Parametric Search and Machine Learning Based Scoring

Reference: Introduction to Information Retrieval
by C. Manning, P. Raghavan, H. Schutze

Parametric Search

Parametric search

- Most documents have, in addition to text, some "meta-data" in fields e.g.,
  - Language = French
  - Format = pdf
  - Subject = Physics etc.
  - Date = Feb 2000

Field → ← Value

- A parametric search interface allows the user to combine a full-text query with selections on these field values e.g.,
  - language, date range, etc.

Parametric search example

CarFinder.com

Over one million fictional vehicles to choose from!

Choose your search criteria from the drop down menus:

Number of results to display: 50

Make BMW **Model** 5-Series **Category** Any **Year** All

City San Francisco **Color** Any **Price** From $10,100 to $15,000

Search

Reset Filters Reset Sorts

Notice that the output is a (large) table. Various parameters in the table (column headings) may be clicked on to effect a sort.

Make	Model	Year	City	Mileage	Price	Category	Description	Color
BMW	5-Series	1995	San Francisco	16100	11100	Luxury	Never driven in winter conditions. Body work makes it look like new. Keyless entry and security features. This is a bargain.	Silver
BMW	5-Series	1995	San Francisco	16600	11100	Luxury	Great first car for your teen-aged kid. Solid, dependable, affordable with 0% down and owner financing.	Blue
BMW	5-Series	1995	San Francisco	16800	11200	Luxury	Upgraded sound system really rocks. Customized interior features wood grain dash and beige leather seats. Power locks, windows, steering. Price firm.	White
BMW	5-Series	1995	San Francisco	16100	11300	Luxury	Safe choice for a young family: ABS, driver and passenger air bags. Roomy interior with power everything. Low mileage driving kids back and forth to soccer.	Maroon
BMW	5-Series	1995	San Francisco	16300	11400	Luxury	This baby's got it all: power steering, cruise, power locks, power windows, remote entry, leather interior, security alarm, AM/FM/CD/Cassette. Priced to sell!	Brown

Parametric search example

CarFinder.com

Over one million fictional vehicles to choose from!

We can add text search.

Choose your search criteria from the drop down menus:

Number of results to display: 50

Make BMW | **Model** 5-Series | **Category** Any | **Year** 1997

City San Francisco | **Color** Any | **Price** From $10,100 to $15,000 | **Description**

Search | Clear Form

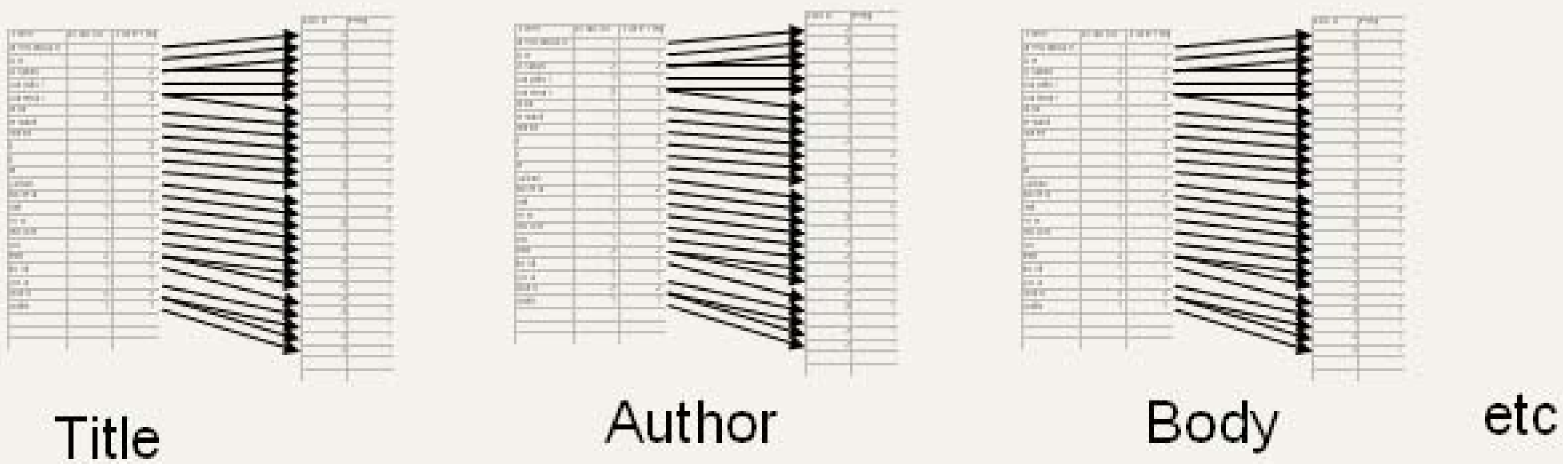
Reset Filters | Reset Sorts

Make	Model	Year	City	Mileage	Price	Category	Description	Color
BMW	5-Series	1997	San Francisco	14300	13100	Luxury	5-speed, heavy-duty suspension, extra wide tires. Well-maintained by mechanic-owner. Cloth seats and upgraded stereo system.	White
BMW	5-Series	1997	San Francisco	14600	13100	Luxury	Is that price for real? You bet it is. Fully loaded with all factory options. Former floor model.	Beige
BMW	5-Series	1997	San Francisco	14900	13100	Luxury	Fun to drive. Manual 5-speed transmission, turbo charger. Garaged all winter and pampered the rest of the year. This is a steal!	Orange
BMW	5-Series	1997	San Francisco	14800	13200	Luxury	Fully loaded, automatic transmission. Power everything. Anti-lock brakes and full safety features. Must test drive. Price firm.	Green
BMW	5-Series	1997	San Francisco	14300	13200	Luxury	Formerly an executive's vehicle. Interior has been professionally maintained, engine factory serviced every 3000 miles. Great gas mileage. Price negotiable.	Maroon
BMW	5-Series	1997	San Francisco	15000	13200	Luxury	Sun roof, air, CD player, driver side air bag. 10% deposit required. Owner financing available. Best offer by end of weekend buys it	Red

Zones

- A zone is an identified region within a doc
  - E.g., Title, Abstract, Bibliography, Body
  - Generally culled from marked-up input or document metadata (e.g., powerpoint)
- Contents of a zone are free text
  - Not a “finite” vocabulary
- Indexes for each zone - allow queries like
  - ***sorting*** in Title AND ***smith*** in Bibliography AND ***recursion*** in Body

Zone indexes – simple view



Scoring and Ranking

Scoring

- Thus far, our queries have all been Boolean
  - Docs either match or not
- OK for expert users with precise understanding of their needs and the corpus
- Not good for (the majority of) users with poor Boolean formulation of their needs
- Most users don't want to wade through 1000's of results – cf. use of web search engines

Scoring

- *We wish to return in order the documents most likely to be useful to the searcher*
- How can we rank order the docs in the corpus with respect to a query?
- Assign a score – say in [0,1] for each doc *d* on each query *q*

Linear zone combinations

- First generation of scoring methods: use a linear combination of Booleans:
  - e.g.,

Score = 0.6*<***sorting*** in Title> + 0.3*<***sorting*** in Abstract> + 0.05*<***sorting*** in Body> + 0.05*<***sorting*** in Boldface>

- Each expression such as <***sorting*** in Title> takes on a value in {0,1}.

Linear zone combinations

- In fact, the expressions between <> on the last slide could be *any* Boolean query
- We are given a weight vector whose components sum up to 1.
  - There is a weight for each zone/field.
- Then the overall score is in [0,1].
  - Remark: For this example, the scores can only take on a finite set of values.

Linear zone combinations

- Given a Boolean query, we assign a score to each doc by adding up the weighted contributions of the zones/fields.
- The retrieval model for document d and query q is:

$$score(d, q) = w_1 s_1(d, q) + \cdots + w_m s_m(d, q)$$

where $s_i(d, q)$ denotes the Boolean result for zone i

and $\sum_i w_i = 1$

Linear zone combinations

- Most commonly, a <u>query parser</u> that takes the user's query and runs it on the indexes for each zone
- Typically - users want to see the K highest-scoring docs.

Machine Learning Based Scoring

Where do these weights come from?

- Machine learned scoring
- Given
  - A *test corpus*
  - A suite of *test queries*
  - A set of *relevance judgments*
- Learn a set of weights such that relevance judgments matched

Simple example

- Each doc has two zones, Title and Body
- For a chosen $w \in [0,1]$, score for doc *d* on query *q*

$$score(d,q) = w \cdot s_T(d,q) + (1-w)s_B(d,q)$$

where:

$s_T(d, q) \in \{0,1\}$ is a Boolean denoting whether *q* matches the Title and

$s_B(d, q) \in \{0,1\}$ is a Boolean denoting whether *q* matches the Body

Learning *w* from training examples

Example	DocID	Query	s_T	s_B	Judgment
Φ_1	37	linux	1	1	Relevant
Φ_2	37	penguin	0	1	Non-relevant
Φ_3	238	system	0	1	Relevant
Φ_4	238	penguin	0	0	Non-relevant
Φ_5	1741	kernel	1	1	Relevant
Φ_6	2094	driver	0	1	Relevant
Φ_7	3191	driver	1	0	Non-relevant

We are given *training examples*, each of which is a triple:
DocID *d*, Query *q*, and Judgment *Relevant/Non-relevant*.

From these, we will learn the best value of *w*.

How?

- For each example Φ_t we can compute the score based on

$$score(d_t, q_t) = w \cdot s_T(d_t, q_t) + (1 - w)s_B(d_t, q_t)$$

- We quantify Relevant as 1 and Non-relevant as 0
  - Would like the choice of *w* to be such that the computed scores are as close to these 1/0 judgments as possible
  - Denote by $r(d_t, q_t)$ the judgment for Φ_t
- Then minimize total squared error

$$\sum_{\Phi_t} (r(d_t, q_t) - score(d_t, q_t))^2$$

Optimizing *w*

- There are 4 kinds of training examples

s_T	s_B	Score
0	0	0
0	1	$1 - w$
1	0	w
1	1	1

Optimizing *w*

- There are 8 possible values for errors

s_T	s_B	Score
0	0	0
0	1	$1 - w$
1	0	w
1	1	1

Judgment=1 $\Rightarrow$ Error=w

Judgment=0 $\Rightarrow$ Error=1-w

- Let n_{01r} be the number of training examples for which $s_T(d, q)=0$, $s_B(d, q)=1$, judgment = *Relevant*.
- Similarly define n_{00r} , n_{10r} , n_{11r} , n_{00i} , n_{01i} , n_{10i} , n_{11i}

Total error – then calculus

- Add up from various cases to get the total error
- The total error E is:

$$E = (n_{01r} + n_{10i})w^2 + (n_{10r} + n_{01i})(1 - w)^2 + n_{00r} + n_{11i}$$

- Now differentiate with respect to *w* to get optimal value
- Set ${}^{d(E)}/_{d(w)} = 0$, we get

$$2w(n_{01r} + n_{10i}) + (n_{10r} + n_{01i})2(1 - w)(-1) = 0$$

Optimal weight parameter

$$2w(n_{01r} + n_{10i}) + (n_{10r} + n_{01i})2(1 - w)(-1) = 0$$

$$w(n_{01r} + n_{10i}) + (w - 1)(n_{10r} + n_{01i}) = 0$$

$$w = \frac{n_{10r} + n_{01i}}{n_{10r} + n_{10i} + n_{01r} + n_{01i}}$$

Full text queries

- Most users more likely to type ***bill rights*** or ***bill of rights***
  - How do we interpret these *full text* queries?
  - No Boolean connectives
  - Of several query terms, some may be missing in a doc
  - Only some query terms may occur in the title, etc.

Scoring: density-based

- Thus far: position and overlap of terms in a doc – title, author etc.
- Obvious next idea: if a document talks about a topic *more,* then it is a better match
- This applies even when we only have a single query term.
- Document relevant if it has many occurrences of the term(s)
- This leads to the idea of term weighting.