# Efficiency/Effectiveness Trade-offs in Learning to Rank

Tutorial @ ICTIR 2017

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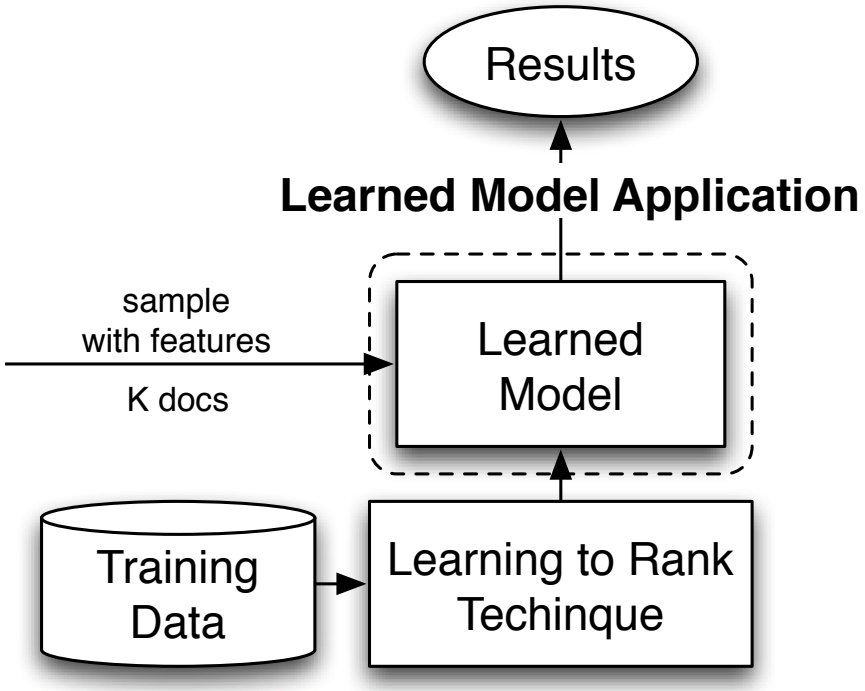
# Two-stage (or more) Ranking Architecture

# Efficiency/Effectiveness Trade-offs

- Efficiency in Learning to Rank (LtR) has been addressed in different ways
- Main research lines
  - Feature selection
  - Optimizing efficiency within the learning process
  - Approximate score computation and efficient cascades
  - Efficient traversal of tree-based models
- Different impact on the architecture



# Feature Selection

# Feature Selection

- Feature selection techniques allows to **reduce redundant features**
  - Redundant features are useless both at training and scoring time
- Filtering out the irrelevant features to enhance the **generalization performance** of the learned model
- Identifying key features also helps to **reverse engineer** the predictive model and to **interpret** the results obtained
- A reduced set of highly discriminative and non redundant features results in a **reduced feature extraction cost** and in a **faster learning and classification/prediction/ranking**

# Feature Selection Methods

- Feature selection for ranking inherits methods from classification
- Classification of feature selection methods [GE03]
  - **Filter** methods: feature selection is defined as a preprocessing step and can be independent from learning
  - **Wrapper** methods: utilizes a learning system as a black box to score subsets of features
  - **Embedded** methods: perform feature selection within the training process
- Wrapper or embedded methods: higher computational cost / algorithm dependent
  - not suitable for a LtR scenario involving hundreds of continuous or categorical features
- Focus on **filter** methods
  - Allow for a fast pre-processing of the dataset
  - Totally independent from the learning process

[GE03] Isabelle Guyon and Andre Elisseff. *An introduction to variable and feature selection*. The Journal of Machine Learning Research, 3:1157–1182, 2003.

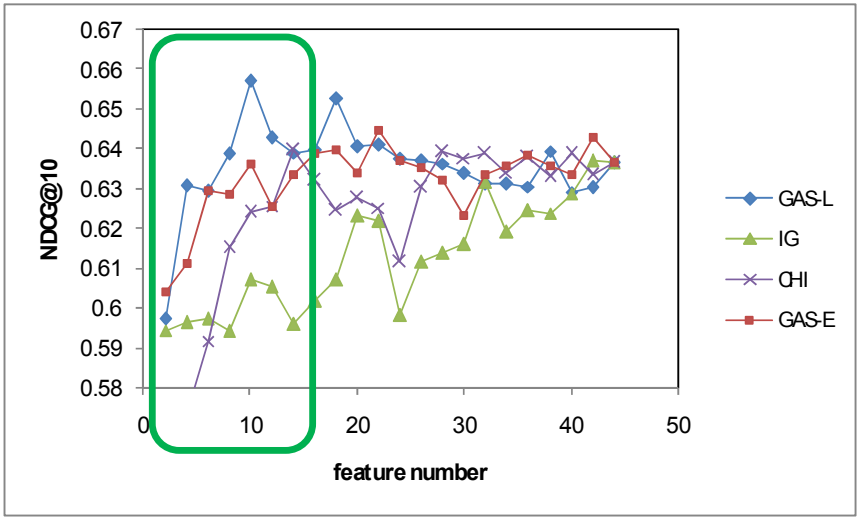
# GAS [GLQL07]

- Geng *et al.* are the first proposing feature selection methods for ranking
- Authors propose to exploit ranking information for selecting features
  - They use IR metrics to measure the **importance** of each feature
    - MAP, NDCG: rank instances by feature, evaluate and take the result as importance score
  - They use **similarities** between features to avoid selecting redundant ones
    - By using ranking results of each feature: Kendall's tau, averaged over all queries
- Feature selection as a **multi-objective optimization problem**: maximum importance and minimum similarity
- Greedy Search Algorithm (GAS) performs feature selection **iteratively**
  - Update phase needs the tuning of an hyper-parameter *c* weighting the impact of the update

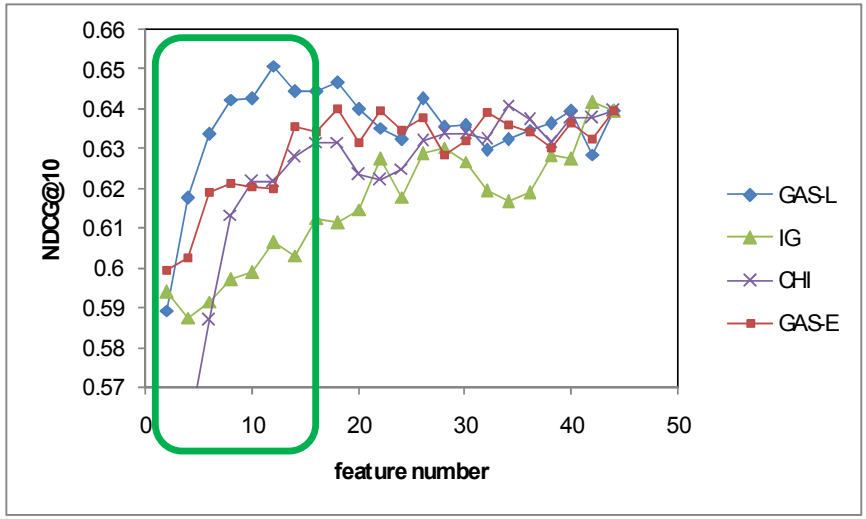
[GLQL07] X. Geng, T. Liu, T. Qin, and H. Li. *Feature selection for ranking*. In Proc. ACM SIGIR, 2007.

# GAS [GLQL07]

- Experiments
  - .gov and TREC 2004 Web Track
  - BM25 as first stage
  - 44 features per doc
- Evaluation Measures
  - MAP
  - NDCG
- Applied to second stage ranker
  - Ranking SVM
  - RankNet



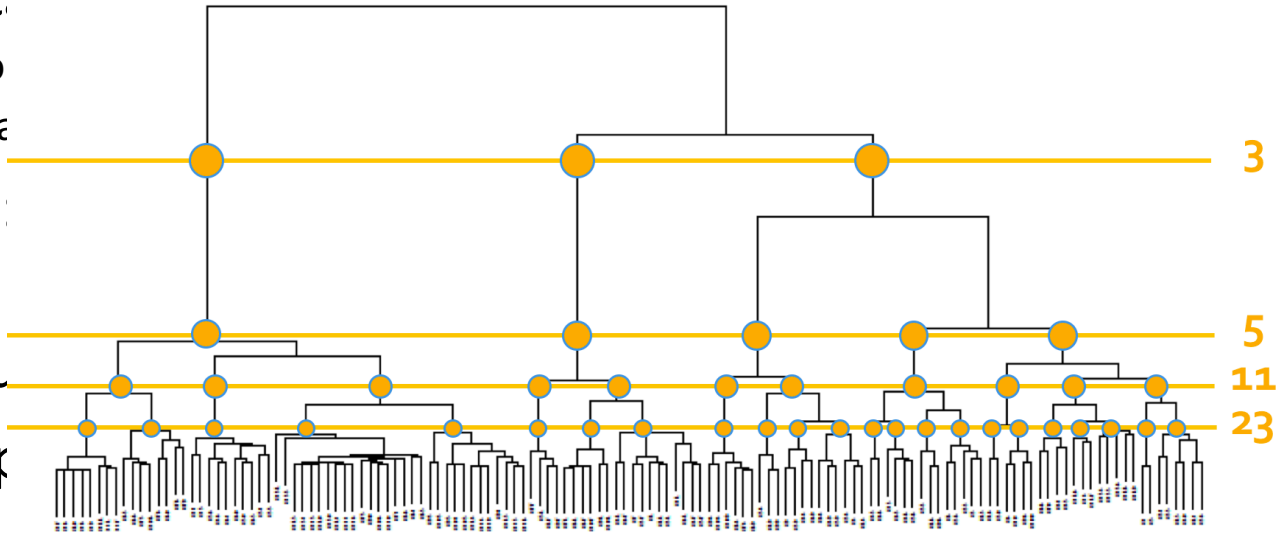

(b) NDCG@10 of Ranking SVM




(b) NDCG@10 of RankNet

# Fast Feature Selection for LtR [GLNP16]

- Lucchese *et al*. propose three novel filter methods providing flexible and model-free feature selection
  - Two parameter-free variations of GAS: NGAS and XGAS
  - HCAS exploits hierarchic
    - Only one feature per gro
    - Two variants: Single-linka
- Importance of a feature
  single feature
- Similarity between featu
- No need to tune hyper-p




[GLNP16] A. Gigli, C. Lucchese, F. M. Nardini, and R. Perego. *Fast feature selection for learning to rank*. In Proc. ACM ICTIR, 2016.

# Fast Feature Selection for LtR

- Experiments
  - MSLR-Web10K (Fold1) and Yahoo LETOR
  - By varying the subset sampled
  - Results confirms Geng *et al.* [GLQL07]
- Evaluation Measures
  - NDCG@10
- For small subsets (5%, 10%, 20%):
  - Best performance by HCAS with “Single Linkage”.
  - Statistically significant w.r.t. GAS
  - Performance against the full model

MSN-1

| Subset | NMI | AGV | S | K | LM-1 |
|---|---|---|---|---|---|
| **5%** | 0.3548 | 0.3340 | 0.3280 | 0.3313 | **0.4304** |
| **10%** | 0.3742 | 0.3416 | 0.3401 | 0.3439 | **0.4310** |
| **20%** | 0.4240 | 0.3776 | 0.3526 | 0.3533 | **0.4330** |
| **30%** | **0.4625** | 0.3798 | 0.4312 | 0.3556 | 0.4386 |
| **40%** | **0.4627** | 0.3850 | 0.4330 | 0.3788 | 0.4513 |
| **Full** | 0.4863 | 0.4863 | 0.4863 | 0.4863 | 0.4863 |

MSN-1

| Subset % | NGAS | XGAS $p = 0.05$ | HCAS “single” | HCAS “ward” | GAS $c = 0.01$ |
|---|---|---|---|---|---|
| **5%** | 0.4011▼ | 0.4376▲ | **0.4423**▲ | 0.4289 | 0.4294 |
| **10%** | 0.4459 | 0.4528 | **0.4643**▲ | 0.4434▼ | 0.4515 |
| **20%** | 0.4710 | 0.4577▼ | **0.4870**▲ | 0.4820 | 0.4758 |
| **30%** | 0.4739▼ | 0.4825 | 0.4854 | **0.4879** | 0.4848 |
| **40%** | 0.4813 | 0.4834 | 0.4848 | 0.4853 | **0.4863** |
| **Full** | 0.4863 | 0.4863 | 0.4863 | 0.4863 | 0.4863 |

# Further Reading

- Pan *et al.* use boosted regression trees to investigate greedy and randomized wrapper methods [PCA+09].
- Dang and Croft propose a wrapper method that uses best first search and coordinate ascent to greedily partition a set of features into subsets to be selected [DC10].
- Hua *et al.* propose a feature selection method based on clustering: *k*-means is first used to aggregate similar features, then the most relevant feature in each cluster is chosen to form the final set [HZL+10].
- Laporte *et al.* [LFC+12] and Lai *et al.* [LPTY13] use embedded methods for selecting features and building the ranking model at the same step, by solving a convex optimization problem.
- Naini and Altingovde use greedy diversification methods to solve the feature selection problem [NA14].

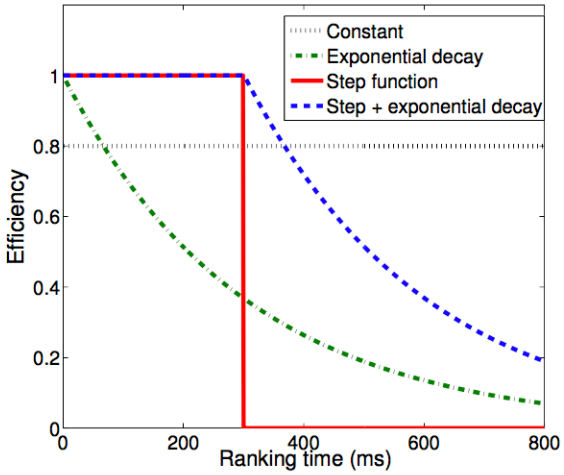
# Optimizing Efficiency within the Learning Process

# Learning to Efficiently Rank [WLM10]

- Wang *et al.* propose a new cost function for learning models that directly optimize the tradeoff metrics: Efficiency-Effectiveness Tradeoff Metric (EET)

$$\text{EET}(Q) = \frac{(1+\beta^2)\cdot\gamma(Q)\,\sigma(Q)}{\beta^2\cdot\sigma(Q)+\gamma(Q)} \longrightarrow \text{MEET}(R) = \frac{1}{N}\sum \text{EET}(Q)$$

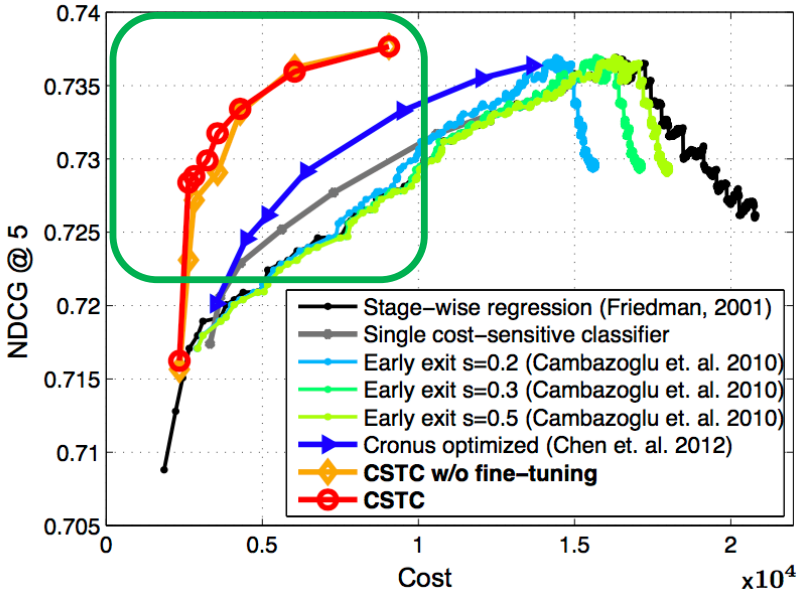
- New efficiency metrics: constant, step, exponential
- Focus on linear feature-based ranking functions
- Learned functions show significant decreased average query execution times




L. Wang, J. Lin, and D. Metzler. *Learning to efficiently rank*. In Proc. SIGIR 2010.

# Cost-Sensitive Tree of Classifiers [XKWC13].

- Xu *et al.* observe that the test-time cost of a classifier is often dominated by the computation required for feature extraction
- Tree of classifiers: each path extract different features and is optimized for a specific sub-partition of th
  - Input-dependent feature selection
  - Dynamic allocation of time budgets: higher b
- Experiments
  - Yahoo LETOR dataset
  - Quality vs Cost budget
- Comparisons against [CZC+10]




Z. Xu, M. J. Kusner, K. Q. Weinberger, and M. Chen. *Cost-sensitive tree of classifiers*. In Proc. ICML, 2013.

# Training Efficient Tree-Based Models for Document Ranking [AL13]

- Asadi and Lin propose techniques for training GBRTs that have efficient runtime characteristics.
  - **compact**, **shallow**, and **balanced** trees yield faster predictions
- Cost-sensitive Tree Induction: jointly minimize the loss and the evaluation cost
- Two strategies
  - By directly modifying the node splitting criterion during tree induction
    - Allow split with maximum gain if it does not increase the maximum depth of the tree
    - Find a node closer to the root which, if split, result in a gain larger than the discounted maximum gain
  - Pruning while boosting with focus on **tree depth** and **density**
    - Additional stages compensate for the loss in effectiveness
    - Collapse terminal nodes until the number of internal nodes reach a balanced tree
- Experiments on MSLR-WEB10K show that the **pruning** approach is superior.
  - 40% decrease in prediction latency with minimal reduction in final NDCG.

N. Asadi and J. Lin. *Training efficient tree-based models for document ranking*. In Proc. ECIR, 2013.

# CLEAVER [LNO+16a]

- Lucchese et al. propose a pruning & re-weighting post-processing methodology
- Several pruning strategies
  - random, last, skip, low weights
  - score loss
  - quality loss
- Greedy line search strategy applied to tree weights
- Experiments on MART and LambdaMART
  - MSLR-Web30K and Istella-S LETOR

C. Lucchese, F. M. Nardini, S. Orlando, R. Perego, F. Silvestri, and S. Trani. *Post-learning optimization of tree ensembles for efficient ranking*. In Proc. ACM SIGIR, 2016.

# CLEAVER

MART on MSN-1

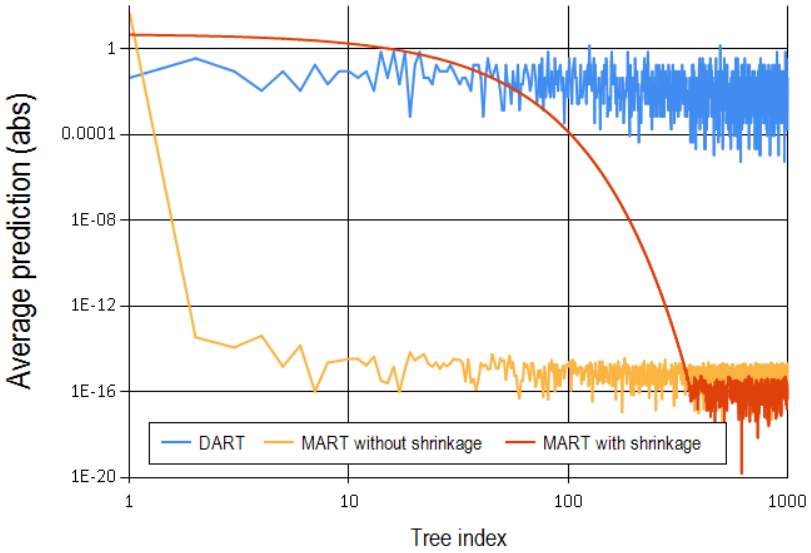
| Strategy | 100 Trees | | | | 500 Trees | | | | 737 Trees | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Trees | Time | Speed-up | *NDCG*@10 | Trees | Time | Speed-up | *NDCG*@10 | Trees | Time | Speed-up | *NDCG*@10 |
| *Reference* | 100 | 5.55 | – | 0.4590 | 500 | 19.36 | – | 0.4749 | 737 | 27.46 | – | 0.4766 |
| Random | 40 | 3.28 | 1.7x | 0.4603 | 350 | 14.27 | 1.4x | 0.4756 | 516 | 19.64 | 1.4x | 0.4768 |
| Last | 60 | 3.93 | 1.4x | 0.4601 | 400 | 16.17 | 1.2x | 0.4755 | 590 | 22.76 | 1.2x | 0.4771 |
| Skip | **30** | **2.84** | **2.0x** | 0.4593 | 300 | 12.98 | 1.5x | 0.4749 | 442 | 17.25 | 1.6x | 0.4766 |
| Low-Weights | 40 | 3.26 | 1.7x | 0.4609 | 400 | 15.75 | 1.2x | 0.4753 | 663 | 25.28 | 1.1x | 0.4779 |
| Quality-Loss | **30** | **2.89** | **1.9x** | 0.4618 | **150** | **7.35** | **2.6x** | 0.4752 | **369** | **14.42** | **1.9x** | 0.4771 |
| Score-Loss | 50 | 3.50 | 1.6x | 0.4591 | 250 | 11.16 | 1.7x | 0.4751 | 442 | 17.47 | 1.6x | 0.4766 |

$\lambda$-MART on Istella

| Strategy | 100 Trees | | | | 500 Trees | | | | 736 Trees | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Trees | Time | Speed-up | *NDCG*@10 | Trees | Time | Speed-up | *NDCG*@10 | Trees | Time | Speed-up | *NDCG*@10 |
| *Reference* | 100 | 5.37 | – | 0.6923 | 500 | 15.74 | – | 0.7397 | 736 | 20.40 | – | 0.7432 |
| Random | 30 | 2.65 | 2.0x | 0.7003 | 250 | 9.10 | 1.7x | 0.7424 | 515 | 14.81 | 1.4x | 0.7449 |
| Last | 70 | 4.22 | 1.3x | 0.6969 | 400 | 13.55 | 1.2x | 0.7418 | 442 | 14.09 | 1.4x | 0.7437 |
| Skip | **20** | **2.36** | **2.3x** | 0.6976 | 250 | 9.09 | 1.7x | 0.7416 | **368** | **11.42** | **1.8x** | 0.7438 |
| Low-Weights | 30 | 2.85 | 1.9x | 0.6986 | 350 | 11.07 | 1.4x | 0.7418 | 589 | 15.55 | 1.3x | 0.7437 |
| Quality-Loss | **20** | **2.29** | **2.3x** | 0.6989 | **200** | **7.83** | **2.0x** | 0.7412 | 442 | 13.22 | 1.5x | 0.7438 |
| Score-Loss | **20** | **2.13** | **2.5x** | 0.6976 | 300 | 10.68 | 1.5x | 0.7407 | **368** | **12.39** | **1.6x** | 0.7433 |

# DART [VGB15]

- Rashmi and Gilad-Bachrach propose to employ *dropouts* from NN while learning a MART: DART
  - Dropouts as a way to fight *over-specialization*
  - Shrinkage helps but does not solve
- DART differs from MART
  - When learning a new tree, a subset of the model is muted (random)
  - Normalization step when adding a new tree to avoid *overshooting*
    - muted trees are still part of the model
    - new tree scaled by a factor of *1/k*
    - *k/(k+1)* normalization of new and muted




R. Korlakai Vinayak and R. Gilad-Bachrach. *DART: Dropouts meet Multiple Additive Regression Trees*. In PMLR, 2015

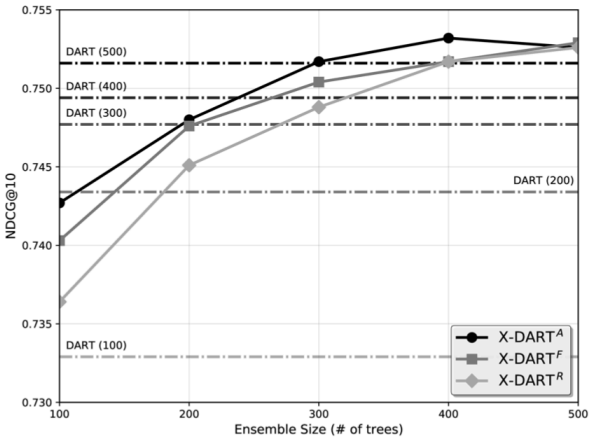
# DART

- Experiments on ranking/regression/classification tasks
  - LambdaMART
  - Ranking on the MSLR-Web10K dataset
  - NDCG@3

| algorithm | Shrinkage | Dropout | Loss function parameter | Feature fraction | NDCG@3 |
|---|---|---|---|---|---|
| **MART** | 0.4 | 0 | 1.2 | 0.75 | 46.31 |
| **DART** | 1 | 0.03 | 1.2 | 0.5 | **46.70** |

# X-DART [LNO+17]

- Lucchese *et al.* merge DART with pruning while training
  - like DART, some trees are muted and this set is actually removed after fitting
- Two good news
  - X-DART builds even more compact models than DART
  - Smaller models are less prone to overfitting: potential for higher effectiveness
- Three strategies for pruning
  - Ratio, Fixed, Adaptive
- Experiments on MSLR-Web30K and Istella-S
  - X-DART (adaptive) provide statistically significant improvements w.r.t. DART

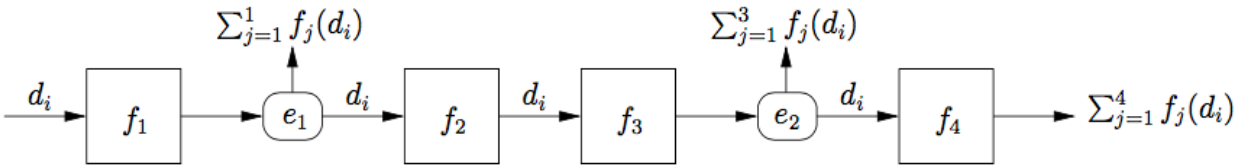



[LNO+17] C. Lucchese, F. M. Nardini, S. Orlando, R. Perego, and S. Trani. *X-DART: Blending dropout and pruning for efficient learning to rank*. In Proc. ACM SIGIR, 2017.

# Approximate Score Computation and Efficient Cascades

# Early Exit Optimizations for Additive Machine Learned Ranking Systems [CZC+10]

- Why short-circuiting the scoring process in additive ensembles
  - For each query, few highly relevant documents and many irrelevant ones
  - most users view only the first few result pages
- Cambazoglu *et al.* introduce additive examples with early exits




- Four techniques
  - Early exits using {Score, Capacity, Rank, Proximity} thresholds
- Evaluation on a state-of-the-art ML platform with GBRT
- With EPT, up to four times faster without loss in quality


[CZC+10] B. B. Cambazoglu, H. Zaragoza, O. Chapelle, J. Chen, C. Liao, Z. Zheng, and J. Degenhardt. *Early exit optimizations for additive machine learned ranking systems*. In Proc. ACM WSDM, 2010.

# Efficient Cost-Aware Cascade Ranking in Multi-Stage Retrieval [CGBC17b]

- Cascade ranking model as a sequence of LtR models (*stages*)
  - ascending order of model complexity, only a fraction of documents in each stage will advance to the next stage
- Chen *et al.* revisit the problem on how best to balance feature importance and feature costs in multi-stage cascade ranking models
  - Three cost-aware heuristics to assign features to each stage
  - cost-aware $L_1$ regularization to learn each stage
    - Automatic feature selection while jointly optimize efficiency and effectiveness
- Experiments
  - Yahoo! Learning to Rank, gov
- Comparisons against [WLM11b]

[CGBC17b] R. Chen, L. Gallagher, R. Blanco, and J. S. Culpepper. *Efficient cost-aware cascade ranking in multi-stage retrieval*. In Proc. ACM SIGIR, 2017.

# Efficient Cost-Aware Cascade Ranking in Multi-Stage Retrieval

| | ERR@k | | | NDCG@k | | | P@k | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| System | @5 | @10 | @20 | @5 | @10 | @20 | @5 | @10 | @20 | Cost |
| *Ground Truth Models* | | | | | | | | | | |
| GBDT-BL | **0.4605** | **0.4751** | **0.4789** | **0.7448** | **0.7872** | **0.8279** | 0.8323 | **0.7577** | **0.5967** | 15988 |
| GBRT-BL | 0.4598 | 0.4744 | 0.4782 | 0.7420 | 0.7852 | 0.8264 | 0.8322 | 0.7562 | 0.5962 | 15876 |
| LambdaMART-BL | 0.4526 | 0.4674 | 0.4712 | 0.7314 | 0.7768 | 0.8203 | **0.8330** | 0.7564 | 0.5964 | 15856 |
| *Cascade Models (including Baseline)* [a] | | | | | | | | | | |
| WLM-BL | 0.3679 | 0.3876 | 0.3933 | 0.5886 | 0.6506 | 0.7088 | 0.7832 | 0.7171 | 0.5673 | 99 |
| LM-C3-C | 0.3950 | 0.4127 | 0.4175 | 0.6461 | 0.7067 | 0.7638 | 0.8086$^{**}$ | 0.7364$^{**}$ | 0.5856$^{**}$ | 1871 |
| LM-C3-E | 0.3871 | 0.4039 | 0.4089 | 0.6503 | 0.7033 | 0.7618 | 0.8192$^{**}$ | 0.7413$^{**}$ | 0.5885$^{**}$ | 1580 |
| LM-C3-F | 0.3876 | 0.4047 | 0.4093 | 0.6541 | 0.7113 | 0.7666 | **0.8226**$^{**}$ | **0.7483**$^{**}$ | **0.5915**$^{**}$ | 5278 |
| GBDT-C3-C | 0.4191 | 0.4357 | 0.4405 | 0.6535 | 0.7100 | 0.7631 | 0.7878$^{*}$ | 0.7245$^{**}$ | 0.5781$^{**}$ | 1760 |
| GBDT-C3-E | 0.4264 | 0.4419 | 0.4466 | 0.6721 | 0.7180 | 0.7703 | 0.7942$^{**}$ | 0.7241$^{**}$ | 0.5778$^{**}$ | 1535 |
| GBDT-C3-F | 0.4178 | 0.4350 | 0.4395 | 0.6554 | 0.7163 | 0.7672 | 0.7866 | 0.7310$^{**}$ | 0.5819$^{**}$ | 4953 |
| GBRT-C3-C | 0.4025 | 0.4203 | 0.4254 | 0.6304 | 0.6931 | 0.7488 | 0.7743 | 0.7168 | 0.5737$^{**}$ | 1760 |
| GBRT-C3-E | 0.4100 | 0.4260 | 0.4313 | 0.6380 | 0.6867 | 0.7431 | 0.7697 | 0.7009 | 0.5637$^{**}$ | 1535 |
| GBRT-C3-F | 0.4158 | 0.4332 | 0.4378 | 0.6479 | 0.7094 | 0.7612 | 0.7862 | 0.7294$^{**}$ | 0.5802$^{**}$ | 4949 |
| LambdaMART-C3-C | 0.4163 | 0.4332 | 0.4379 | 0.6577 | 0.7145 | 0.7673 | 0.7994$^{**}$ | 0.7328$^{**}$ | 0.5820$^{**}$ | 1760 |
| LambdaMART-C3-E | 0.4183 | 0.4346 | 0.4394 | 0.6629 | 0.7133 | 0.7671 | 0.7968$^{**}$ | 0.7268$^{**}$ | 0.5786$^{**}$ | 1535 |
| LambdaMART-C3-F | **0.4353** | **0.4513** | **0.4557** | **0.6847** | **0.7354** | **0.7851** | 0.8060$^{**}$ | 0.7379$^{**}$ | 0.5847$^{**}$ | 4929 |

# Further Reading

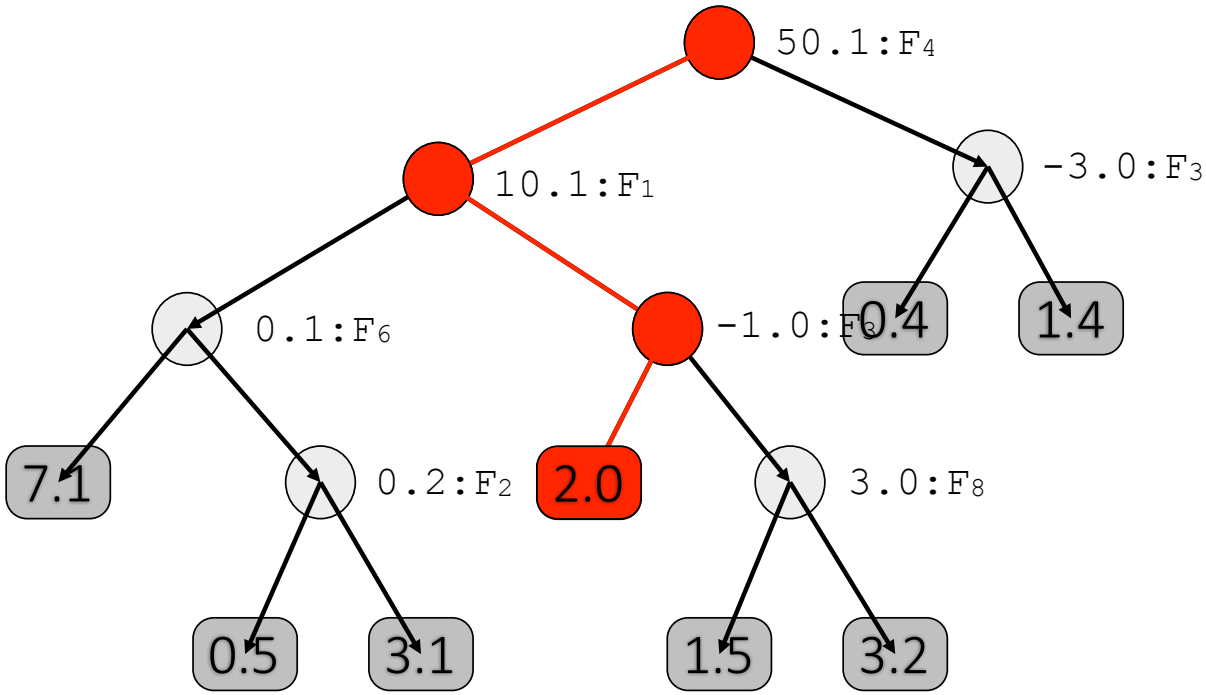
- Wang *et al.* [WLM11b] propose a cascade ranking model for efficient ranked retrieval
  - Retrieval as a multi-stage progressive refinement problem, where each stage considers successively richer and more complex ranking models, but over successively smaller candidate document sets
  - Boosting algorithm (modified AdaRank) to jointly learn the model structure and the set of documents to prune at each stage
  - Experiments show the model is able to simultaneously achieve high effectiveness and fast retrieval
- Xu *et al.* [XKW+14a] propose to post-process classifiers to reduce their test time complexity
  - Focus on execution time and feature extraction cost with skewed classes
  - Reduction of the average cost of a classifier during test time by an order of magnitude on real-world Web search ranking data sets

[WLM11b] L. Wang, J. Lin, and D. Metzler. *A cascade ranking model for efficient ranked retrieval*. In Proc. ACM SIGIR, 2011.
[XKW+14a] Z. Xu, M. J. Kusner, K. Q. Weinberger, M. Chen, and O. Chapelle. *Classifier cascades and trees for minimizing feature evaluation cost*. JMLR, 2014.

# Efficient Traversal of Tree-based Models

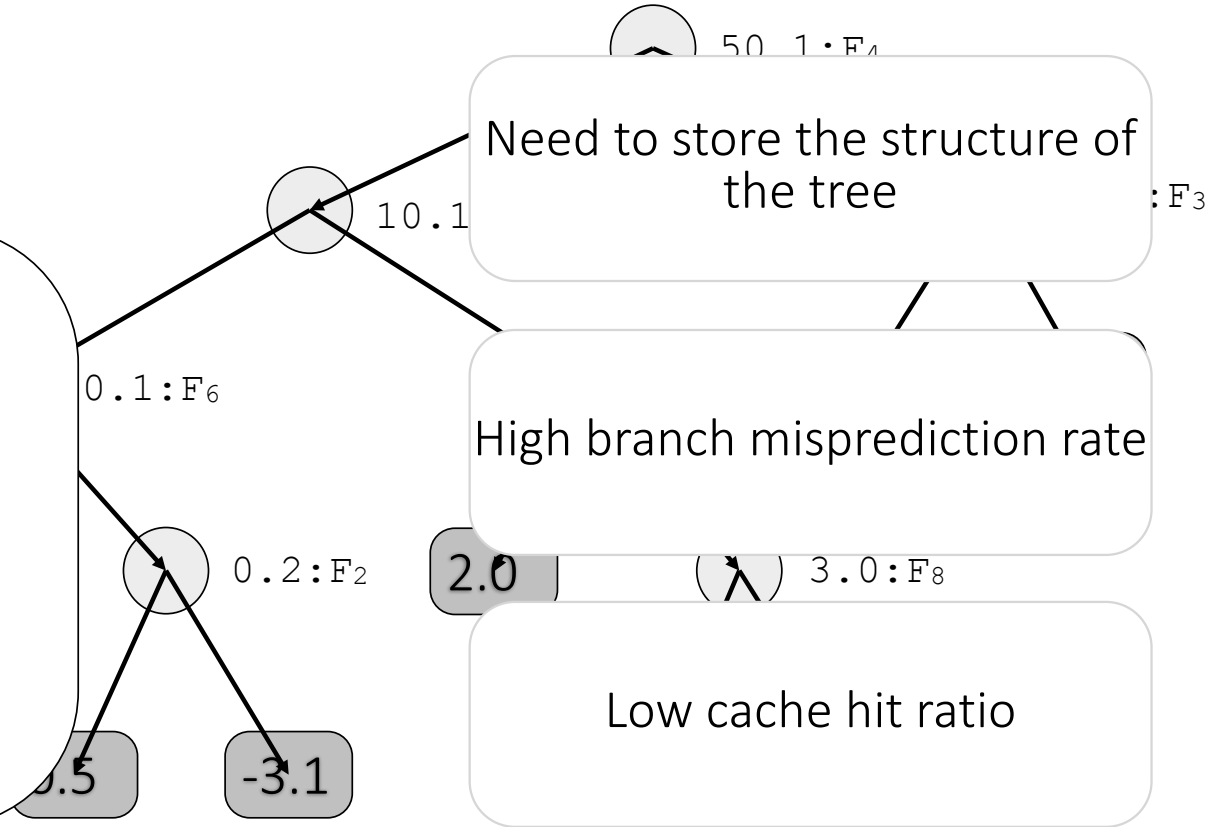
# Efficient Traversal of Tree-based models

- From Yahoo! Learning to Rank Challenge Overview: *"The winner proposal used a linear combination of 12 ranking models, 8 of which were LambdaMART boosted tree models, having each up to 3,000 trees"* [YLTRC].

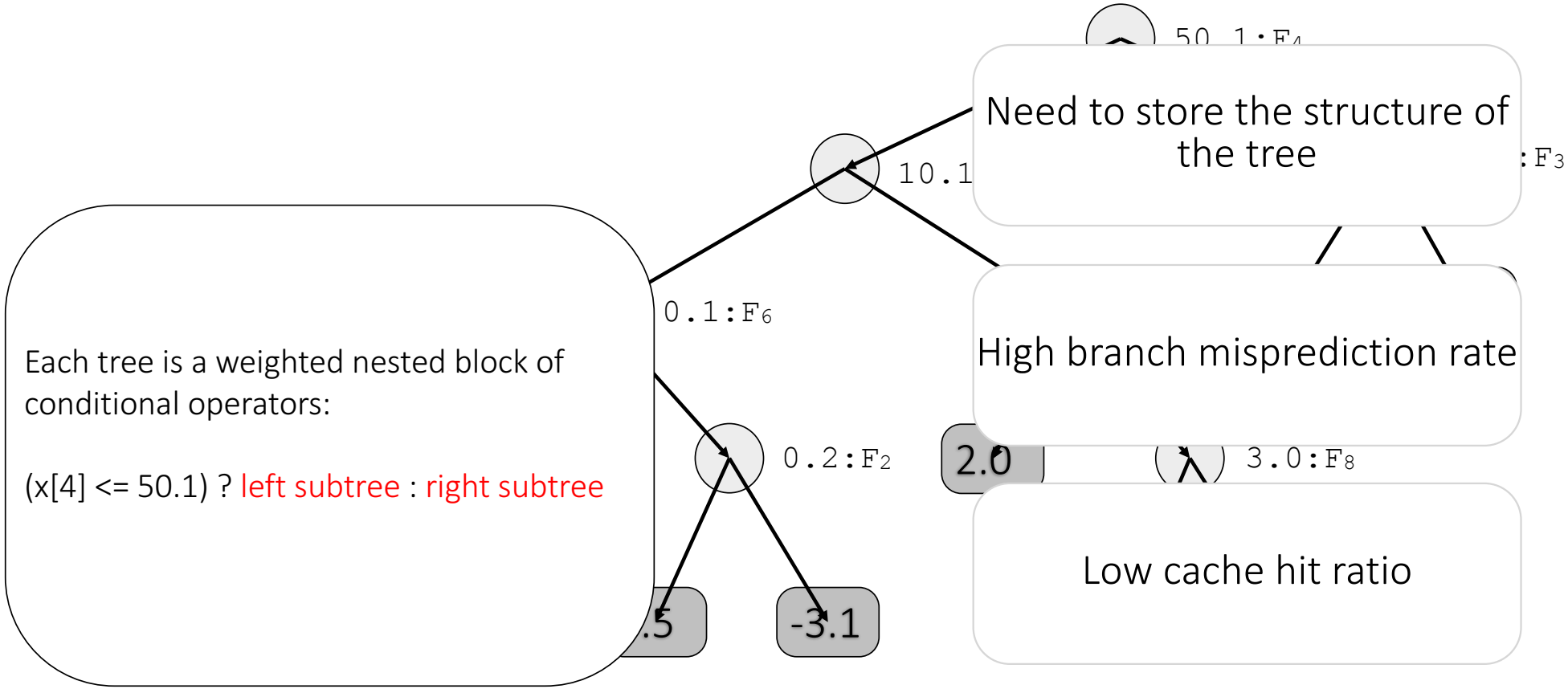


# If-Then-Else

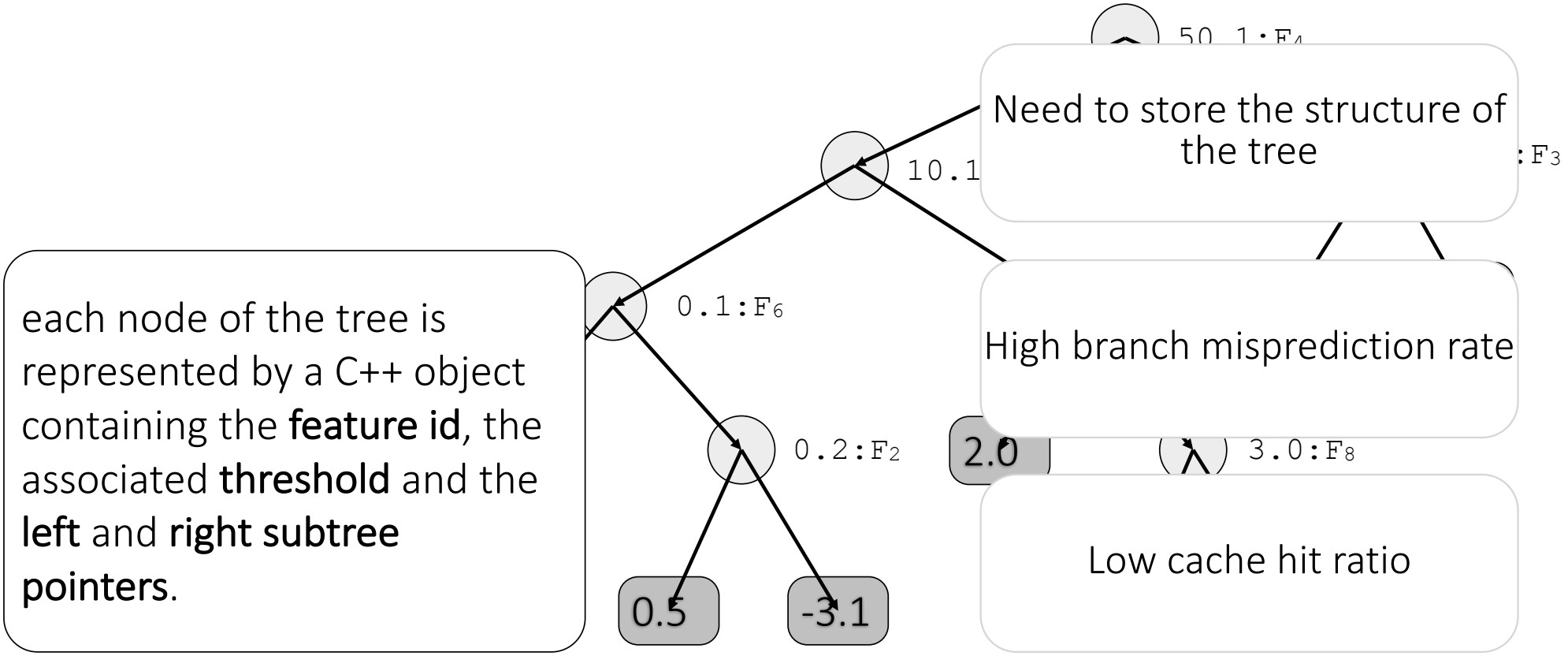
```
if (x[4] <= 50.1) {
        // recurses on the left subtree
        ...
} else {
        // recurses on the right subtree
        if(x[3] <= -3.0)
                result = 0.4;
        else
                result = -1.4;
}
```



# Conditional Operators



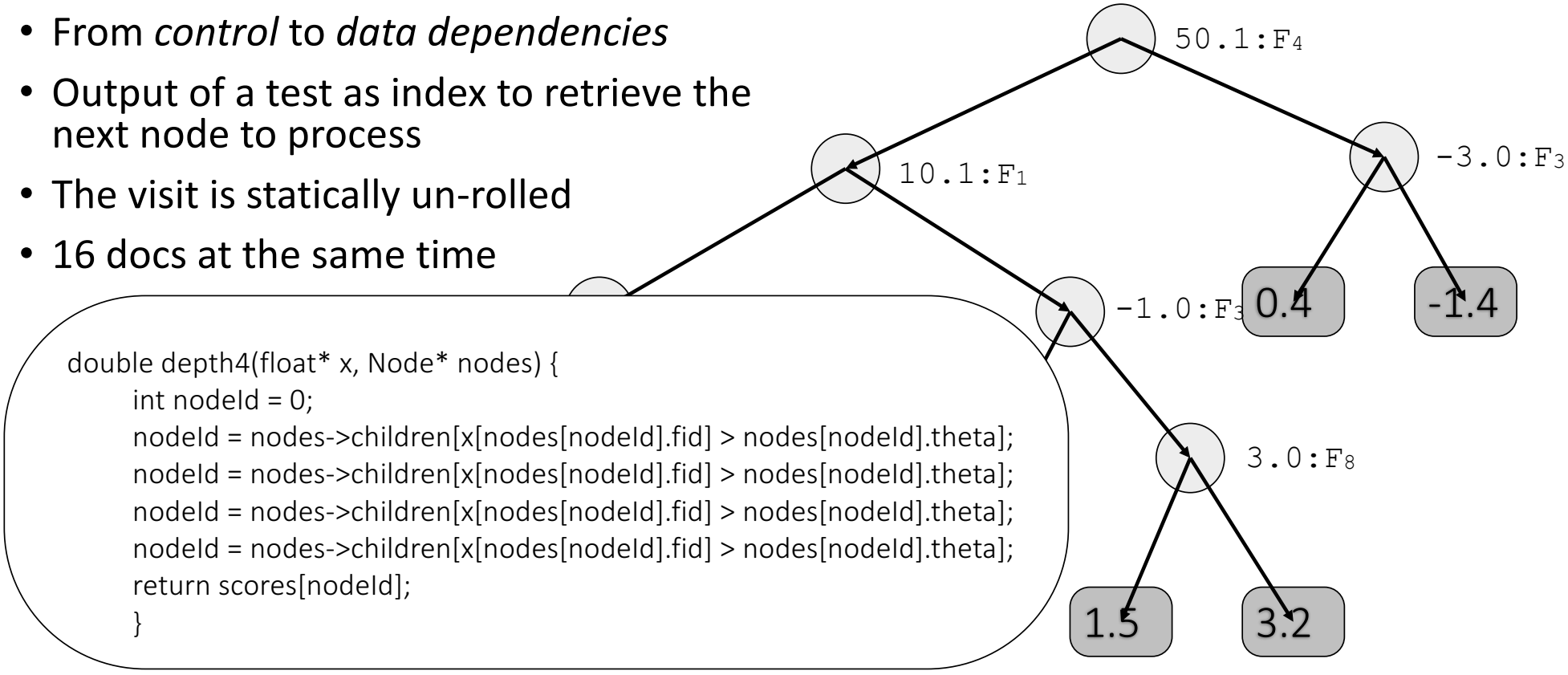
# Struct+ [ALdV14]




[ALdV14] N. Asadi, J. Lin, and A. P. de Vries. *Runtime optimizations for tree-based machine learning models*. IEEE TKDE, 2014.

# VPred [ALdV14]

- From *control* to *data dependencies*
- Output of a test as index to retrieve the next node to process
- The visit is statically un-rolled
- 16 docs at the same time

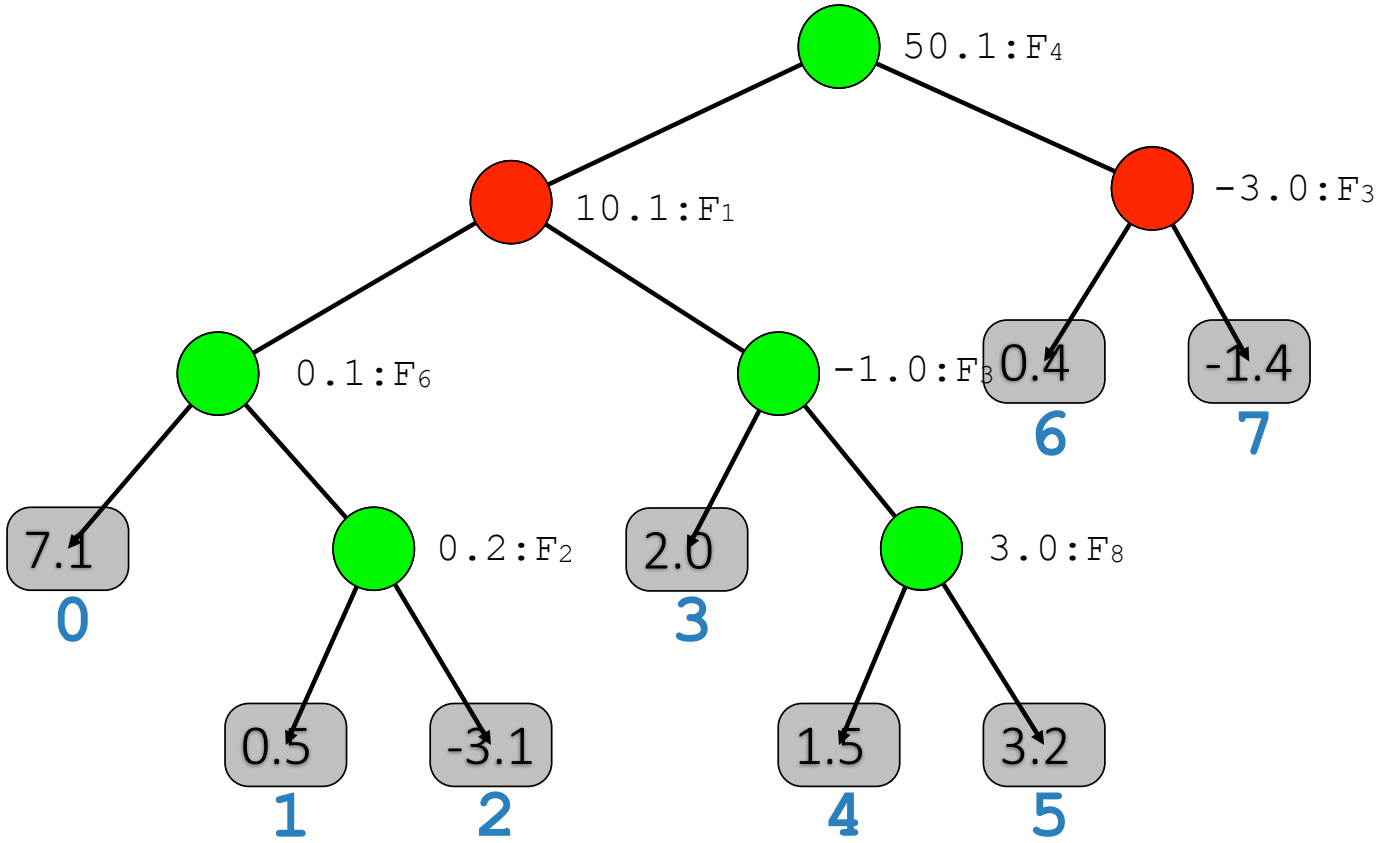



```
double depth4(float* x, Node* nodes) {
        int nodeId = 0;
        nodeId = nodes->children[x[nodes[nodeId].fid] > nodes[nodeId].theta];
        nodeId = nodes->children[x[nodes[nodeId].fid] > nodes[nodeId].theta];
        nodeId = nodes->children[x[nodes[nodeId].fid] > nodes[nodeId].theta];
        nodeId = nodes->children[x[nodes[nodeId].fid] > nodes[nodeId].theta];
        return scores[nodeId];
        }
```

[ALdV14] N. Asadi, J. Lin, and A. P. de Vries. *Runtime optimizations for tree-based machine learning models*. IEEE TKDE, 2014.

# QuickScorer [LNO+15]

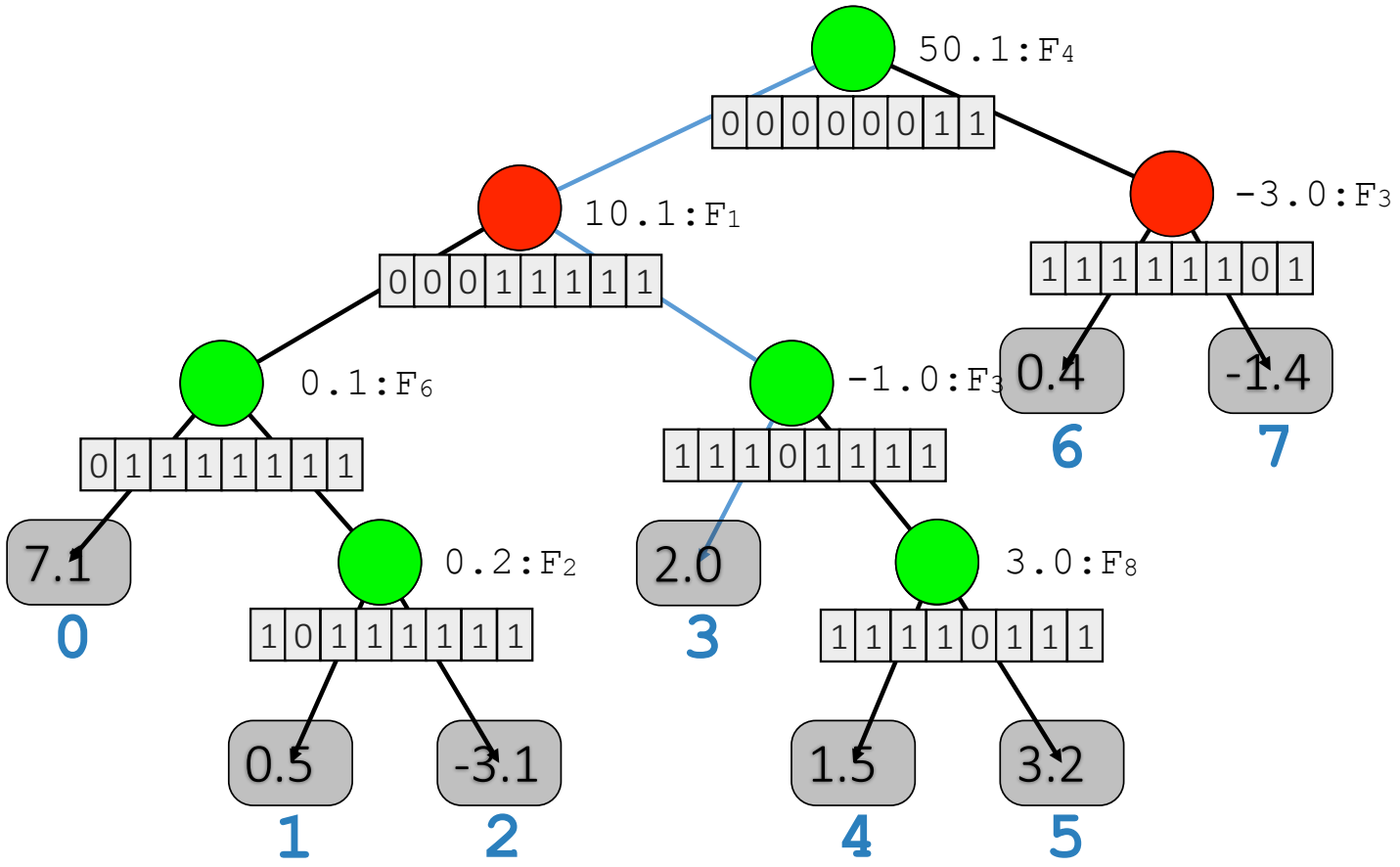
- Given a document, each node of a tree can be classified as True or False
- The exit leaf can be identified by knowing **all (and only) false nodes of a tree**
- From per-tree scoring to per-feature scoring
  - Per-feature linear scan of thresholds in the forest




[LNO+15] C. Lucchese, F. M. Nardini, S. Orlando, R. Perego, N. Tonellotto, and R. Venturini. *Quickscorer: A fast algorithm to rank documents with additive ensembles of regression trees*. In Proc. ACM SIGIR, 2015.

# QuickScorer [LNO+15]

- Bitmasks storing leafs “disappearing” if the node is False.
- ANDing masks of false nodes lead to the identification of the exit leaf.
  - Leftmost bit set to 1 in the resulting mask.
- Few operations insensitive to node processing order.



# QuickScorer [LNO+15]

- Public datasets: MSLR-Web10K and Yahoo LETOR
- Experiments on LambdaMART models: 1K, 5K, 10K, 20K trees and 8, 16, 32, 64 leaves.
  - trained with QuickRank [QR].

| Method | Λ | Number of trees/dataset | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1,000 | | 5,000 | | 10,000 | | 20,000 | |
| | | MSN-1 | Y!S1 | MSN-1 | Y!S1 | MSN-1 | Y!S1 | MSN-1 | Y!S1 |
| QS | 8 | **2.2** (–) | **4.3** (–) | **10.5** (–) | **14.3** (–) | **20.0** (–) | **25.4** (–) | **40.5** (–) | **48.1** (–) |
| VPred | | 7.9 (3.6x) | 8.5 (2.0x) | 40.2 (3.8x) | 41.6 (2.9x) | 80.5 (4.0x) | 82.7 (3.3) | 161.4 (4.0x) | 164.8 (3.4x) |
| If-Then-Else | | 8.2 (3.7x) | 10.3 (2.4x) | 81.0 (7.7x) | 85.8 (6.0x) | 185.1 (9.3x) | 185.8 (7.3x) | 709.0 (17.5x) | 772.2 (16.0x) |
| Struct+ | | 21.2 (9.6x) | 23.1 (5.4x) | 107.7 (10.3x) | 112.6 (7.9x) | 373.7 (18.7x) | 390.8 (15.4x) | 1150.4 (28.4x) | 1141.6 (23.7x) |
| QS | 16 | **2.9** (–) | **6.1** (–) | **16.2** (–) | **22.2** (–) | **32.4** (–) | **41.2** (–) | **67.8** (–) | **81.0** (–) |
| VPred | | 16.0 (5.5x) | 16.5 (2.7x) | 82.4 (5.0x) | 82.8 (3.7x) | 165.5 (5.1x) | 165.2 (4.0x) | 336.4 (4.9x) | 336.1 (4.1x) |
| If-Then-Else | | 18.0 (6.2x) | 21.8 (3.6x) | 126.9 (7.8x) | 130.0 (5.8x) | 617.8 (19.0x) | 406.6 (9.9x) | 1767.3 (26.0x) | 1711.4 (21.1x) |
| Struct+ | | 42.6 (14.7x) | 41.0 (6.7x) | 424.3 (26.2x) | 403.9 (18.2x) | 1218.6 (37.6x) | 1191.3 (28.9x) | 2590.8 (38.2x) | 2621.2 (32.4x) |
| QS | 32 | **5.2** (–) | **9.7** (–) | **27.1** (–) | **34.3** (–) | **59.6** (–) | **70.3** (–) | **155.8** (–) | **160.1** (–) |
| VPred | | 31.9 (6.1x) | 31.6 (3.2x) | 165.2 (6.0x) | 162.2 (4.7x) | 343.4 (5.7x) | 336.6 (4.8x) | 711.9 (4.5x) | 694.8 (4.3x) |
| If-Then-Else | | 34.5 (6.6x) | 36.2 (3.7x) | 300.9 (11.1x) | 277.7 (8.0x) | 1396.8 (23.4x) | 1389.8 (19.8x) | 3179.4 (20.4x) | 3105.2 (19.4x) |
| Struct+ | | 69.1 (13.3x) | 67.4 (6.9x) | 928.6 (34.2x) | 834.6 (24.3x) | 1806.7 (30.3x) | 1774.3 (25.2x) | 4610.8 (29.6x) | 4332.3 (27.0x) |
| QS | 64 | **9.5** (–) | **15.1** (–) | **56.3** (–) | **66.9** (–) | **157.5** (–) | **159.4** (–) | **425.1** (–) | **343.7** (–) |
| VPred | | 62.2 (6.5x) | 57.6 (3.8x) | 355.2 (6.3x) | 334.9 (5.0x) | 734.4 (4.7x) | 706.8 (4.4x) | 1309.7 (3.0x) | 1420.7 (4.1x) |
| If-Then-Else | | 55.9 (5.9x) | 55.1 (3.6x) | 933.1 (16.6x) | 935.3 (14.0x) | 2496.5 (15.9x) | 2428.6 (15.2x) | 4662.0 (11.0x) | 4809.6 (14.0x) |
| Struct+ | | 109.8 (11.6x) | 116.8 (7.7x) | 1661.7 (29.5x) | 1554.6 (23.2x) | 3040.7 (19.3x) | 2937.3 (18.4x) | 5437.0 (12.8x) | 5456.4 (15.9x) |

# Vectorized QuickScorer [LNO+16b]

- Extends QuickScorer by exploiting SIMD capabilities of modern CPUs (SSE 4.2 and AVX 2).
- V-QuickScorer exploits 128 bit registers (SSE 4.2) and 256 bit registers (AVX 2) to:
  - perform mask computation: with 32 leaves models, 4 docs in parallel (SSE 4.2), 8 docs in parallel (AVX 2).
  - perform score computation: with 32 leaves models, 2 docs in parallel (SSE 4.2), 4 docs in parallel (AVX 2).
- Tests on MSN10K, Yahoo LETOR and istella datasets.
- Experiments on LambdaMART models: 1K, 10K trees and 32, 64 leaves.
  - trained with QuickRank [QR].

| Λ | Method | Number of trees/dataset | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1,000 | | | 10,000 | | |
| | | MSN-1 | Y!S1 | istella | MSN-1 | Y!S1 | istella |
| 32 | QS | 6.3 (–) | 12.5 (–) | 8.9 (–) | 73.7 (–) | 88.7 (–) | 69.9 (–) |
| | vQS (SSE 4.2) | 3.2 (2.0x) | 5.2 (2.4x) | 4.2 (2.1x) | 46.2 (1.6x) | 53.7 (1.7x) | 38.6 (1.8x) |
| | vQS (AVX-2) | **2.6 (2.4x)** | **3.9 (3.2x)** | **3.1 (2.9x)** | **39.6 (1.9x)** | **43.7 (2.0x)** | **30.7 (2.3x)** |
| 64 | QS | 11.9 (-) | 18.8 (-) | 14.3 (-) | 183.7 (-) | 182.7 (-) | 162.2 (-) |
| | vQS (SSE 4.2) | 10.2 (1.2x) | 13.9 (1.4x) | 11.0 (1.3x) | 173.1 (1.1x) | 164.3 (1.1x) | 132.2 (1.2x) |
| | vQS (AVX-2) | **7.9 (1.5x)** | **10.5 (1.8x)** | **8.0 (1.8x)** | **138.2 (1.3x)** | **140.0 (1.3x)** | **104.2 (1.6x)** |

[LNO+16b] C. Lucchese, F. M. Nardini, S. Orlando, R. Perego, N. Tonellotto, and R. Venturini. *Exploiting CPU SIMD extensions to speed-up document scoring with tree ensembles*. . In Proc. ACM SIGIR, 2016.

# Further Reading

- Tang *et al.* [TJY14] investigates data traversal methods for fast score calculation with large ensembles of regression trees. Authors propose a 2D blocking scheme for better cache utilization.
  - Introduction of document and tree blocking for a better exploitation of cache layers of modern CPUs. The technique is used by Lucchese *et al.* [LNO+15].
- Jin *et al.* [JYT16] provide an analytical comparison of cache blocking methods. Moreover, they propose a technique to select a traversal method and its optimal blocking parameters for effective use of memory hierarchy.

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Thanks a lot for your attention!

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