Efficiency/Effectiveness Trade-offs in Learning to Rank

Tutorial @ ICTIR 2017
http://learningtorank.isti.cnr.it/

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The Ranking Problem

Ranking is at the core of several IR Tasks:

- Document Ranking in Web Search
- Ads Ranking in Web Advertising
- Query suggestion & completion
- Product Recommendation
- Song Recommendation
- …

The Ranking Problem

Definition:

> Given a query q and a set of objects/documents D,
> to rank D so as to maximize users' satisfaction Q.

Goal #1: Effectiveness

- Maximize Q !
  - but how to measure Q?

Goal #2: Efficiency

- Make sure the ranking process is feasible and not too expensive
  - In Bing ... "every 100msec improves revenue by 0.6%. Every millisecond counts." [KDF+13]

[KDF+13] Kohavi, R., Deng, A., Frasca, B., Walker, T., Xu, Y., & Pohlmann, N. (2013, August). **Online controlled experiments at large scale**. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 1168-1176). ACM.

Agenda

1. **Introduction to Learning to Rank** (LtR)
   - Background, algorithms, sources of cost in LtR, multi-stage ranking
2. **Dealing with the Efficiency/Effectiveness trade-off**
   - Feature Selection, Enhanced Learning, Approximate scoring, Fast Scoring
3. **Hands-on I**
   - Software, data and publicly available tools
   - Traversing Regression Forests, SoA tools and analysis
4. **Hands-on II**
   - Training models, Pruning strategies, Efficient scoring

At the end of the day you'll be able to train a high quality ranking model, and to exploit SoA tools and techniques to ***reduce its computational cost up to 18x !***

Document Representations and Ranking

Document Representations

A document is a multi-set of words

A document may have fields, it can be split into zones, it can be enriched with external text data (e.g., anchors)

Additional information may be useful, such as In-Links, Out-Links, PageRank, # clicks, social links, etc.

Hundred signals in public LtR Datasets

Ranking Functions

Term-weighting [SJ72]
Vector Space Model [SB88]

BM25 [JWR00], BM25f [RZT04]
Language Modeling [PC98]

Linear Combination of features [MC07]

How to combine hundreds of signals?

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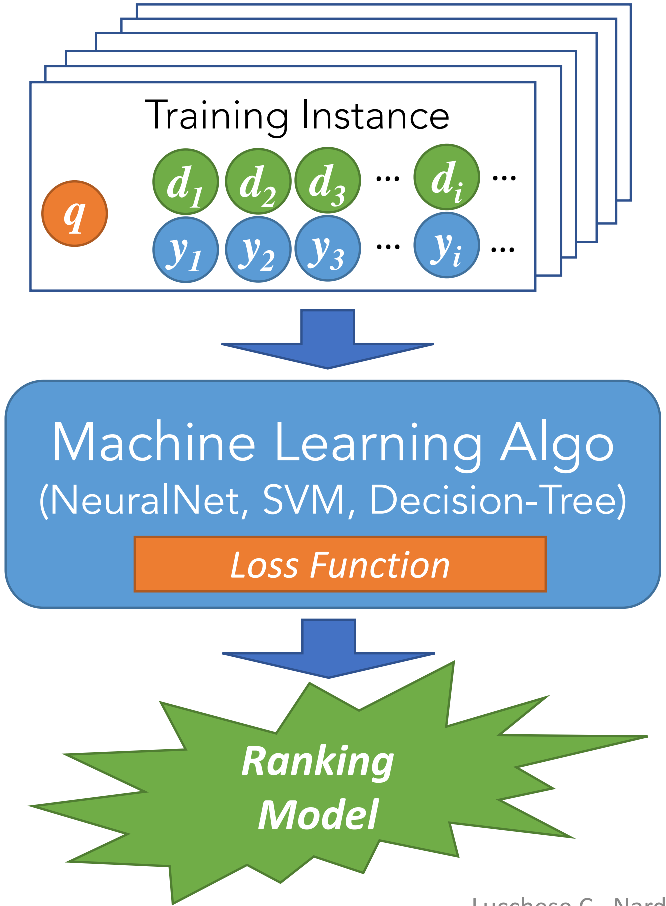
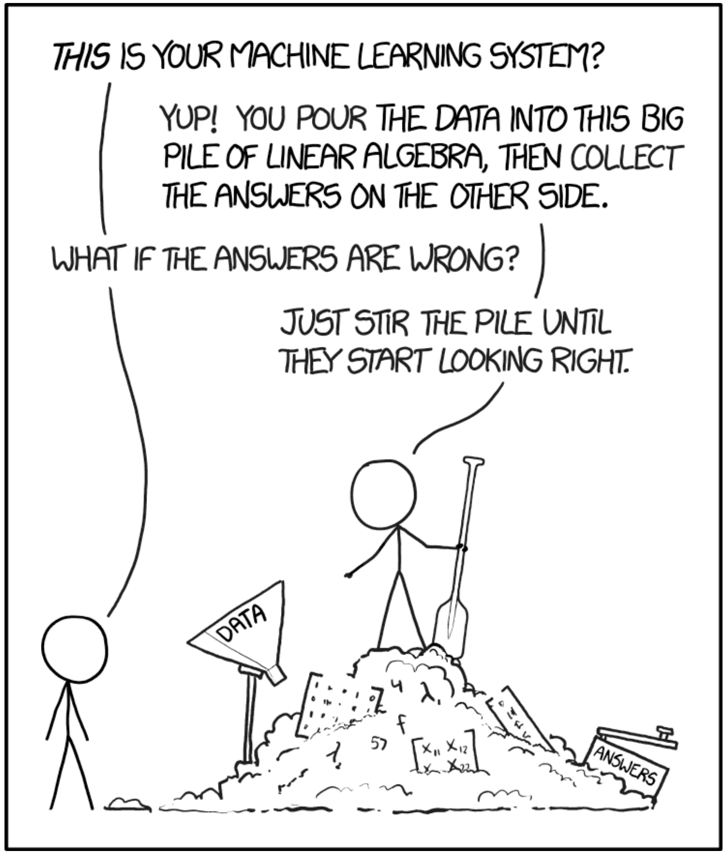
Ranking as a Supervised Learning Task





Query/Document Representation

q d ***Useful signals***

- Link Analysis [H+00]
- Term proximity [RS03]
- Query classification [BSD10]
- Query intent mining [JLN16, LOP+13]
- Finding entities documents [MW08] and in queries [BOM15]
- Document recency [DZK+10]
- Distributed representations of words and their compositionality [MSC+13]
- Convolutional neural networks [SHG+14]
- ….

Relevance Labels Generation

y

- ***Explicit Feedback***
  - Thousands of Search Quality Raters
  - Absolute vs. Relative Judgments [CBCD08]
- ***Implicit Feedback***
  - clicks/query chains [JGP+05, Joa02, RJ05]
  - De-biasing/click models [JSS17]
- ***Minimize annotation cost***
  - Active Learning [LCZ+10]
  - Deep versus Shallow labelling [YR09]

Evaluation Measures for Ranking

Many are in the form: $$Q@k = \sum_{\texttt{ranks}\ r=1\ldots k} \text{Gain}(d^r) \cdot \text{Discount}(r)$$

- (N)DCG [JK00]: $\text{Gain}(d) = 2^y - 1 \quad \text{Discount}(r) = \dfrac{1}{\log(r+1)}$
- RBP [MZ08]: $\text{Gain}(d) = \mathbb{I}(y) \quad \text{Discount}(r) = (1-p)p^{r-1}$
- ERR [CMZG09]: $\text{Gain}(d) = R_i \prod_{j=1}^{i-1}(1-R_j)\ with\ R_i = (2^y - 1)/2^{y_{max}} \quad \text{Discount}(r) = 1/r$

Do they match User satisfaction ?

- ERR correlates better with user satisfaction (clicks and editorials) [CMZG09]
- Results Interleaving to compare two rankings [CJRY12]
  - "major revisions of the web search rankers [Bing] ... The differences between these rankers involve changes of over *half a percentage point*, in absolute terms, of NDCG"

[JK00] Kalervo J arvelin and Jaana Kekalainen. **Ir evaluation methods for retrieving highly relevant documents**. In Proceedings of the 23rd annual international ACM SIGIR conference on Research and development in information retrieval, pages 41–48. ACM, 2000.
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Is it an easy or difficult task?

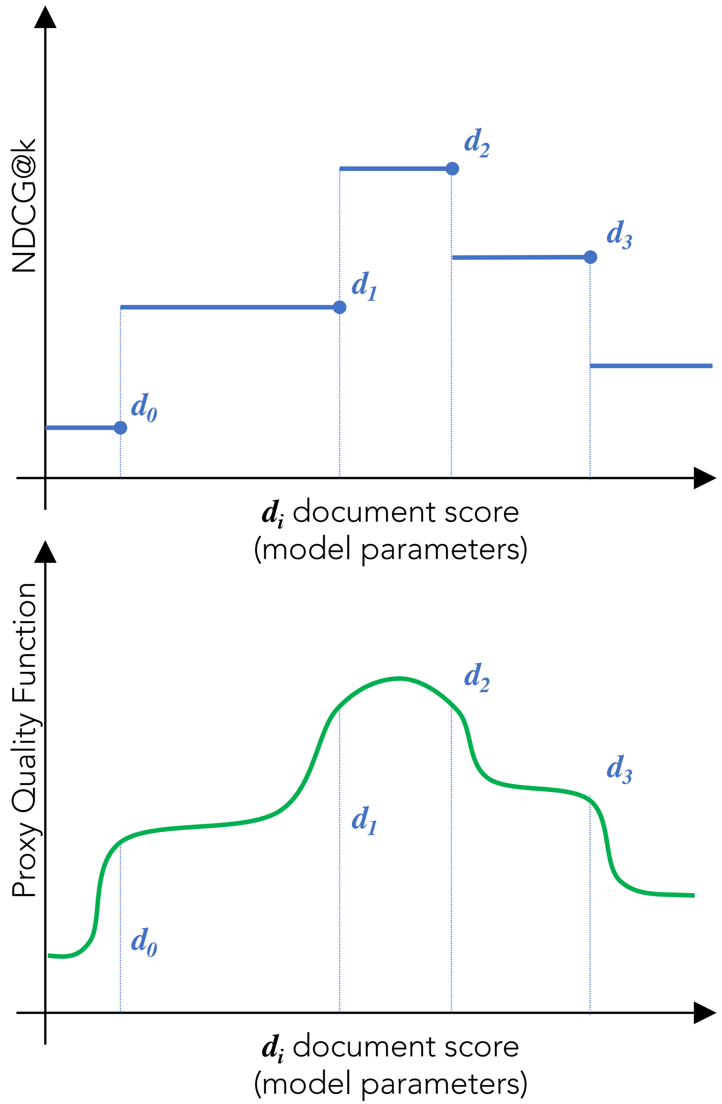
Gradient descent cannot be applied directly

Rank-based measures (NDCG, ERR, MAP, …) depend on ***documents sorted order***

- ***gradient is either 0*** (sorted order did not change) or ***undefined*** (discontinuity)

Solution: we need a proxy Loss function

- it should be ***differentiable***
- and with a ***similar behavior of the original cost function***



Point-Wise Algorithms

<u>Each document is considered independently</u> from the others

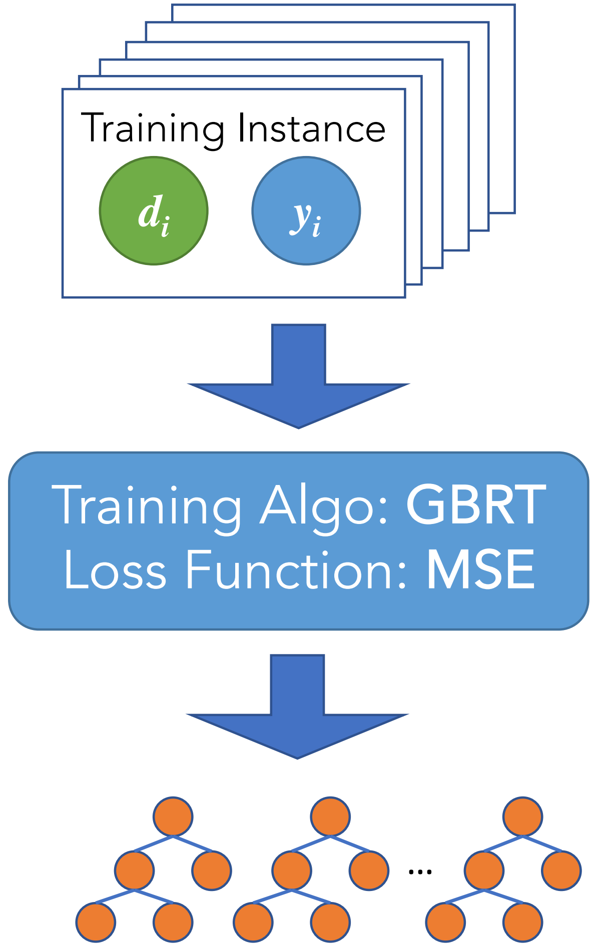
- No information about other candidates for the same query is used at training time

A different cost-function is optimized

- Several approaches: Regression, Multi-Class Classification, Ordinal regression, … [Liu11]

Among Regression-Based:
Gradient Boosting Regression Trees [Fri01]

- ***Mean Squared Error*** is minimized



[Liu11] Tie-Yan Liu. **Learning to rank for information retrieval**, 2011. Springer.
[Fri01] Jerome H Friedman. **Greedy function approximation: a gradient boosting machine**. Annals of statistics, pages 1189–1232, 2001.

Gradient Boosting Regression Trees

Iterative algorithm: $$F(d) = \sum_i f_i(d)$$

Weak Learner

Each f_i is regarded as a step in the best optimization direction, i.e., a ***steepest descent step***:

by line-search

negative gradient

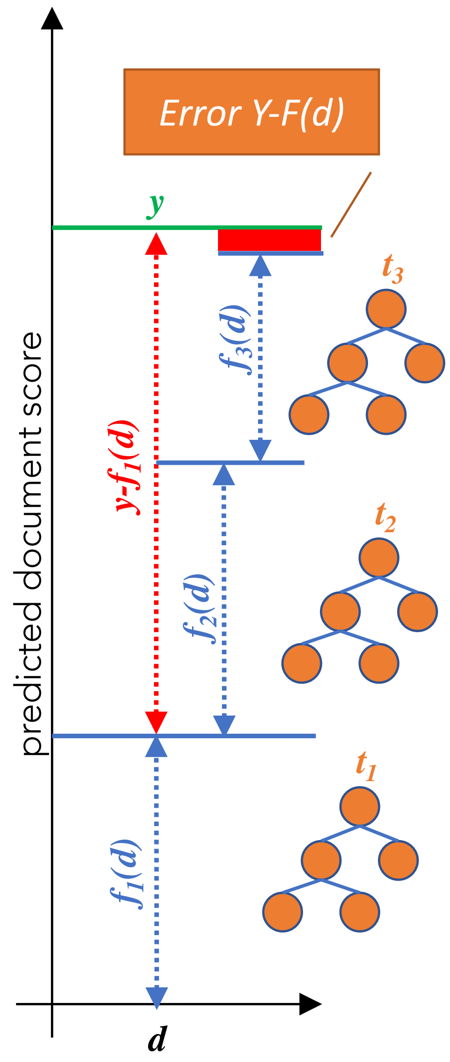
$$f_i(d) = -\rho_i \; g_i(d) \qquad - g_i(d) = -\left[\frac{\partial L(y, f(d))}{\partial f(d)}\right]_{f=\sum_{j<i} f_j}$$

Given $L = MSE/2$:

pseudo-response

$$-\frac{\partial \left[\frac{1}{2} MSE(y, f(d))\right]}{\partial f(d)} = -\frac{\partial \left[\frac{1}{2}\sum(y - f(d))^2\right]}{\partial f(d)} = y - f(d)$$

Gradient g_i is approximated by a Regression Tree t_i



Pair-wise Algorithms: RankNet[BSR+05]

Documents are considered in pairs

Estimated probability that ***d_i is better than d_j*** is:

$$P_{ij} = \frac{e^{o_{ij}}}{1 + e^{o_{ij}}}$$

$o_{ij} = F(d_i)\text{-}F(d_j)$

Let Q_{ij} be the true probability, the ***Cross Entropy Loss*** is:

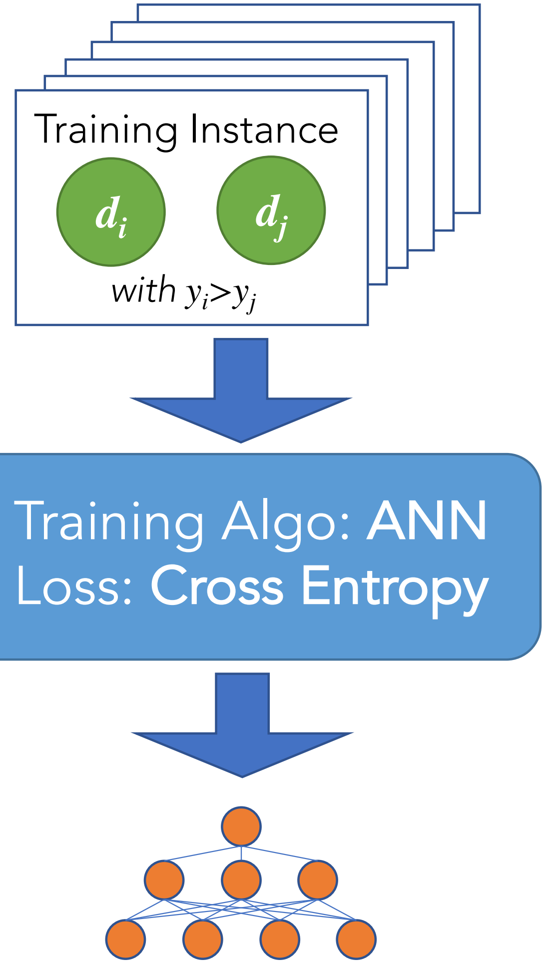
$$C_{ij} = -Q_{ij} \log P_{ij} - (1 - Q_{ij}) \log(1 - P_{ij})$$

We consider ***only pairs where d_i is better than d_j ,ie., $y_i > y_j$:***

If $o_{ij} \rightarrow +\infty$
(i.e., correctly ordered)
$C_{ij} \rightarrow 0$

$$C_{ij} = \log(1 + e^{-o_{ij}})$$

If $o_{ij} \rightarrow -\infty$
(i.e., mis-ordered)
$C_{ij} \rightarrow +\infty$



This is ***differentiable***: used to train a ***Neural Network with back-propagation***.

Other approaches: Ranking-SVM[Joa02], RankBoost[FISS03], …

[BSR+05] Chris Burges, Tal Shaked, Erin Renshaw, Ari Lazier, Matt Deeds, Nicole Hamilton, and Greg Hullender. **Learning to rank using gradient descent**. In Proceedings of the 22nd international conference on Machine learning, pages 89–96. ACM, 2005.
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Pair-wise Algorithms

***RankNet** performs **better** than other pairwise algorithms*

***RankNet** cost is **not** nicely correlated with NDCG quality*

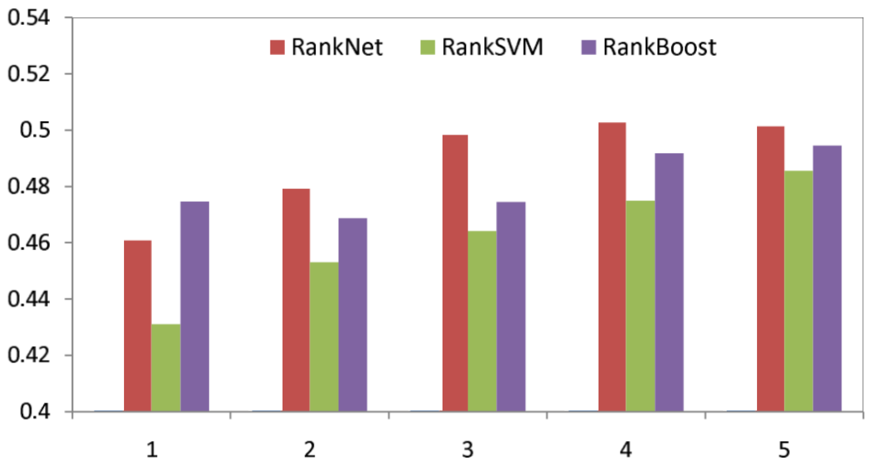


Figure 1. Ranking accuracies in terms of NDCG@n on TREC

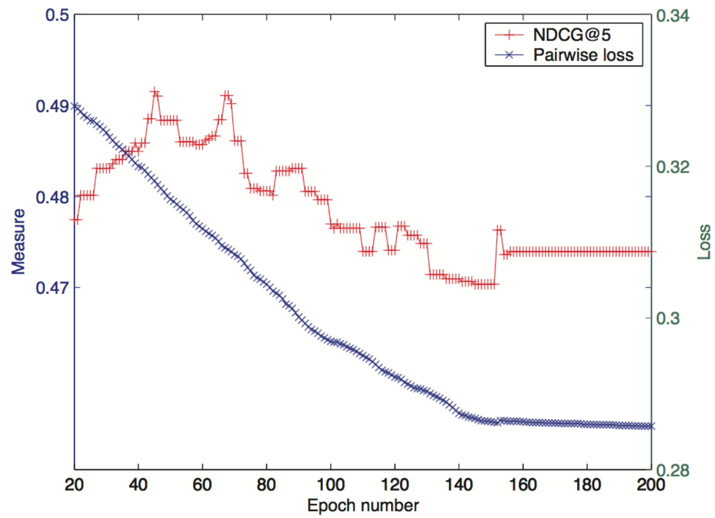


Figure 4. Pairwise loss v.s. NDCG@5 in RankNet

[CQL+07] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. **Learning to rank: from pairwise approach to listwise approach**. In Proceedings of the 24th international conference on Machine learning, pages 129–136. ACM, 2007.

List-wise Algorithms: LambdaMart[Bur10]

Recall: ***GBRT requires a gradient g_i for every d_i***

First: ***estimate the gradient comparing to d_j***, with $y_i > y_j$:

derivative of the negative RankNet cost

Δ Quality after swapping d_i with d_j

$$\lambda_{ij} = \frac{1}{1 + e^{o_{ij}}} \; |\Delta NDCG| = -\lambda_{ji}$$

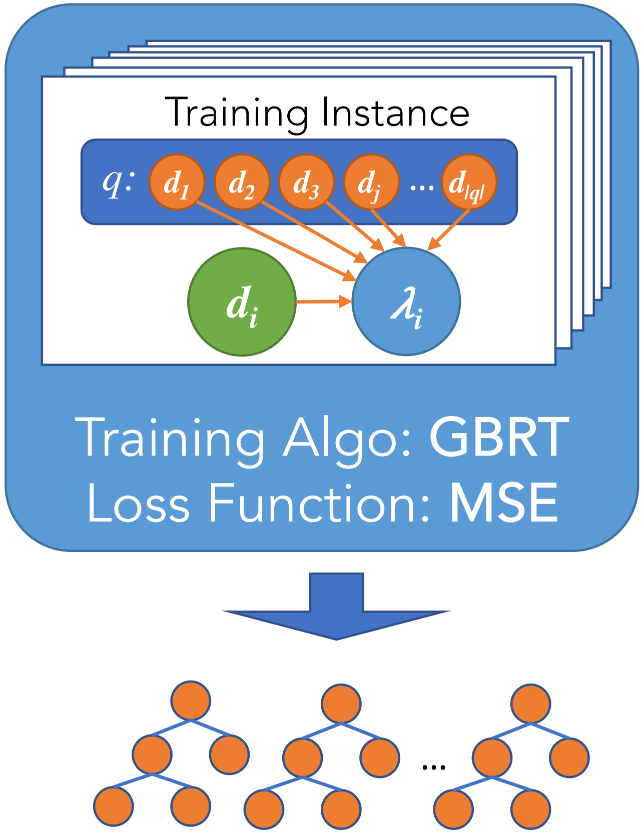
If $o_{ij} \rightarrow +\infty$ (i.e., correctly ordered) $\lambda_{ij} \rightarrow 0$

If $o_{ij} \rightarrow -\infty$ (i.e., mis-ordered) $\lambda_{ij} \rightarrow |\Delta\, NDCG|$

Top documents are more relevant !

Then: ***estimate the gradient comparing to every other d_j for q***

$$g_i = \lambda_i = \sum_{y_i > y_j} \lambda_{ij} - \sum_{y_i < y_j} \lambda_{ij}$$



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List-wise Algorithms: some results

- NDCG@10 on public LtR Datasets

Algorithm	MSN10K	Y!S1	Y!S2	Istella-S
RankingSVM	0.4012	0.7238	0.7306	N/A
GBRT	0.4602	**0.7555**	**0.7620**	0.7313
LambdaMART	**0.4618**	0.7529	0.7531	**0.7537**

Other approaches: ListNet/ListMLE[CQL+07], Approximate Rank[QLL10], SVM AP[YFRJ07], RankGP[YLKY07], others ...

[CQL+ 07] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. **Learning to rank: from pairwise approach to listwise approach**. In Proceedings of the 24th international conference on Machine learning, pages 129–136. ACM, 2007.
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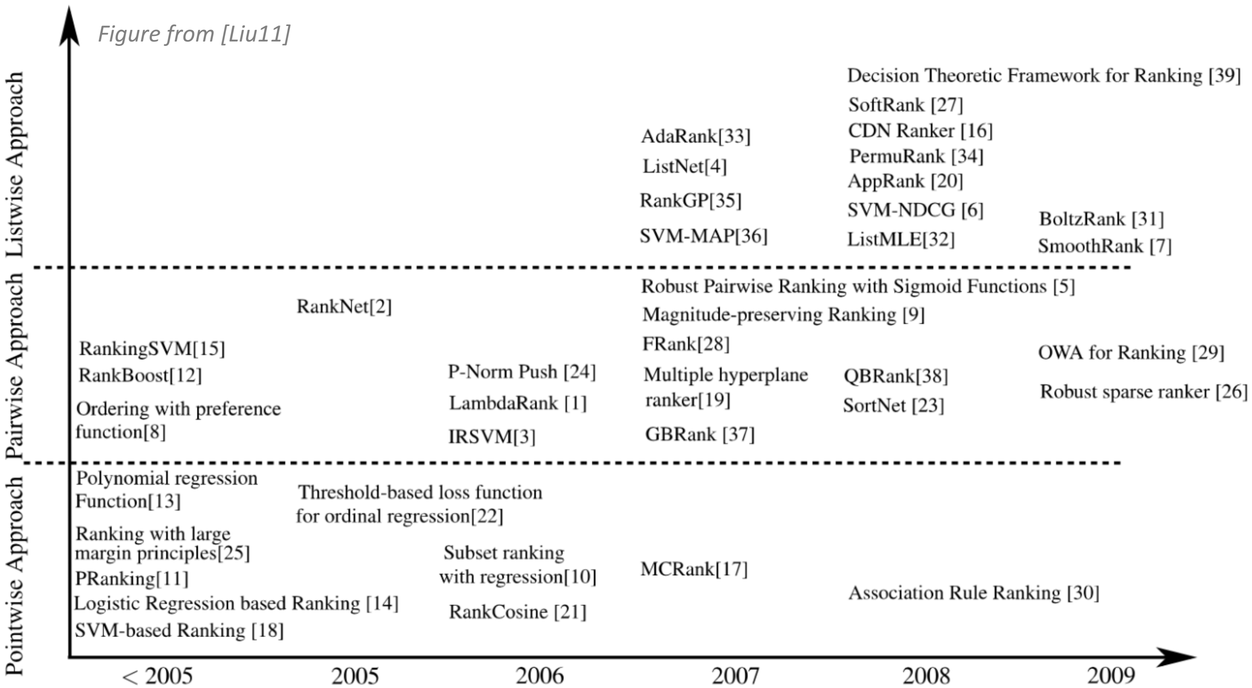
Learning to Rank Algorithms



- New approaches to **optimize IR measures:**
  - DirectRank[XLL+08], LambdaMart[Bur10], BLMart[GCL11], SSLambdaMART[SY11], CoList[GY14], LogisticRank[YHT+16], … *See [Liu11][TBH15].*
- **Deep Learning** to improve query-document matching:
  - Conv.DNN[SM15], DSSM[HHG+13], Dual-Embedding[MNCC16], Local and Distributed repr.[MDC17], Weak Supervision[DZS+17], Neural Click Model[BMdRS16], …
- **On-line learning**:
  - Multi-armed bandits [RKJ08], Dueling bandits [YJ09], K-armed dueling bandits[YBKJ12], online learning[HSWdR13][HWdR13], …

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In this tutorial we focus on GBRTs

Ads Click Prediction: GBDT as a ***feature extractor***, then LogReg [HPJ+14]

Ads Click Prediction: refine/***boost NN*** output [LDG+17]

Product Ranking: 100 GBDTs with pairwise ranking [SCP16]

Document Ranking: GBDT named LogisticRank [YHT+16]

Ranking, forecasting & recommendations: ***Oblivious GBRT***

[HPJ+14] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Atallah, Ralf Herbrich, Stuart Bowers, et al. **Practical lessons from predicting clicks on ads at facebook**. In Proceedings of the Eighth International Workshop on Data Mining for Online Advertising, pages 1–9. ACM, 2014.
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In this tutorial we focus on GBRTs

- Successful in several ***Data Challenges***:
  - Winner of the ***Yahoo! LtR Challenge***: combination of 12 ranking models, 8 of which were Lambda-MART models, each having up to 3,000 trees [CC11]
  - According to the 2015 statistics, GBRTs were adopted by the majority of the winning solutions among the ***Kaggle*** competitions, even more than the popular deep networks, and all the top-10 teams qualified in the ***KDDCup 2015*** used GBRT-based algorithms [CG16]

- New interesting ***open-source implementations***:
  - XGBoost, LightGBM by ***Microsoft***, CatBoost by ***Yandex***

- ***Pluggable*** within ***Apache Lucene/Solr***

[CC11] Olivier Chapelle and Yi Chang. **Yahoo! learning to rank challenge overview**. In Proceedings of the Learning to Rank Challenge, pages 1–24, 2011.
[CG16] Tianqi Chen and Carlos Guestrin. **Xgboost: A scalable tree boosting system**. In Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’16, pages 785–794, New York, NY, USA, 2016. ACM.

Single-Stage Ranking

Requires to apply the learnt *model* to *every matching document*, and to generate the required *features*.

Not feasible!

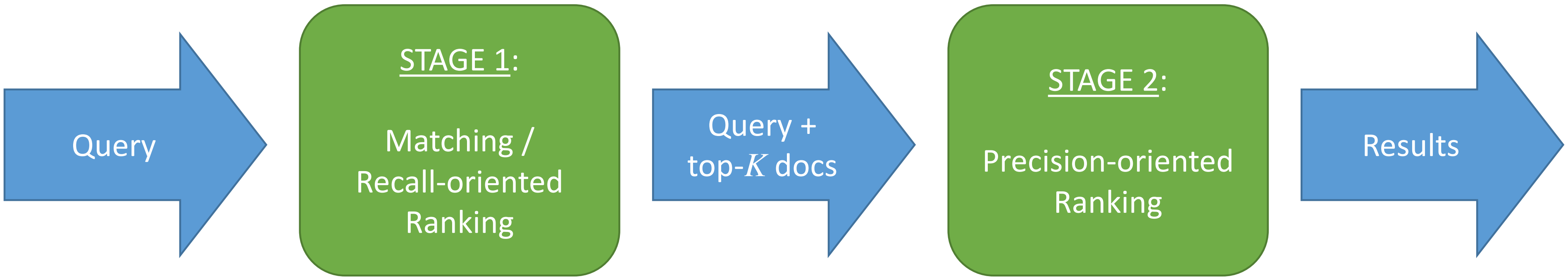
We have at least ***3 efficiency vs. effectiveness trade-offs***.

Single-Stage Ranking

① *Feature Computation Trade-off*

- Computationally ***Expensive*** & ***highly discriminative*** features vs. computationally ***Cheap*** & ***slightly discriminative*** features

Two-Stage Ranking



Expensive features are computed only for the *top-K candidate documents* passing the first stage.
How to chose K?

②***Number of Matching Candidates Trade-off*** :

- a ***Large set*** of candidates is ***Expensive*** and produces ***high-quality*** results vs.
  a ***Small set*** of candidates is ***Cheap*** and produces ***low-quality*** results
  - 1000 documents [DBC13] (Gov2, ClueWeb09-B collections)
  - 1500-2000 documents [MSO13] (ClueWeb09-B)
  - “hundreds of thousands” (over “hundreds of machines”) [YHT+16a]

[DBC13] Van Dang, Michael Bendersky, and W Bruce Croft. **Two-stage learning to rank for information retrieval**. In Advances in Information Retrieval, pages 423–434. Springer, 2013.
[MSO13] Craig Macdonald, Rodrygo LT Santos, and Iadh Ounis. **The whens and hows of learning to rank for web search**. Information Retrieval, 16(5):584–628, 2013.
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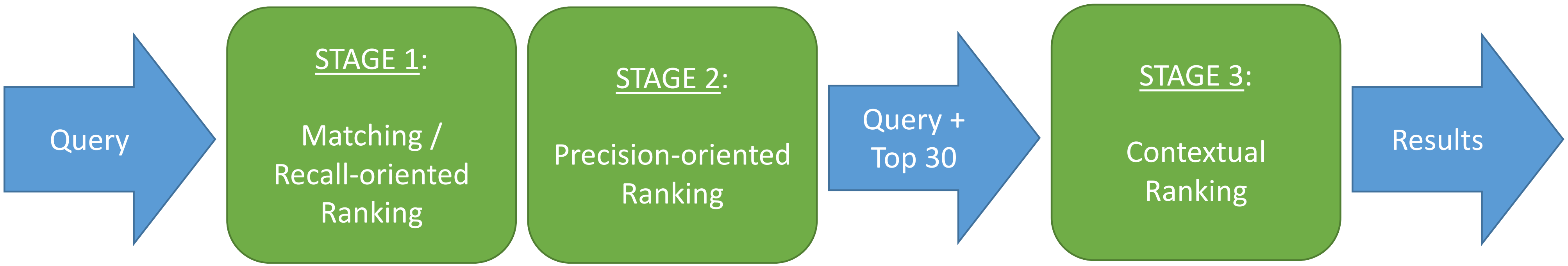
Multi-Stage Ranking



- 3 stages [YHT+16]: ***Contextual features*** are considered in the 3rd stage
  - Contextual => ***about the current result set***
  - Rank based on specific features, Mean, Variance, Standardized features (see also [LNO+15a]), Topic model similarity
  - First two stages are executed at each serving node
- *N* stages [CGBC17]: Which ***model*** in each stage? Which ***features***? How many ***documents***?
  - About ***200 configurations tested***
  - best results with N=3 stages, 2500 and 700 docs between stages
- A proper methodology/algorithm for choosing the best configuration is still missing.

[YHT+16] Dawei Yin, Yuening Hu, Jiliang Tang, Tim Daly, Mianwei Zhou, Hua Ouyang, Jianhui Chen, Changsung Kang, Hongbo Deng, Chikashi Nobata, et al. **Ranking relevance in yahoo search**. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 323–332. ACM, 2016.
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Multi-Stage Ranking

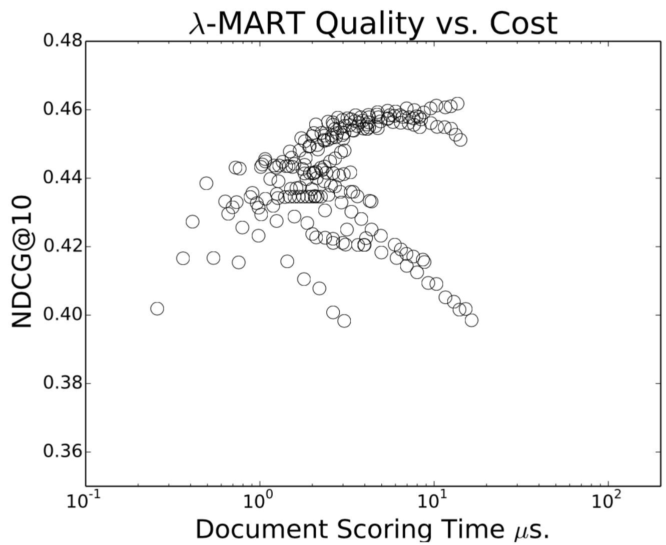
③ *Model Complexity Trade-off* :

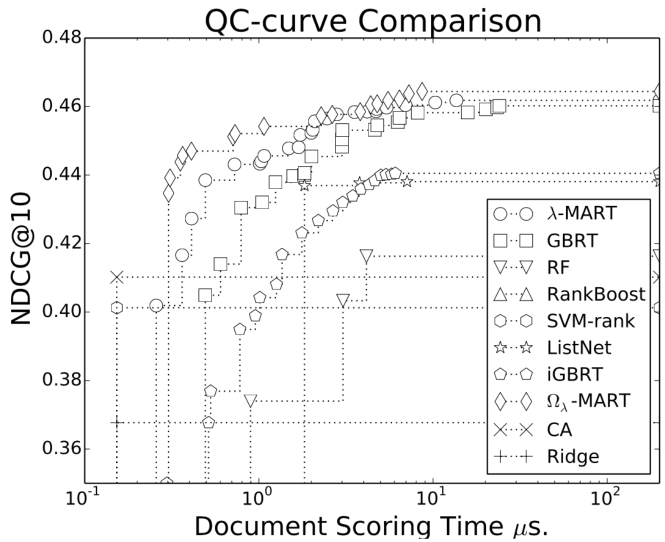
- ***Complex*** & ***Slow*** ***high-quality*** vs. ***Simple*** & ***Fast*** ***low-quality*** models:
  - ***Complex*** as: Random Forest, GBRT, Initialized GBRT, Lambda-MART,
  - ***Simple*** as: Coordinate Ascent, Ridge Regression, SVM-Rank, RankBoost
  - ***In-between*** as: Oblivious Lambda-Mart, ListNet

Model Complexity Trade-off

- Comparison on varying training parameters [CLN+16]:
  - #trees, #leaves, learning rate, etc.
- ***Complex models*** achieve significantly ***higher quality***
- Best model depends on ***time budget***

- ***Today is about Model Complexity Trade-off!***





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Next …

Efficiency/Effectiveness trade-offs in:

- Feature Selection
- Enhanced Learning Algorithms
- Approximate scoring
- Fast Scoring

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