

Notes on IR

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Notes from [1]

- Probability Ranking Principle

The probability ranking principle (Robertson, 1977) states that for optimal performance, documents should be ranked in order of probability of relevance to the request or information need, as calculated from whatever evidence is available to the system

This is a nice principle, but may not be appropriate for a system designed to help someone learn, rather than just retrieve information. Given context (i.e. user state), some information that is not “most relevant” to what the user has asked may be more advantageous from the perspective of learning. This is more in line with the notion of trying to maximize “information content” transmitted across a channel, i.e. some documents not most relevant to a query may help a user learn more, perhaps even if they are not as relevant. Given context (i.e. user state), some information that is not “most relevant” to what the user has asked may be more advantageous from the perspective of learning. This is more in line with the notion of trying to maximize “information content” transmitted across a channel. In particular, what a student must see in order to learn what they want to learn may be very indirectly related to a query, especially if the query is ill-founded (consider a wise teacher helping his students learn, he should be more of a guide than a presenter of information).

- RSJ Weight

$$\begin{aligned} p_i &= P(\text{document contains } t_i \mid \text{document is relevant}) \\ q_i &= P(\text{document contains } t_i \mid \text{document is not relevant}) \end{aligned}$$

$$RSJ(t_i) = \log \frac{p_i(1 - q_i)}{q_i(1 - p_i)}$$

This can be given a simple estimate in terms of counting. Note that p_i and $(1 - q_i)$ can be called “hits,” in that the events correspond to a term’s appearance and relevance coinciding. Let the complimentary events be

called “misses,” and the function $-\log(P(\cdot))$ be the “measure of surprise” of an event (something like “information content”). Then RSJ is the difference between the measure of surprise of misses and hits. I.e. a term is weighted heavily if that term having a miss is very surprising, while getting a hit is not very surprising.

Note that, while it was Robertson’s intention to remove the information-theoretic content from tf-idf, I’m putting it back into his measure.

- RSJ as IDF I don’t think I’m smart enough to see how a fudged RSJ being equivalent to a naive Bayes model is better than the information-theoretic explanation given by Aizawa.

He is definitely right that the question of event space is troubling... It is hard to see what the right space should be. My initial thought was to remove the notion of event space altogether, and consider the query/response action as a act of communication – an attempt by multiple parties to compute a function using a channel as infrequently as possible.

- Document Normalization E.g., if a document is very long, under certain circumstances it should be normalized. It may be long because the author is wordy, or it may be long because the actual content is vast.

Notes from [2]

- Definition

Communication complexity studies ways to arrange *communications* between several parties so that at the end of the day they learn what they are supposed to learn, and to do this in the most efficient, or least *complex* way.

- Protocol Given inputs $x \in X$ (Alice), $y \in Y$ (Bob), we seek to calculate $f(x, y)$ transmitting as few bits as possible.

x				y
$f_1(x)$	\rightarrow	a_1	\rightarrow	$f_2(y, a_1)$
	\leftarrow	b_1	\leftarrow	
$f_1(x, a_1, b_1)$	\rightarrow	a_2	\rightarrow	$f_2(y, a_1, b_1, a_2)$
	\leftarrow	b_1	\leftarrow	
\vdots		\vdots		\vdots
	\rightarrow	a_t	\rightarrow	$f_2(y, \dots, a_t) = f(x, y)$

The cost associated with the above protocol instance $P = P(f_1, f_2)$ is

$$C(P, x, y) = \sum_{i=1}^t |a_i| + |b_i|$$

There is a useful and general argument for lower bounding the complexity of a distributed problem made by considering the space of all possible message sequences (histories R_h) possibly made by a protocol $\{0, 1\}^C(P)$, then relating these to coverings by combinatorial rectangles of the input space. The main idea is that the only thing that needs to be considered is $R_h = (a_1, b_1, \dots, a_t, b_t)$. I.e. f_1 depends only on x , and (b_1, b_2, \dots) (this is some sort of an independence property). The argument is similar to the discrete geometric argument relating coverings to δ -nets on a ball: we upper bound the size by volumetric and counting arguments. Here, we lower bound the complexity because the complexity must be “complex enough” to cover all the rectangles. The rectangles exists due to the “independence” mentioned before.

Notes from [3]

- Looks useful:

The core idea of Ingwersen and Jarvelin’s framework is “how evidence of a searcher’s information behavior may be applied to guide or adjust algorithmic information processing in system components through IR interaction”

- *Intellectual Perspective*

- Information Searching
interaction, goals/ tasks, behaviors/ strategies
- Information Retrieval
representing, storing, and finding information objects
- Both

- *Theoretical Orientation*

- People
- Technology
- Information

Not all seventeen concepts

Information – Information Searching

- *Hierarchical Relationship of Information*
- *Perceived Benefits*

Information – Both

- *Relevance*

Information – Information Retrieval

- *Representation* (sum of attributes)
- *Ranking*
- *Document Similarity*

People – Information Searching

- *Least Effort*
- *Iterative Process*

People – Both

- *Interaction*
- *Resolving an Uncertainty*

People – Information Retrieval

- *Provision* (assumed that providing information helps a user accomplish some task)

Technology – Information Searching

- *Channel Preference*

Technology – Both

- *Information Obtainability*

Technology – Information Retrieval

- *Query* (transformed input)
- *Neutrality of Technology*
- *Memex Vision*

Multiple Definitions Information has physical (entropy), cognitive (state-change), and affective (touchy-feely) “aspects.” As-process, as-knowledge, as-thing, as-attribute.

Hierarchical Relationships DIKW: *data, information, knowledge, wisdom* (database, **IR**, **IS**, AI)

Information Ranking In information searching, information ranking also is a notion well accepted; however, information searching researchers tend to focus more on the cognitive, affective, or contextual factors that determine the evaluation of search results and eventually the usefulness of information.

Relevance	Saracevic(2007b) defined relevance as a relation between information and contexts (e.g., information need, intent, topic, problem) based on some property reflecting a relevance manifestation (e.g., topicality, utility, cognitive match).
Query	a set of one or more symbols that is combined with other syntax and used as a command for an information retrieval system to locate possibly relevant content indexed by that system
Memex Vison	By nature though, both fields focus on the benefits of the use of technology, with little consideration of other options. As Rosenberg (1974) stated, the computer is not just a tool or machine but rather it is a way of looking at the world (p. 264) for these fields.
Information Obtainability	<p>information will be used in direct proportion to how easy it is to obtain (Summit, 1993).</p> <p>The lines of research in both fields hone in on making information easier to access, in terms of interfaces, expression of need or query, contextual help, and information visualization.</p>

Notes from [4]

- A major assumption of the probability ranking principle (PRP) for IR is that
 - the relevance of a document to a query is independent of the relevance of other documents the user has seen before. The task addressed by the PRP is the user's scanning through the list of ranked documents.
- Often user's want different answers to the same problem (aspectual recall), and query reformulation is a more crucial (i.e. 'expensive') user operation.
- Model Assumptions:
 1. Only consider functional level of interaction
 - e.g. don't consider the cost of an action depending on the interface used.
 2. Decisions are the major activity
 - system offers binary choices to user. User may accept, in which case the decision is **positive**. If the user does not wish to modify the decision immediately after learning its consequences, the decision is **correct**.
 3. Users evaluate choices in linear order
 4. Only positive, correct decisions are of benefit to the user
- *Situations.* A *situation* consists of the list of choices, the user's information need, and the system's knowledge of the user. A positive decision changes the situation. The information need is static for a given situation.

- **Expected benefit to user**

Event Space

S set of situations

s_i situation i

C_i set of choices for s_i

n_i $|C_i|$

c_{ij} a choice for s_i

Probabilistic Parameters

p_{ij} probability c_{ij} is accepted in s_i

q_{ij} probability choice is correct

Cost Parameters

e_{ij} effort of making choice c_{ij}

b_{ij} benefit of making choice c_{ij}

g_{ij} effort of correcting choice c_{ij}

- The independence assumption is that p_{ij} is independent of choices *rejected* before (incorrect past choices).
- The formula:

$$E(c_{ij}) = e_{ij} + p_{ij}(q_{ij}b_{ij} + (1 - q_{ij})g_{ij})$$

Average Benefit

$$a_{ij} = q_{ij}b_{ij} + (1 - q_{ij})g_{ij}$$

$$E(c_{ij}) = e_{ij} + p_{ij}a_{ij}$$

- Choices with $p_{ij} = 0$ are implicitly excluded from the list, as their expected benefit will be negative ($e_{ij} < 0$).
- Three strategies for maximizing c_{ij} :
 1. minimize e_{ij} (effort)
 2. maximize p_{ij} (selection probability)
 3. maximize g_{ij} (correctness probability)

- Expected benefit of list. Given a list of choices $r_i = \langle c_{i1}, c_{i2}, \dots, c_{in} \rangle$, the expected benefit is

$$r_i = e_{i1} + p_{i1}a_{i1} + (1 - p_{i1})(e_{i2} + p_{i2}a_{i2} + (1 - p_{i2})(e_{i3} + p_{i3}a_{i3} + \dots$$

$$r_i = \sum_{j=1}^n \left[(e_{ij} + p_{ij}a_{ij}) \prod_{k=1}^{j-1} (1 - p_{ik}) \right]$$

Note the similarity of this to a Markov Model...

- **Comparing choice orders**

Let

$$t_i^{l,l+1} = (e_{il} + p_{il}a_{il}) \prod_{k=1}^{l-1} (1 - p_{ik})$$

then we can compare the expected benefit of a list with the list made from transposing two elements by analyzing the term

$$t_i^{l,l+1} - t_i^{l+1,l}$$

If this term is non-negative, then the terms should not be transposed (c_{il} and $c_{i(l+1)}$ are in the right order in list r_i). After some algebra, the following ranking function is arrived at:

$$\rho(c_{ij}) = a_{ij} + \frac{e_{ij}}{p_{ij}}$$

Remember that e_{ij} is negative!

- **IIR-PRP** (*Probability ranking principle for interactive information retrieval*)

Order the list of choices in decreasing values of

$$\rho(c_{ij}) = a_{ij} + \frac{e_{ij}}{p_{ij}}$$

- **Parameter Groups**

p_{ij} (Selection Probability)

make dynamic for changing information requirements

e_{ij}, g_{ij}, q_{ij} (Effort Parameters)

UI, expertise of user

a_{ij} (Benefit)

general problem, entropy

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