCP: Pr(R |q, d) = Pr(q | d)
  - models based on imaging:
    - RbLI: Pr(R |q, d) = Pr(d→q) by imaging
  - models based on general imaging:
    - RbGLI: Pr(R |q, d) = Pr(d→q) by general imaging
- Like looking at IR models as “through a microscope”
- Insights on how to build better IR models were obtained, but experimental results were inconclusive

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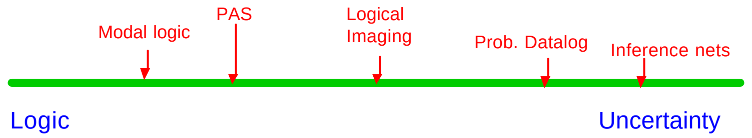
Other logical-uncertainty models

- Here we have no time to talk about other models, but there are many others
- There is a continuum of models in this class:



- The more we move towards uncertainty theory, the simplest it become to implement the models, but we loose in representation power

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Meta-Models of IR

- A completely different class of logical models is: Meta-Models of Information Retrieval
  - Models aiming at formally studying the properties and the characteristics of IR systems within a uniform framework
- A few meta models have been proposed:
  - "Aboutness"
  - Formal mathematical studies
  - Flow of information and channel theory
  - Probabilistic inference
- Here I will present a meta-model for "Aboutness" by Huibers and Bruza

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Advantages of Meta-Models

- Logic-based approach provides a framework for studying IR in a neutral setting and theoretical investigations can take place independently from any given retrieval model
- "Aboutness" is one such area of investigation:
  - IR determines whether one information object (e.g. document) is about another (e.g. query)
  - What properties does this aboutness relation have within and across IR models?
  - What properties of aboutness are beneficial/detrimental to retrieval effectiveness?
- Several logics for meta-theoretical investigations have been proposed

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Aboutness

- **A |= B** denotes that A is about B
- **A Þ B** denotes that information B carries is also carried by A (e.g. salmon $\Rightarrow$ fish)
- **A Ä B** denotes the combination of the information carried by A and B (e.g. information $\otimes$ retrieval)
- **A ^ B** denotes that information carried by A and B is incompatible (e.g. sleeping $\perp$ working)

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Some properties of aboutness

$A \models A$ — reflexivity *(under debate)*

$$\frac{A \models B \text{ and } B \models C}{A \models C}$$ transitivity *(precision degrading)*

$$\frac{A \models B}{B \models A}$$ symmetry *(overlap measure)*

$$\frac{A \models B \text{ and } B \Rightarrow C}{A \models C}$$ right weakening *(degrading?)*

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Monotonicity

- Classical logic: $$\frac{A \models B}{A \wedge C \models B}$$
- Aboutness is non-monotonic: $$\frac{\text{surfing} \models \text{wave}}{\text{surfing} \otimes \text{internet} \models \text{wave}}$$
- Monotonicity degrades precision
- Vector space model is monotonic

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Different notions of monotonicity

- Clearly monotonicity has to be constrained
- Several have been proposed for this purpose (adapted from non-monotonic reasoning)

$$\frac{A \models B \quad A \models C}{A \otimes B \models C}$$ cautious monotonicity

$$\frac{A \models B \quad \neg (A \perp C)}{A \otimes C \models B}$$ rational monotonicity

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Limitations

- Cautious monotonicity is very conservative, and is probably not useful in practical setting
- Rational monotonicity states that C can only be composed with A if it is not incompatible with it
- But these notions of monotonicity can be used for "sound" query expansion

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Non-aboutness

- It is sometimes useful to know when an item is not a bout another

$$\frac{A \not\models B}{A \not\models B \oplus C}$$ negation rational *(desirable)*

$$\frac{A \models B}{B \not\models A}$$ asymmetry *(not desirable)*

$$\frac{A \perp B}{A \not\models B \text{ and } B \not\models A}$$ preclusion *(debatable)*

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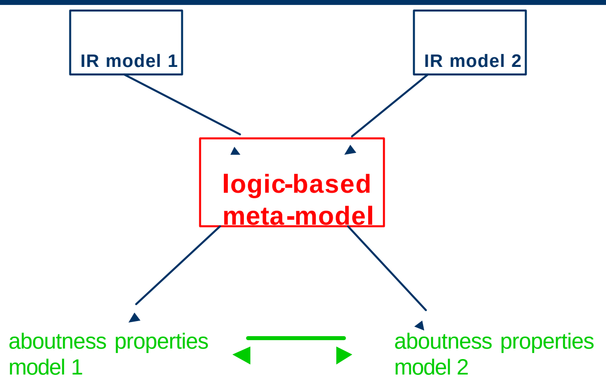
Practical use of meta-models



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Conclusions on meta-models

- Provide a better understanding of aboutness
- Choice of framework can determine aboutness properties
- Theoretical comparison of IR models is beginning, but more work is needed
  - Exploitation of the results
  - Analysing aboutness in probabilistic systems
  - Relationship between aboutness properties and retrieval performance (soundness vs precision, completeness vs recall)

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Current work on logical models

- Complexity reduction for implementation
- Applications to
  - Cross-language IR and query expansion
  - Structured document retrieval
  - Multimedia IR
  - Context IR
- Semantics for the Web
  - Ontologies + logical IR models
  - Semantic Web

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Future work (1)

- Use logical models to capture the semantics of data for retrieval purpose
  - Better representation models for complex objects (e.g. structured documents, multimedia documents)
  - Better implementation of these models (e.g. open to external knowledge)
  - Better validation of these models (in terms of effectiveness, efficiency and usability)

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Future work (2)

- Integration of logic and uncertainty models with
  - Artificial intelligence methods (e.g. inference engine)
  - Databases methods (e.g. data access optimisation)
  - Computational linguistics methods (e.g. information extraction)
- Work on effectiveness of implementation for access to large data repositories
  - Web
  - Digital libraries
  - Distributed systems
  - Heterogeneous data (XML, image, video, etc)

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Final conclusions

While it can be argued that logical models of IR have still to prove that they can provide efficient and effective access to information, it is without doubts that they provide a very valuable contribution to the study of IR in directions that are complimentary to classical IR research

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Acknowledgements

- The work presented here has been carried out by many researchers over several years
- A full list of references to the work presented in this lecture will be provided on the ESSIR web site
- This lecture is heavily based on the lecture “Logic and Uncertainty in Information Retrieval”, by Crestani and Lalmas, presented at ESSIR 2000

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