Information Retrieval Models

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Course objectives

- Introduce the main concepts, models and algorithms behind (textual) information access

- We will focus on:
  - Standard models for Information Retrieval (IR)
  - IR & the Web: from PageRank to learning to rank models
    - Machine learning approach
    - How to exploit user clicks?
  - Dynamic IR
Overview

1. Standard IR models
2. IR & the Web
3. Dynamic IR
Standard IR models

- Boolean model
- Vector-space model
- Prob. models
Boolean model (1)

Simple model based on set theory and Boole algebra, characterized by:

- Binary weights (presence/absence)
- Queries as boolean expressions
- Binary relevance
- System relevance: satisfaction of the boolean query
Boolean model (2)

Example

$q = \text{programming} \land \text{language} \land (C \lor \text{java})$

$(q = [\text{prog.} \land \text{lang.} \land C] \lor [\text{prog.} \land \text{lang.} \land \text{java}])$

<table>
<thead>
<tr>
<th></th>
<th>programming</th>
<th>language</th>
<th>C</th>
<th>java</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_1$</td>
<td>3 (1)</td>
<td>2 (1)</td>
<td>4 (1)</td>
<td>0 (0)</td>
<td>...</td>
</tr>
<tr>
<td>$d_2$</td>
<td>5 (1)</td>
<td>1 (1)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>...</td>
</tr>
<tr>
<td>$d_0$</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>3 (1)</td>
<td>...</td>
</tr>
</tbody>
</table>

Relevance score

$RSV(d_j, q) = 1 \text{ iff } \exists q_{cc} \in q_{dnf} \text{ s.t. } \forall w, t^d_w = t^q_w ; 0 \text{ otherwise}$
**Algorithmic considerations**

Sparse term-document matrix: inverted file to select all document in conjunctive blocks (can be processed in parallel) - intersection of document lists

<table>
<thead>
<tr>
<th>term</th>
<th>$d_1$</th>
<th>$d_2$</th>
<th>$d_3$</th>
<th>$\ldots$</th>
</tr>
</thead>
<tbody>
<tr>
<td>programming</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>$\ldots$</td>
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<tr>
<td>langage</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>$\ldots$</td>
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<tr>
<td>C</td>
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</tr>
</tbody>
</table>
**Boolean model (4)**

**Advantages and disadvantages**

- Easy to implement (at the basis of all models with a union operator)
  - Binary relevance not adapted to topical overlaps
  - From an information need to a boolean query

**Remark** At the basis of many commercial systems
Vector space model (1)

Corrects two drawbacks of the boolean model: binary weights and relevance

It is characterized by:

- Positive weights for each term (in docs and queries)
- A representation of documents and queries as vectors (see before on bag-of-words)
Docs and queries are vectors in an $M$-dimensional space the axes of which corresponds to word types.

**Similarity** Cosine between two vectors

$$RSV(d_j, q) = \frac{\sum_w t^d_w t^q_w}{\sqrt{\sum_w (t^d_w)^2} \sqrt{\sum_w (t^q_w)^2}}$$

**Property** The cosine is maximal when the document and the query contain the same words, in the same proportion! It is minimal when they have no term in common (similarity score).
**Advantages and disadvantages**

+ Total order (on the document set): distinction between documents that completely or partially answer the information need
  
  - Framework relatively simple; not amenable to different extensions

*Complexity* Similar to the boolean model (dot product only computed on documents that contain at least one query term)
Probalistic models

- Binary Independence Model and BM25 (S. Robertson & K. Sparck Jones)
- Inference Network Model (Inquery) - Belief Network Model (Turtle & Croft)
- (Statistical) Language Models
  - Query likelihood (Ponte & Croft)
  - Probabilistic distance retrieval model (Zhai & Lafferty)
- Divergence from Randomness (Amati & Van Rijsbergen) - Information-based models (Clinchant & Gaussier)
Generalities

Boolean model → binary relevance
Vector space model → similarity score
Probabilistic model → probability of relevance

Two points of view: document generation (probability that the document is relevant to the query - BIR, BM25), query generation (probability that the document ”generated” the query - LM)
Let $D_1$ and $D_2$ two (standard) die such that, for small $\epsilon$:

For $D_1$, $P(1) = P(3) = P(5) = \frac{1}{3} - \epsilon$, $P(2) = P(4) = P(6) = \epsilon$
For $D_2$, $P(1) = P(3) = P(5) = \epsilon$; $P(2) = P(4) = P(6) = \frac{1}{3} - \epsilon$

Imagine you observe the sequence $Q = (1, 3, 3, 2)$. Which dice most likely produced this sequence?

Answer

$P(Q|D_1) = (\frac{1}{3} - \epsilon)^3\epsilon$; $P(Q|D_2) = (\frac{1}{3} - \epsilon)\epsilon^3$
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**Answer**

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Documents are die; a query is a sequence → What is the probability that a document (dice) generated the query (sequence)?

\[
(RSV(q, d) \Rightarrow P(q|d) = \prod_{w \in q} P(w|d)^{x_w^q}
\]

How to estimate the quantities \(P(w|d)\)?
→ Maximum Likelihood principle \(\Rightarrow p(w|d) = \frac{x_w^d}{\sum_w x_w^q}\)

Problem with query words not present in docs
Language model - QL (2)

Solution: smoothing
One takes into account the collection model:
\[ p(w|d) = (1 - \alpha_d) \frac{x_w^d}{\sum_w x_w^d} + \alpha_d \frac{F_w}{\sum_w F_w} \]

Example with Jelinek-Mercer smoothing: \( \alpha_d = \lambda \)

- \( \mathcal{D} \): development set (collection, some queries and associated relevance judgements)
- \( \lambda = 0 \):
- Repeat till \( \lambda = 1 \)
  - IR on \( \mathcal{D} \) and evaluation (store evaluation score and associated \( \lambda \))
  - \( \lambda \leftarrow \lambda + \epsilon \)
- Select best \( \lambda \)
Advantages and disadvantages

+ Theoretical framework: simple, well-founded, easy to implement and leading to very good results
  + Easy to extend to other settings as cross-language IR
- Training data to estimate smoothing parameters
- Conceptual deficiency for (pseudo-)relevance feedback

Complexity similar to vector space model
Evaluation interlude (1)

- Binary judgements: the doc is relevant (1) or not relevant (0) to the query
- Multi-valued judgements:
  \( \texttt{Perfect} > \texttt{Excellent} > \texttt{Good} > \texttt{Correct} > \texttt{Bad} \)
- Preference pairs: doc \( d_A \) more relevant than doc \( d_B \) to the query

Several (large) collections with many (> 30) queries and associated (binary) relevance judgements: TREC collections (trec.nist.gov), CLEF (www.clef-campaign.org), FIRE (fire.irs.i.res.in)
Evaluation interlude (2)

- MAP (Mean Average Precision)
- MRR (Mean Reciprocal Rank)
  - For a given query $q$, let $r_q$ be the rank of the first relevant document retrieved
  - MRR: mean of $r_q$ over all queries
- WTA (Winner Takes All)
  - If the first retrieved doc is relevant, $s_q = 1$; $s_q = 0$ otherwise
  - WTA: mean of $s_q$ over all queries
- NDCG (Normalized Discounted Cumulative Gain)
• Measures for a given position (e.g. list of 10 retrieved documents)

• NDCG is more general than MAP (multi-valued relevance vs binary relevance)

• Non continuous (and thus non derivable)
Content

1. PageRank
2. IR and ML: Learning to Rank (L2R)
3. Which training data?
What is the particularity of the web?

→ A collection with hyperlinks, the graph of the web, and anchor texts

1. Possibility to augment the standard index of a page with anchor texts
2. Possibility to use the importance of a page in the retrieval score (PageRank)
3. Possibility to augment the representation of a page with new features
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What is the importance of a page?

1. Number of incoming links
2. Ratio of incoming/outgoing links
3. A page is important if it is often linked by important pages
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A simple random walk

Imagine a walker that starts on a page and randomly steps to a page pointed to by the current page. In an infinite random walk, he/she will have visited pages according to their "importance" (the more important the page is, the more likely the walker visits it).

Problems

1. Dead ends, black holes
2. Cycles
Solution: teleportation

- At each step, the walker can either randomly choose an outgoing page, with prob. \( \lambda \), or teleport to any page of the graph, with prob. \( 1 - \lambda \).
- It’s as if all web pages were connected (completely connected graph).
- The random walk thus defines a Markov chain with probability matrix:

\[
P_{ij} = \begin{cases} 
\lambda \frac{A_{ij}}{\sum_{j=1}^{N} A_{ij}} + (1 - \lambda) \frac{1}{N} & \text{si } \sum_{j=1}^{N} A_{ij} \neq 0 \\
\frac{1}{N} & \text{sinon}
\end{cases}
\]

where \( A_{ij} = 1 \) if there is a link from \( i \) to \( j \) and 0 otherwise.
Definitions and notations

**Definition 1** A sequence of random variables $X_0, ..., X_n$ is said to be a *(finite state)* Markov chain for some state space $S$ if for any $x_{n+1}, x_n, ..., x_0 \in S$:

$$
P(X_{n+1} = x_{n+1}|X_0 = x_0, ..., X_n = x_n) = P(X_{n+1} = x_{n+1}|X_n = x_n)
$$

$X_0$ is called the initial state and its distribution the initial distribution.

**Definition 2** A Markov chain is called homogeneous or stationary if $P(X_{n+1} = y|X_n = x)$ is independent of $n$ for any $x, y$.

**Definition 3** Let $\{X_n\}$ be a stationary Markov chain. The probabilities $P_{ij} = P(X_{n+1} = j|X_n = i)$ are called the one-step transition probabilities. The associated matrix $P$ is called the transition probability matrix.
**Definition 4** Let \( \{X_n\} \) be a stationary Markov chain. The probabilities \( P_{ij}^{(n)} = P(X_{n+m} = j | X_m = i) \) are called the \( n \)-step *transition probabilities*. The associated matrix \( P^{(n)} \) is called the *transition probability matrix*.

Remark: \( P \) is a stochastic matrix.

**Theorem (Chapman-Kolgomorov equation)** Let \( \{X_n\} \) be a stationary Markov chain and \( n, m \geq 1 \). Then:

\[
P_{ij}^{m+n} = P(X_{m+n} = j | X_0 = i) = \sum_{k \in S} P_{ik}^m P_{kj}^n
\]
Regularity (ergodicity)

Definition 5 Let \( \{X_n\} \) be a stationary Markov chain with transition probability matrix \( P \). It is called regular if there exists \( n_0 > 0 \) such that \( p_{ij}^{(n_0)} > 0 \) \( \forall i, j \in S \)

Theorem (fundamental theorem for finite Markov chains) Let \( \{X_n\} \) be a regular, stationary Markov chain on a state space \( S \) of \( t \) elements. Then, there exists \( \pi_j, j = 1, 2, \ldots, t \) such that:

(a) For any initial state \( i \),
\[
P(X_n = j | X_0 = i) \to \pi_j, j = 1, 2, \ldots, t
\]

(b) The row vector \( \pi = (\pi_1, \pi_2, \ldots, \pi_t) \) is the unique solution of the equations \( \pi P = \pi \), \( \pi 1 = 1 \)

(c) Any row of \( P^r \) converges towards \( \pi \) when \( r \to \infty \)

Remark: \( \pi \) is called the long-run or stationary distribution
Stationary, regular Markov chains admit a stationary (steady-stable) distribution.

This distribution can be obtained in different ways:

1. Power method: let the chain run for a sufficiently long time!
   \[ \pi = \lim_{k \to \infty} P^k \]

2. Linear system: solve the linear system associated with
   \[ \pi P = \pi, \; \pi \mathbf{1} = 1 \] (e.g. Gauss-Seidel)

3. \( \pi \) is the left eigenvector associated with the highest eigenvalue (1) of \( P \) (eigenvalue decomposition, e.g. Cholevsky)

The PageRank can be obtained by any of these methods.
Two main innovations at the basis of Web search engines at the end of the 90’s:

1. Rely on additional index terms contained in anchor texts
2. Integrate the importance of a web page (PageRank) into the score of a page

→ Towards another innovation in the first decade of 21st century: learning to rank
Introduction to ML and SVMs (1)

One looks for a decision function that takes the form:

\[ f(x) = \text{sgn}(\langle w, x \rangle + b) = \text{sgn}(w^T x + b) = \text{sgn}(b + \sum_{j=1}^{p} w_j x_j) \]

The equation \( \langle w, x \rangle + b = 0 \) defines an hyperplane with margin \( \frac{2}{||w||} \).
Finding the *separating* hyperplane with maximal margin amounts to solve the following problem, from a training set \( \{(x^{(1)}, y^{(1)}), \ldots (x^{(n)}, y^{(n)})\} \):

\[
\begin{align*}
&\text{Minimize} \quad \frac{1}{2} w^T w \\
&\text{subject to} \quad y^{(i)} (\langle w, x^{(i)} \rangle + b) \geq 1, \quad i = 1, \ldots, n
\end{align*}
\]

Non separable case:

\[
\begin{align*}
&\text{Minimize} \quad \frac{1}{2} w^T w + C \sum_i \xi_i \\
&\text{subject to} \quad \xi_i \geq 0, \quad y^{(i)} (\langle w, x^{(i)} \rangle + b) \geq 1 - \xi_i, \quad i = 1, \ldots, n
\end{align*}
\]
The decision functions can take two equivalent forms. The "primal" form:

\[ f(x) = \text{sgn}(\langle w, x \rangle + b) = \text{sgn}(\langle w^*, x^{\text{aug}} \rangle) \]

and the "dual" form:

\[ f(x) = \text{sgn}\left(\sum_{i=1}^{n} \alpha_i y^{(i)} \langle x^{(i)}, x \rangle + b\right) \]
Modeling IR as a binary classification problem

What is an example? A doc? A query?

→ A (query,doc) pair: \( x = (q, d) \in \mathbb{R}^p \)

General coordinates (features) \( f_i(q, d), i = 1, \cdots, p \), as:

- \( f_1(q, d) = \sum_{t \in q \cap d} \log(t^d) \), \( f_2(q, d) = \sum_{t \in q} \log(1 + \frac{t^d}{|C|}) \)
- \( f_3(q, d) = \sum_{t \in q \cap d} \log(idf(t)) \), \( f_4(q, d) = \sum_{t \in q \cap d} \log(\frac{|C|}{t^C}) \)
- \( f_5(q, d) = \sum_{t \in q} \log(1 + \frac{t^d}{|C|} \cdot idf(t)) \), \( f_6(q, d) = \sum_{t \in q} \log(1 + \frac{t^d}{|C|} \cdot \frac{|C|}{t^C}) \)
- \( f_7(q, d) = RSV_{\text{Vect}}(q, d) \)
- \( f_8(q, d) = \text{PageRank}(d) \)
- \( f_9(q, d) = RSV_{\text{LM}}(q, d) \)
- ...
Application

Each pair \( x(= (q, d)) \) containing a relevant (resp. non relevant) doc for the query in the pair is associated to the positive class \(+1\) (resp. to the negative class \(-1\))

Remarks

1. One uses the value of the decision function (not its sign) to obtain an order on documents

2. Method that assigns a score for a (query,doc) pair independently of other documents → *pointwise method*

3. Main advantage over previous models: possibility to easily integrate new (useful) features

4. Main disadvantage: need for many more annotations

5. Another drawback: objective function different from evaluation function (true objective)
Preference pairs and ranking

1. Relevance is not an absolute notion and it is easier to compare relative relevance of say two documents.

2. One is looking for a function $f$ that preserves partial order between docs (for a given query): $x_i \prec x_j \iff f(x_i) < f(x_j)$, with $x_i$ being again a (query, doc) pair: $x_i = (d_i, q)$

Can we apply the same approach as before? Idea: transform a ranking information into a classification information by forming the difference between pairs.

From two documents $(d_i, d_j)$, form:

$$x^{(i,j)} = (x_i - x_j, z = \begin{cases} +1 & \text{if } x_i \prec x_j \\ -1 & \text{if } x_j \prec x_i \end{cases})$$

then apply previous method!
Remarks on ranking SVM

How to use $w^*$ in practice? ( 

Property: $d \succ_q d'$ iff $\text{sgn}(w^*, \langle d, q \rangle - \langle d', q \rangle)$ positive

However, a strict application is too costly and one uses the SVM score:

$$RSV(q, d) = (w^*, \langle q, d \rangle)$$

But

- No difference between errors made at the top or at the middle of the list
- Queries with more relevant documents have a stronger impact on $w^*$
RSVM-IR (1)

Idea: modify the optimization problem so as to take into account the doc ranks \( (\tau_k(l)) \) and the query type \( (\mu_q(l)) \)

\[
\begin{align*}
\text{Minimize} & \quad \frac{1}{2} w^T w + C \sum_l \tau_k(l) \mu_q(l) \xi_l \\
\text{subject to} & \quad \xi_l \geq 0, \quad y^{(l)}(w^* . x^{(l)}) \geq 1 - \xi_l, \quad l = 1, \ldots, p
\end{align*}
\]

where \( q(l) \) is the query in the \( l^{th} \) example and \( k(l) \) is the rank type of the docs in the \( l^{th} \) example.
Once $w^*$ has been learnt (standard optimization), it is used as in standard RSVM.

The results obtained are state-of-the-art, especially on web-like collections.

*Pairwise* approach, that dispenses with a limited view of relevance (absolute relevance).
General remarks

1. *Listwise* approach: directly treat lists as examples; however no clear gain wrt pairwise approaches

2. Difficulty to rely on an optimal objective function

3. Methods that require *a lot of* annotations
Which training data?
Building training data

• Several annotated collections exist
  - TREC (TREC-vido)
  - CLEF
  - NTCIR

• For new collections, as intranets of companies, such collections do not exist and it may be difficult to build them → standard models, with little training

• What about the web?
Training data on the web

- An important source of information; click data from users
  - Use clicks to infer preferences between docs (preference pairs)
  - In addition, and if possible, use eye-tracking data

- What can be deduced from clicks?
Exploiting clicks (1)

Clicks can not be used to infer absolute relevance judgements; they can nevertheless be used to infer relative relevance judgements. Let \((d_1, d_2, d_3, \cdots)\) be an ordered list of documents retrieved for a particular query and let \(C\) denote the set of clicked documents. The following strategies can be used to build relative relevance judgements:

1. If \(d_i \in C\) and \(d_j \notin C\), \(d_i \succ_{pert-q} d_j\)
2. If \(d_i\) is the last clicked doc, \(\forall j < i, d_j \notin C, d_i \succ_{pert-q} d_j\)
3. \(\forall i \geq 2, d_i \in C, d_{i-1} \notin C, d_i \succ_{pert-q} d_{i-1}\)
4. \(\forall i, d_i \in C, d_{i+1} \notin C, d_i \succ_{pert-q} d_{i+1}\)
Exploiting clicks (2)

- The above strategies yield a partial order between docs
- Leading to a very large training set on which one can deploy learning to rank methods
- IR on the web has been characterized by a "data rush":
  - Index as many pages as possible
  - Get as many click data as possible
Letor


Approaches aiming at exploiting all the available information (60 features for the gov collection for example - including scores of standard IR models)

Approaches aiming at ") ranking" documents (pairwise, listwise)

Many proposals (neural nets, `boosting` and ensemble methods, ...); no clear difference on all collections

State-of-the-art methods when many features available
References (1)


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• Cao et al. *Adapting Ranking SVM to Document Retrieval*, SIGIR 2006


• Goswami et al. *Query-based learning of IR model parameters on unlabelled collections*, ICTIR 2015

• Joachims et al. *Accurately Interpreting Clickthrough Data as Implicit Feedback*, SIGIR 2005


• Manning et al. *Introduction to Information Retrieval*. Cambridge University Press 2008

References (2)

• Nallapati *Discriminative model for Information Retrieval*, SIGIR 2004
• Yue et al. *A Support Vector Method for Optimizing Average Precision*, SIGIR 2007
• Workshop LR4IR, 2007 (Learning to Rank for Information Retrieval).
In recent years, will to go beyond the paradigm

\[\text{one information need} \rightarrow \text{one query} \rightarrow \text{one result (ordered list of docs)}\]

Considering complete sessions in which queries are refined/rewritten depending on results displayed

Two main "tracks":

1. Session search
2. Dynamic domain track

None really adapted to what one wants!
Session search & Dynamic IR (2)


Remarks:
- However not enough data to fully train such a system
- Simulation can help (but need for human intervention)

(http://www.slideshare.net/marcCsloan/dynamic-information-retrieval-tutorial)
Conclusion

- Rich history of models: boolean, vector space, probabilistic (BIR & Okapi, language models, deviation from randomness, information-based, quantum) and ML (learning to rank, transfer learning)

- Need to go beyond the standard *query & rank* paradigm; dynamic IR is a way forward

- We, academics, nevertheless face the same problems we faced some years ago for ML approaches: lack of training data

- How to organize our community to be major players in this field?
Thank you!