December 2, 2010

Motivation

- How does Google sort its results?
- Given a document and a query, which sorting is most useful?
- Ranking is based on **features**, such as
  - **Term occurrence**
  - **Term proximity**
  - **Linguistic Features**
  - **Etc…**

Motivation

- But, which features should we choose?
- What trade-off between cost and quality of results is optimal?
- Can we complete Ranking in a certain time?
- Common Approach:
  1. Hope
  2. Dilligence

Ranking Under Temporal Constraints

Seminar on Information Retrieval

Andreas Frische, UdS

Outline

- **Constrained Linear Ranking**
  - **Linear Ranking Functions**
  - **Constrained Linear Ranking**
  - **Algorithm: Indept**
  - **Feature Weight**
  - **Feature Cost**
  - **Joint Prediction Model**
  - **Algorithm: Joint Ranking**
  - **Open Questions**
- Experiments
  - Experimental Setup
  - MAP vs. time
  - Satisfying Time Constraints
- Wrap Up

Linear Ranking Functions

- Many widely used Ranking Models use *Linear Ranking*
- Simple, yet effective class of ranking functions
- Given
  1. Query q
  2. Document d
  3. Features $F = f_1 \ldots f_N$ with
  4. Model Parameters $\Lambda = \lambda_1 \ldots \lambda_N$

$$Score(q,d) = \sum_i \lambda_i f_i(q,d)$$

Linear Ranking Functions

- Problem: Computational Cost is query dependent
- Example:
  - Feature Set: { (Phrase,λ_P), (TF,λ_T)
  - Q1: White House
  - Q2: White House, Rose Garden

	Phrase	TF
Cost Q1	1 bigram	2 unigrams
Cost Q2	3 bigrams	4 unigrams

Constrained Linear Ranking

- Basic Idea: Fill as much features into a "sack"/threshold as possible
  - » *Knapsack Problem*
- To instantiate a model we need to
  1. Define the Cost of Features
  2. Determine the Weight of Features
  3. Select subset of features for each [class of] queries
- *For now, assume we have 1 and 2 done*

Algorithm: Indept

- Features are selected independently from each other

In: Time Constraint T(q), Feature Set FS(q), Feature Weights $\Lambda(q)$, Feature Cost C(q)
Out: Constrained Ranking Function R(q)

$R = \emptyset$, $totalcost = 0$
Compute Feature Profit Density $\forall_i \; p_i := \frac{\lambda_i(q)}{C(f_i)}$
Queue *F* := Features sorted by profit density
While (F $not\ empty$) *Do*
    Let f be the Head of F
    Remove it
    If ($totalcost + Cost(f) < T(q)$)
        Add (f with λ_f) to R(q)
        $totalcost = totalcost + Cost(f)$
    Fi
Od

Feature Weight

- Feature Weights should depend on the query
  - Chocolate Milk vs Johannes Brahms
- Given
  1. Meta Features G
  2. Meta Feature Weights W

$$\lambda_i(q) := \sum_j w_j g_j(q)$$

- Example meta feature
  #times q occurs in a collection, such as
  Wikipedia Titles

Feature Cost

- Heuristic: features with more ~Operations get a higher cost
- Weak part of the paper
- But works surprisingly well

Joint Prediction Model

- In a large Feature Set, some features may be redundant
- Solution:

After adding a feature,
penalize features with a similar concept

Algorithm: Joint Ranking

In: Time Constraint T(q), Feature Set FS(q), Meta-Features G, Meta-Feature Weights W(q) , Feature Cost C(q),
Out: Constrained Ranking Function R(q)
$R = \emptyset\, , totalcost = 0$
Compute Feature Weights: $\lambda_i(q) := \sum_j w_j g_j(q)$
Compute Feature Profit Density $\forall_i\, p_i := \frac{\lambda_i(q)}{C(f_i)}$
Queue *F1* := Features sorted by profit density, F2 := empty Queue
Group features by concept: $G_e := features$ of concept e
While ($F1$ *or* $F2$ *not empty*) *Do*
    Let f be max(head F1, head F2)
    Remove it
    If ($totalcost + Cost(f) < T(q)$)
        Add (f with λ_f) to R(q)
        $totalcost = totalcost + Cost(f)$
        If (concept of f not covered AND $\lambda_e < \alpha$)
            Reduce weight of e by Redundancy Penalty
            Move Features with same concept as f to F2
            Mark concept covered
        Fi
Fi ; Od

Open Questions

- Where do the meta-feature weights come from?
- Where does the Redundancy Penalty come from?
- Where does α come from?

Outline

- ~~Constrained Linear Ranking~~
  - ~~Linear Ranking Functions~~
  - ~~Constrained Linear Ranking~~
  - ~~Algorithm: Indept~~
  - ~~Feature Weight~~
  - ~~Feature Cost~~
  - ~~Joint Prediction Model~~
  - ~~Algorithm: Joint Ranking~~
  - ~~Open Questions~~
- **Experiments**
  - **Experimental Setup**
  - **quality vs. time**
  - **Satisfying Time Constraints**
- Wrap Up

Experimental Setup

- We operate on the following test collections

	Wt10g	Gov2	Clue
Topics	451-550	701-850	1-50
# docs	1,692,096	25,205,179	50,220,423
#docs / Topics	~3400	~33000	~2000000
avg qlen (title)	2.50	2.96	1.88
Avg qlen(desc)	6.08	5.90	5.88

Experimental Setup

- And test these Algorithms
  - ALL (features) – acts as a upper bound
  - QL (Query Likelihood) – Baseline Algorithm
  - Indept
  - Joint

- X-axis denotes time, measured in QL time cost
- Thus we become hardware independent
- Y-axis denotes quality of results
- (MAP := Mean Average Precision)

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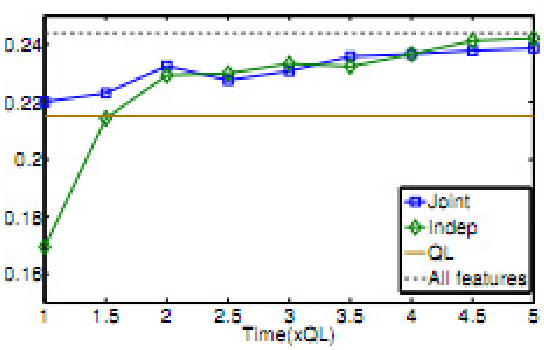
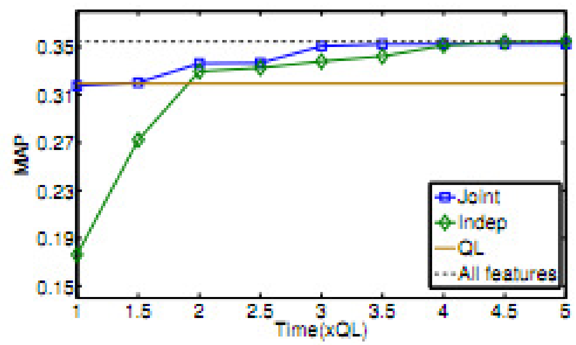
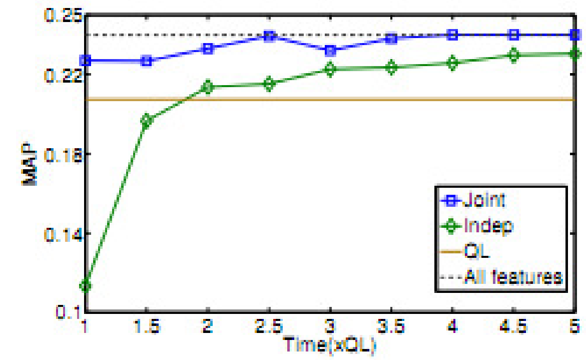
MAP vs. time



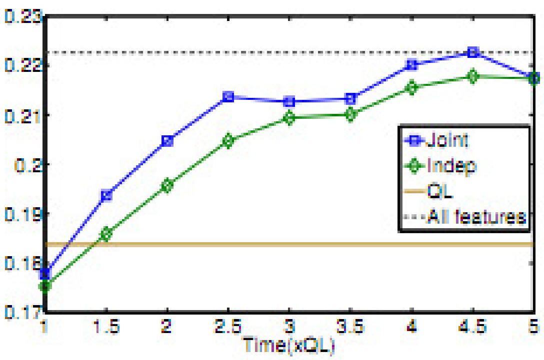
(i) Wt10g title



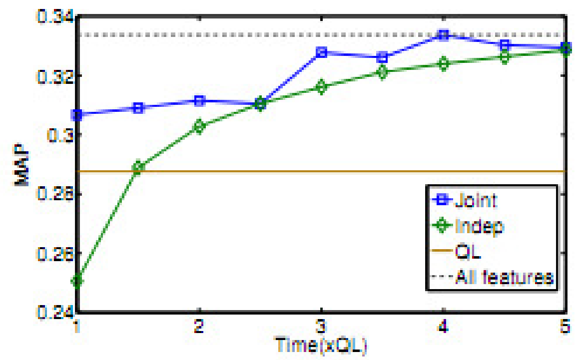
(ii) Gov2 title



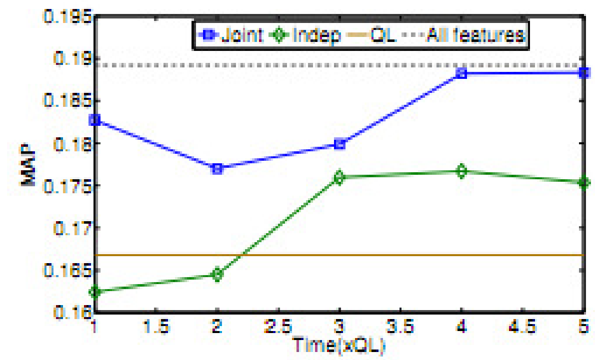
(iii) Clue title



(iv) Wt10g description

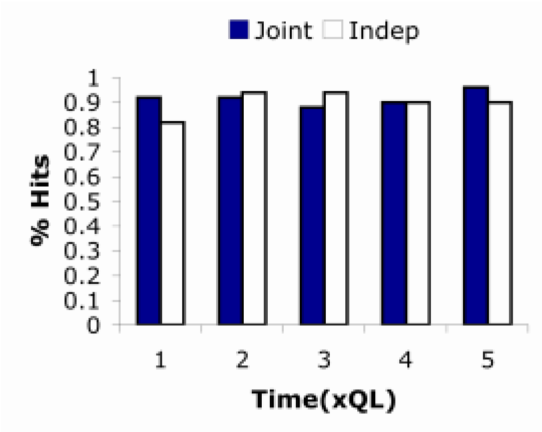


(v) Gov2 description

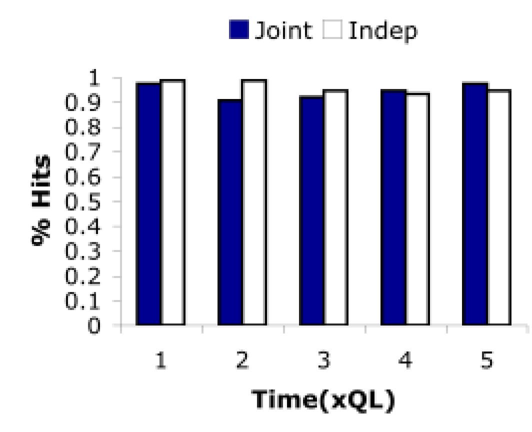


(vi) Clue description

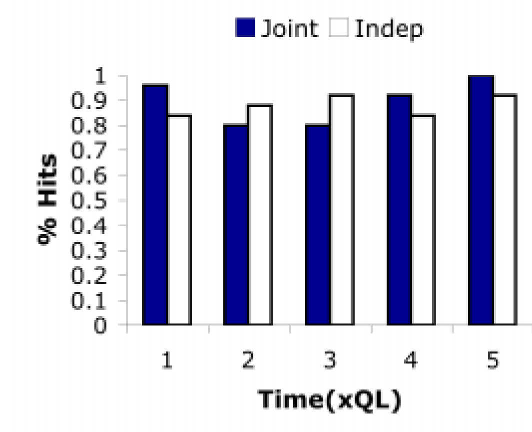
Satisfying Time Constraints



(i) Wt10g title



(ii) Gov2 title



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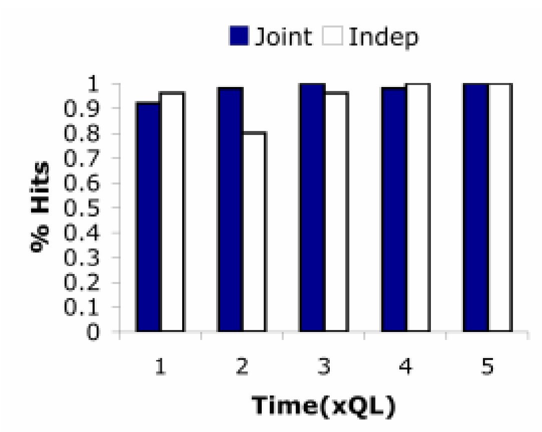
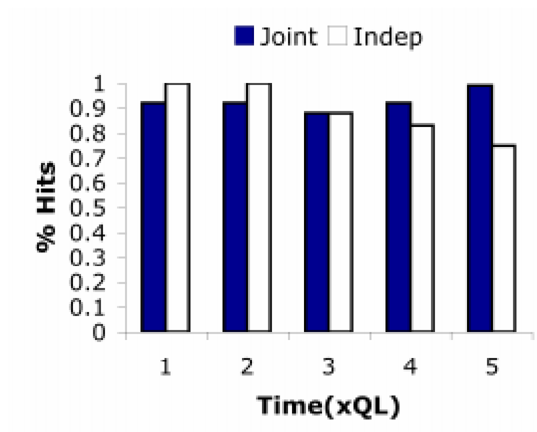
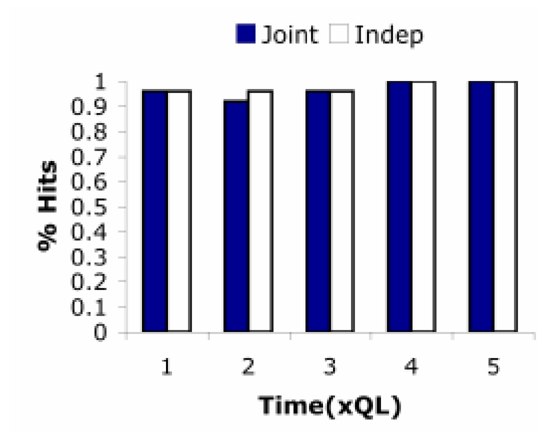


(iv) Wt10g description



(v) Gov2 description



(vii) Clue description

Wrap Up

- Ranking is vital for returning useful results to a query
- Time constraints may apply
- Constraint Linear Ranking allows to construct a Ranking Function for a query and time constraint
- More time leads to better results (mostly)

Thank You

- Questions?