THE UNIVERSITY of EDINBURGH

Text Technologies for Data Science

INFR11145

Learning to Rank

Instructor:
Walid Magdy

21-Nov-2017

Lecture Objectives

- Learn about:
  - IR as a classification task
  - Learning to Rank approaches

Text Classification in IR

- Text Classification:
  - Classify a document into one of two or more classes
  - Different features could be used, e.g. BOW
- Can we model IR as classification?
  - Classify document to C1: R or C2: NR
  - Challenges?
    - Training data?
    - Features?
- BOW features cannot work
  - Spam? Viagra, @ed.ac.uk
  - Sentiment? happy, sad
  - Relevant? Trump, hurricane
  - Relevance is a query-dependent class

Getting Classification to IR

- Transforming features
  - Text classification: Input (D) → output (yes/no)
  - Information Filtering: Input (D|Q) → output (yes/no)
- Features set:
  - Independent of absolute words
  - More on relation between doc and query
  - Mostly are numbers (formulas, frequencies, …)
  - Consistent as much as possible among different Q,D pairs
  - e.g.:
    - TFIDF, BM25
    - Query in page title? Heading?
    - Query in anchor text linking pages
    - PageRank of doc
    - Number of times page clicked for the same query

Popular Features

Column in Output	Description
1	TF(Term frequency) of body
2	TF of anchor
3	TF of title
4	TF of URL
5	TF of whole document
6	IDF(Inverse document frequency) of body
7	IDF of anchor
8	IDF of title
9	IDF of URL
10	IDF of whole document
11	TF*IDF of body
12	TF*IDF of anchor
13	TF*IDF of title
14	TF*IDF of URL
15	TF*IDF of whole document
16	DL(Document length) of body
17	DL of anchor
18	DL of title
19	DL of URL
20	DL of whole document
21	BM25 of body
22	LMIR.ABS of body
23	LMIR.DIR of body

Column in Output	Description
24	LMIR.JM of body
25	BM25 of anchor
26	LMIR.ABS of anchor
27	LMIR.DIR of anchor
28	LMIR.JM of anchor
29	BM25 of title
30	LMIR.ABS of title
31	LMIR.DIR of title
32	LMIR.JM of title
33	BM25 of URL
34	LMIR.ABS of URL
35	LMIR.DIR of URL
36	LMIR.JM of URL
37	BM25 of whole document
38	LMIR.ABS of whole document
39	LMIR.DIR of whole document
40	LMIR.JM of whole document
41	PageRank
42	Inlink number
43	Outlink number
44	Number of slash in URL
45	Length of URL
46	Number of child page

Training Data

- Training data: {R,X}
  - X: feature representation of (D,Q) pairs
  - R = {-1,+1} … is D relevant to Q or no
- Samples:
  - Large set of (D,Q) pairs
  - Wide range of Q's (long/short, frequent/rare, …)
  - Wide range of D's for each Q (top/deep ranked, recent/old pages, …)
- Labels:
  - Manually labelled: assessors judge relevance of docs to queries (similar to standard IR)
  - Automatically labelled: click-through data

Classification or Ranking?

- Click-through data
  - User clicks can give indication of relevance
  - What about non-relevance?
  - A list of ranked results: D1 → D2 → D3
    user clicked on D3 and neglected D1 & D2
    what does it mean?
    - D3 is relevant and D1 & D2 are not relevant?
    - Relevance: D3 > D1 & D2?
- It might be better to model the problem as ranking
  - Label→ Ranking preference (e.g. gain={4,3,2,1,0})
  - Learning→ to optimize $Doc_X > Doc_Y$
    not to classify them to R/NR
  - Input: features for set of docs for a given query
    Objective: rank them (sort by relevance)

ML & IR: History

- Considerable interaction between these fields
  - Rocchio algorithm (60s) is a simple learning approach
  - 80s, 90s: learning ranking algorithms based on user feedback
  - 2000s: text categorization
- Limited by amount of training data
- Web query logs have generated new wave of research
  - L2R: "Learning to Rank"

What is Learning-to-Rank?

- Purpose
  - Learn a function automatically to rank results effectively
- Point-wise approach
  - Classify document to R / NR
- List-wise
  - The function is based on a ranked list of items
  - given two ranked list of the same items, which is better
- Pair-wise
  - The function is based on a pair of item
  - e.g., given two documents, predict partial ranking

Point-wise Approaches

- The function is based on features of a single object
  - e.g., regress the rel. score, classify docs into R and NR
- Very similar to classification
  - Examples of (D,Q) pairs with labels 1 or 0
- Classic retrieval models are also point-wise:
  - Calculate score(Q, D)
  - *If* score(Q,D) > θ → relevant
    else, irrelevant
- Referred to as information filtering
  - Standing query + new documents coming
  - Decide weather a new document is R on NR

List-based Approaches

- Need a loss function on a list of documents
- Challenge is scale
  - Huge number of potential lists
- Can develop tricks
  - Consider only possible re-rankings of top N retrieved by some fixed method
- Still expensive
  - No clear benefits over pairwise ones (so far)

Pair-wise Approaches

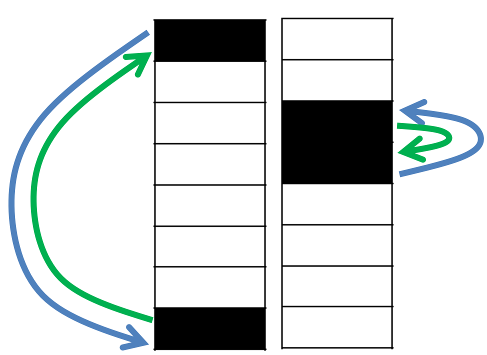
- Trying to classify
  - Which document of two should be ranked at a higher position?
- Optimize based on:
  - Margin between decision hyperplane and instances
  - Errors
  - Weighted based on some hyper-parameter C
  - Evaluation metric
- Example: Ranking SVM
  - A generalization of SVM that supports ranking [Herbrichet al. 1999, 2000; Joachims et al. 2002]

Pair-wise Approaches

- The most popular approach
- Learning method: Ranking SVM, RankBoost, GBRank, Ranknet, LambdaRank, LambdaMART
- Several issues of ranking SVM
  - Still, it does not directly optimize an evaluation metric
  - But pairwise ranking error often better correlations with evaluation metrics than the loss/objective functions in point-wise approaches
    - Why: evaluation measures only care about rankings!
    - e.g., ground-truth: rel(D1) = 2, rel(D2) = 1
      - Regression model 1: pred.rel(D1) = 2, pred.rel(D2) = 3
      - Regression model 2: pred.rel(D1) = 1, pred.rel(D2) = 0
      - Model 1 is better than model 2 by criterion of evaluation regression (the prediction error), but model 2 yields a correct ranking of docs

Pair-wise Approaches

- LambdaMART:
  - Misordered pairs are not equally important
  - Depends on how much they contribute to the changes in the target evaluation measure



Pair-wise Approaches

- Optimizing for an evaluation metric
  - The general idea is to weight loss/objective function or gradient with pairwise changes in evaluation measure.
  - e.g., in LambdaMART: lambda gradient
- Can we optimize all measures?
  - Not necessarily
  - For some measures, pairwise change do not only relate to the two documents themselves, but also others …
    - Position-based measures do not have the issues (pairwise change only depends on the two documents)
    - Cascade measures may have issues

THE UNIVERSITY *of* EDINBURGH

Pair-wise Approaches: Example

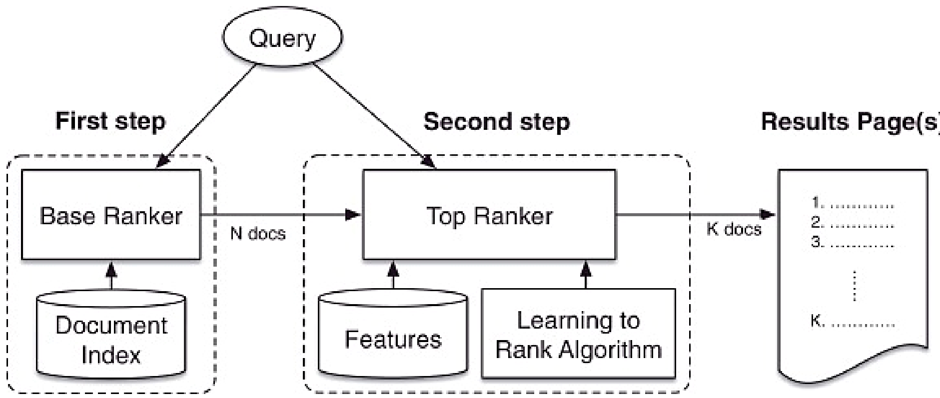
- Experiments
  - 1.2k queries, 45.5K documents with 1890 features
  - 800 queries for training, 400 queries for testing

	MAP	P@1	ERR	MRR	NDCG@5
ListNET	*0.2863*	*0.2074*	*0.1661*	*0.3714*	*0.2949*
LambdaMART	**0.4644**	**0.4630**	**0.2654**	**0.6105**	**0.5236**
RankNET	0.3005	0.2222	0.1873	0.3816	0.3386
RankBoost	0.4548	0.4370	0.2463	0.5829	0.4866
RankingSVM	0.3507	0.2370	0.1895	0.4154	0.3585
AdaRank	0.4321	0.4111	0.2307	0.5482	0.4421
pLogistic	0.4519	0.3926	0.2489	0.5535	0.4945
Logistic	0.4348	0.3778	0.2410	0.5526	0.4762

Honglin Wang Slides

THE UNIVERSITY *of* EDINBURGH

L2R in Practice



Capannini, G., et al.
Quality versus efficiency in document scoring with learning-to-rank models.
IP&M 2016.

Ranking SVM Example

Q1
```
3 qid:1 1:1 2:1 3:0 4:0.2 5:0 # 1A
2 qid:1 1:0 2:0 3:1 4:0.1 5:1 # 1B
1 qid:1 1:0 2:1 3:0 4:0.4 5:0 # 1C
1 qid:1 1:0 2:0 3:1 4:0.3 5:0 # 1D
```
Q2
```
1 qid:2 1:0 2:0 3:1 4:0.2 5:0 # 2A
2 qid:2 1:1 2:0 3:1 4:0.4 5:0 # 2B
1 qid:2 1:0 2:0 3:1 4:0.1 5:0 # 2C
1 qid:2 1:0 2:0 3:1 4:0.2 5:0 # 2D
```
Q3
```
2 qid:3 1:0 2:0 3:1 4:0.1 5:1 # 3A
3 qid:3 1:1 2:1 3:0 4:0.3 5:0 # 3B
4 qid:3 1:1 2:0 3:0 4:0.4 5:1 # 3C
1 qid:3 1:0 2:1 3:1 4:0.5 5:0 # 3D
```

relevance (rank importance)

Set of features for (D,Q) pair

- Q3: 3C>3A, 3C>3B, 3C>3D, 3B>3A, 3B>3D, 3A>3D

Summary

- IR as a classification task
- Learning to rank (L2R) approaches
  - Point-wise
  - List-wise
  - Pair-wise
    - Ranking SVM
    - LambdaMART

Resources

- Nallapati, Ramesh.
  Discriminative models for information retrieval.
  SIGIR 2004.
- Burges, C. J. (2010).
  From ranknet to lambdarank to lambdamart: An overview.
  Learning, *11*(23-581), 81.
- SVM^{Rank}: http://svmlight.joachims.org/

Walid Magdy, TTDS 2017/2018

THE UNIVERSITY of EDINBURGH