Learning to Rank under Tight Budget Constraints

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4th of September, 2012

Problem

Given:

- Document corpus D and index
- Query $q = (t_1, \cdots, t_n)$ of n terms t_i
- Budget B and costs C

Task:

- Find top k documents for the query (Ranking model)
- Keep budget B, (i.e. all costs together are below B)

Costs

We assume that the calculation of the ranking costs a certain amount of effort:

- accessing and loading of the elements of an index
- processing the information from the index.

This costs

- access and processing time
- network traffic and energy consumption.

To reflect these efforts, we estimate costs for loading information from an index and processing the information by a ranking model.

Idea

- Load only partial information from the index and process only some parts of the ranking model.
- Estimate importance of parts of the index and ranking model
- Try to use an optimal combination of parts of the index and ranking model that budget is kept
- Parameterize the ranking model with respect to what needs to be loaded and what needs to be processed

Loading

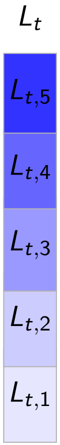
Index (term postings)

$$L_t = \{\{pos_i^j\}, id_j | t = d_j[pos_i]\}$$

Additional information about documents length and corpus size

- Separate index list into blocks, that can be loaded independently
- Estimate use and costs of loading a block

Example of blocks



- Blocks sorted by impact (expected use for ranking)
- In the blocks, postings sorted by doc id (compression)

Processing

Ranking model as additive ensemble of base rankers F_r

$$score(q,d) = \sum_r F_r(S(q),d)$$
$$S(q) = \{q' | q' \subseteq 2^q\}$$

- Combine features to base rankers F_r to estimate the relevance of documents to a given query
- Calculate features from postings from index blocks and additional information about documents and corpus

Parameterization

Parameterized model with X parameter vector

$$score(q,d,X) = \sum_r F_r(S(q,d,X),d) \cdot X_r$$
$$S(q,d,X) = \{q' | q' \subseteq 2^q \ \wedge X_{q'}(d) = 1\}$$

- $X_q(d) = X_{q,k}$ s.t. $d \in L_{q,k}$
- $X = (X_{t_i,k}, X_{t_i,t_{i+1},k}, X_r)$

Loading costs

$$\begin{aligned} costs_l(t_i t_{i+1}, X) &= 0 \\ costs_l(t_i, X) &= \sum_k costs_l(t_i, k) \cdot X_{t_i,k} \\ costs_l(t_{i,k}) &= |L_{t_i,k}| \cdot k_l \end{aligned} \quad (1)$$

- Costs for using term t_i depends on the blocks to be loaded
- Since bigram $t_i t_{i+1}$ can only be used when terms t_1 and t_{i+1} are already loaded no further costs occur
- Costs for loading a block depends on its size and a constant

Processing costs

$$
\begin{aligned}
costs_p(F_r, X) &= (k_p \cdot I(F_{r' \neq r}) + k_r) \cdot \\
&\quad \sum_{X_{t_i, t_{i+1}, k} = 1} (|L_{t_{i,k}}| + |L_{t_{i+1,k}}|) \cdot X_r \\
&+ (k_p \cdot I(F_{r' \neq r}) + k_r) \cdot \sum_{X_{t_i, k} = 1} |L_{t_{i,k}}| \cdot X_r
\end{aligned}
\tag{2}
$$

- Costs of processing loaded blocks
- How many postings must be processed multiplied by a constant
- Iterate over postings from the blocks only once

Use

Given a query, different posting lists, resp. blocks, and different base rankers have different expected value for the final ranking.

- Some terms or bigrams are more important
- Not all blocks have equal expected value for the ranking
- Value for applying base rankers inherent different and depends on order of application

Expected use of loading

$$
\begin{aligned}
U(t_i, X) &= \sum_k \delta_k \cdot X_{t_{i,k}} \\
&+ U(t_i t_{i+1}) + U(t_{i-1} t_i) \\
U(t_i t_{i+1}, X) &= \sum_{k,k'} (\delta_k + \delta_{k'}) \cdot X_{t_{i,k}} \cdot X_{t_{i+1,k'}}
\end{aligned} \tag{3}
$$

- Assume functional dependency $\delta_{k+1} = f(\delta_k)$ with decreasing use for additionally load blocks
- Assume additive use when using two terms as bigram

Expected use of processing

$$U(F_r) = \epsilon_r \cdot \rho_t \tag{4}$$

- Each base ranker has expected use ϵ_r
- Use depends also on the position t when the ranker is applied
- We expect decreasing use when applying more and more rankers ρ_t

Optimal parameterization of ranking model

$$
\begin{aligned}
X &= argmax_{X'} \sum_{q' \in S(q), r} U(q', F_r, X') \cdot X'_r \cdot X'_{q'} \quad (5) \\
s.t. & \sum_{q' \in S(q)} costs_l(q', X') + \sum_r costs_c(F_r, X') \leq B
\end{aligned}
$$

- Knap-sack like approach
- Greedy optimization of benefit: $\frac{use}{costs}$
- $U(q', F_r, X) = U(q', X) \cdot U(F_r)$

Find optimal use parameters

$$argmax_{\delta,\epsilon,\rho} \frac{1}{|Q_{tr}|} \cdot \sum_{q \in Q_{tr}} \sum_{B} E(D, score_{X(B)}(q,.)) \tag{6}$$

- Optimize ranking quality E over the parameters
- Use training data set Q_{tr} with labeled queries
- Linear search over parameter values

Related Approaches

- Cambazoglu et al. WSDM'10
- Wang et al. SIGIR'11

Results on WT10g

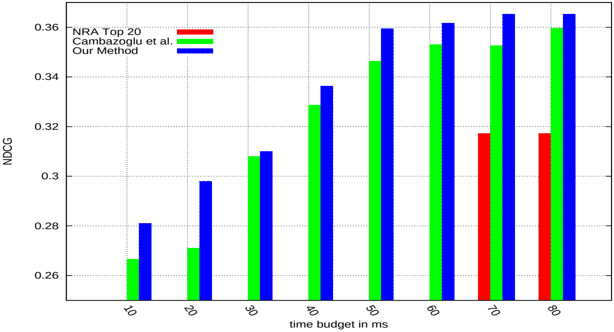


Figure: NDCG for different budget on the WT10g data set.

Results on .gov2

Table: Mean NDCG@20 and Precision@20 over all tested budgets. Error notes how many test queries could not actually end before the budget was exceeded. Bold numbers show best results for the data sets. *Shows significant improvements.

Data set	.Gov2: Topics 776 to 850		
Method	Error	NDCG	P20
Early exit	4%	54.35*	50.75*
Our method	4%	**55.39***	**52.07***

Conclusion

- Estimated use and costs of applying (parts of) a ranking model
- Defined search for optimal loading and application strategy as knap-sack optimization problem
- Learned use of parts of the ranking model by optimizing ranking quality
- Evaluated on a large benchmark collection

Problems

- Too many parameters
- Not directly applicable to more complex ranking models
- Does not work with (gradient) boosting

Thanks for your attention

- Questions?