# Learning Early Exit Strategies for Additive Ranking Ensembles

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#### **ABSTRACT**

Modern search engine ranking pipelines are commonly based on large machine-learned ensembles of regression trees. We propose LEAR, a novel - learned - technique aimed to reduce the average number of trees traversed by documents to accumulate the scores, thus reducing the overall query response time. LEAR exploits a classifier that predicts whether a document can early exit the ensemble because it is unlikely to be ranked among the final top-k results. The early exit decision occurs at a sentinel point, i.e., after having evaluated a limited number of trees, and the partial scores are exploited to filter out non-promising documents. We evaluate LEAR by deploying it in a production-like setting, adopting a state-of-theart algorithm for ensembles traversal. We provide a comprehensive experimental evaluation on two public datasets. The experiments show that LEAR has a significant impact on the efficiency of the query processing without hindering its ranking quality. In detail, on a first dataset, LEAR is able to achieve a speedup of 3× without any loss in NDCG@10, while on a second dataset the speedup is larger than 5× with a negligible NDCG@10 loss (< 0.05%).

## **KEYWORDS**

Learning to Rank, Early Exiting, Efficiency/Effectiveness Trade-offs

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#### 1 INTRODUCTION

Query processors of modern search engines rely on sophisticated ranking pipelines aimed at optimizing precision-oriented metrics at small cutoffs. Learning-to-rank (LtR) techniques are commonly used to train complex models able to precisely re-rank a set of candidate documents. State-of-the-art solutions include additive ensembles of regression trees, such as MART [7] and  $\lambda$ -Mart [2, 14], learned by gradient boosting algorithms. Since such ensemble are made of hundreds of additive regression trees, the tight constraints on query response time require suitable solutions able to provide an optimal trade-off between document scoring time and ranking effectiveness [4]. Among the main contributions in the area, we cite the algorithms for the efficient traversal of tree ensembles

[6, 10, 16]. Alternative methods are concerned with strategies for pruning the ensemble during or after the training phase [8, 9, 11], and budget-aware learning-to-rank algorithms [1, 13]. Furthermore, researchers investigated early termination heuristics aimed to reduce, on a document- or query-level basis, the cost of the scoring process [3, 12, 15]. These works studied the impact of the proposed early termination strategies on both the latency and ranking accuracy. Finally, other techniques looked at a composite scenario, where feature extraction costs and system effectiveness are balanced across multiple re-ranking stages [5].

In this paper, we investigate document-level early exit strategies for additive ranking ensembles by generalizing and building upon the state-of-the-art method introduced by Cambazoglu et al. [3], who proposed some heuristic techniques to force documents to early exit the ensemble if they are unlikely to be included in the top-k results. We devise a machine learning framework (ML), called LEAR (Learned EArly exit Ranking), for early terminating document scoring. LEAR is based on a binary classifier that exploits querydocument features along with their score/rank cumulated up to a given ensemble's tree, called "sentinel". The classifier predicts whether the document should exit the ensemble because it will unlikely be ranked among the top-k ones or it should continue the traversal of the rest of the ensemble. We provide an in-depth study of the possible solutions to training effective early-exiting classifiers, we discuss their accuracy and their placements in the ensemble at specific sentinels<sup>1</sup>. We also provide an analysis of the speedup achieved by the introduction of LEAR in QUICKSCORER, a stateof-the art algorithm for ensemble traversal [10]. The experiments, conducted on two well-known public LtR datasets, namely MSN-1 and Istella, show that our learned solution for document-level early exit provides up to 5× speedup with a negligible loss, lower than 0.05%, in terms of NDCG@10 and significantly outperforms the previous state-of-the-art solution by Cambazoglu et al. [3].

# 2 LEARNING EARLY EXIT STRATEGIES

In this section, we discuss LEAR, our method to force documents to early exit (EE) the ensemble. To motivate and introduce our contribution, we first evaluate the main limits of the heuristics proposed by Cambazoglu *et al.* [3].

**Heuristic EE techniques.** Four EE heuristic techniques are proposed in [3], where the best are *EE Using Rank Thresholds* (ERT) and *EE Using Proximity Thresholds* (EPT). At a given sentinel s in the ensemble, ERT sorts the candidate documents for a given query in decreasing order of their partial scores computed by evaluating

 $<sup>^{1}</sup> Code\ available\ at\ https://github.com/hpclab/learning-exit-strategies-ensembles for the control of the$ 

Table 1: Best strategies in [3] vs Full and EE<sub>ideal</sub>.

Method	NDCG@10	Δ	Speedup	$k_s^\mu$	$k_s^{\sigma}$
Full	0.5249	0%	1	-	-
$EE_{ideal}$	0.5249	0%	3.06×	25.04	19.97
ERT $(k_s = 15)$	0.5169	-1.53%	5.74×	-	-
ERT ( $k_s = 20$ )	0.5204	-0.85%	$4.71 \times$	-	-
EPT $(k_s = 15, p = 0.2)$	0.5229	-0.37%	$3.53 \times$	28.56	12.06
EPT $(k_s = 15, p = 0.5)$	0.5241	-0.15%	1.95×	57.49	31.35

the first s trees. Then, given a pre-tuned rank threshold  $k_s$ , only the top- $k_s$  documents are evaluated by the remainder of the ensemble, while the other documents maintain their ranking at the sentinel without any additional computation. Besides ranks, EPT exploits document ranks to select also those document in proximity of the top- $k_s$ . Let  $\sigma_{k_s}$  be the partial score of the  $k_s$ -th best document at the sentinel, all documents with a score smaller than  $\sigma_{k_s}-p$  early exit the ensemble, where p is a fine-tuned proximity threshold.

The rationale of EPT is to avoid a short-sighted top- $k_s$  selection when several documents have close scores and therefore they are equally likely to be ranked among the best results by the whole ensemble. In the case of such uncertain queries, EPT allows a larger number of candidate documents to be selected.

To motivate LEAR, i.e., our novel ML-based EE technique, we evaluate ERT and EPT when applied to a  $\lambda$ -MART additive ensemble made up of 1,047 trees and trained on the MSN-1<sup>2</sup> dataset (fold 1) using the LightGBM³ library. Table 1 compares the performance figures – in terms of NDCG@10 and speedup – obtained by the following methods on the test set:

- a ranking that exploits the complete ensemble without EE (Full);
- the ideal EE strategy ( $\text{EE}_{ideal}$ ), where for each query q an oracle predicts the optimal value for  $k_s^q$ , where all the documents of rank greater than  $k_s^q$  at the sentinel s can safely early exit the ensemble. The value  $k_s^q$  is the minimum one to guarantee that the measure NDCG@10 for query q is the same as the original one (Full), i.e., we select a distinct cut  $k_s^q$  per each query that guarantees that all the top-10 documents, appearing at the end of the original whole ensemble, are kept in the ensemble and continue to score.
- two versions of ERT, with  $k_s = 15$  and  $k_s = 20$ . We experimentally fine-tuned  $k_s$  and these values resulted the best performing ones;
- two versions of EPT, where we use  $k_s = 15$  and two values of score proximity p (p = 0.2 and p = 0.5). Larger values of p imply less documents that are stopped at the sentinel.

In these experiments, EE is applied in all the cases at sentinel s=50 and speedup is estimated by considering as scoring cost the number of trees traversed for each document in the test set. Note that the EE heuristic that achieves the best effectiveness – i.e., a limited decrease in NDCG@10 with respect to Full ( $\Delta=-0.15\%$ ) – is EPT ( $k_s=15$ , p=0.5). Unfortunately, in this setting, also the resulting speedup is limited and lower than 2×. On the other hand, EE $_{ideal}$  obtains by construction the same NDCG@10 as Full, but with a speedup of

3.06×. We also report in the table mean and standard deviation for the cut  $k_s$  of each query  $(k_s^\mu$  and  $k_s^\sigma)$ . Obviously, speedup is inversely proportional to  $k_s^\mu$ , as a smaller  $k_s^\mu$  implies more documents that early exit the ensemble. Note the  $k_s^\sigma$  increases when we increment the EPT score proximity p, because the number of documents that continue in the ensemble changes greatly for each query. This is true also for the ideal case (EE $_{ideal}$ ), but much less than EPT with proximity score p=0.5.

We can conclude saying that there is room to improve over the heuristic techniques proposed by Cambazoglu *et al.* The goal is to find a trade-off between ERT ( $k_s = 15$ ), with speedups close to 6× and a very reduced ranking quality ( $\Delta = -1.53\%$ ), and EPT ( $k_s = 15, p = 0.5$ ), which obtains a very small reduction in the final ranking quality ( $\Delta = -0.15\%$ ), but a speedup lower than 2×.

**LEAR Learned EArly exit Ranking.** From the previous analysis, we conclude that there is space for investigating a solution that tries to improve speedup by keeping  $\Delta_{NDCG@10}$  as small as possible.

We propose LEAR, an ML-based solution where a binary classifier at the sentinel filters a possibly small subset of documents that are then evaluated by the remaining trees of the ensemble. The goal is thus to discard the largest possible number of documents to boost the speedup of the ensemble computation and to select the best documents so as to provide a ranking quality as close as possible to the one achieved with the full evaluation of all candidates. These contrasting objectives pose the following challenges: (*i*) how to build the training set for the classifier; (*ii*) how to cope with imbalance of selected versus discarded documents; (*iii*) which efficient and accurate classification algorithm to use; and, finally, (*iv*) how to manage the trade-off between efficiency and effectiveness.

Building the training set. We distinguish between Exit documents and Continue documents for training the classifier. The classification label is assigned on the basis of the final ranking position generated by the ensemble and the relevance label associated with the document. The set Continue includes those documents that are relevant and included in the top-k results by the full ensemble. The complementary documents define the Exit set. At the sentinel s we would like to select all the Continue documents so as to mimic the behaviour of the full ensemble. Conversely, the Exit documents do not contribute to the top-k results and their scoring should be stopped. Note that since the Continue set includes only relevant documents, and all Continue documents are, by design, ranked higher than Exit documents, a perfect classifier might drop some irrelevant documents and possibly lead to a better ranking than the full ensemble.

To train our classifier with *Continue* and *Exit* examples we use an augmented representation for the documents including information that becomes available at the sentinel s. Specifically, besides the features exploited by the ensemble, we use: the rank of the document at the sentinel, the score accumulated up to that point, its per-query min-max normalized value, and the number of candidates for the corresponding query.

Handling imbalance. Continue documents are in general a small fraction of all the instances, resulting in a highly imbalanced training set. Moreover, when using quality metrics such as NDCG@k, documents contribute differently to the quality of the result set depending on their relevance label. We tackle this issue by exploiting

<sup>&</sup>lt;sup>2</sup>https://www.microsoft.com/en-us/research/project/mslr/

 $<sup>^3</sup> https://github.com/Microsoft/LightGBM\\$ 

a cost-sensitive training where each instance d having relevance label  $r_d$  and classification label  $l_d$ , is associated with a different weight  $w_d = 2^{r_d}/f_q(l_d)$ , where  $f_q(l_d)$  is the frequency, among the candidates for query q, of the Continue/Exit classification label  $l_d$ . This pushes the classifier to prioritize loss reduction on documents with large relevance labels proportionally to their contribution to the NDCG metric, and on the infrequent Continue documents. Note that this weighting scheme is query-based and allows the classifier to adapt to the different queries in the dataset.

Classifier efficiency. Several options are available for building a binary classifier, e.g., logistic regression, SVM, etc. Note that the classification task performed for each document is a potential overhead that we are introducing. After experimental evaluation, not included in this work due to space constraints, we chose a small forest of 10 trees trained by minimizing the logistic loss. We found that such a small forest provides the best results with a limited additional cost.

Efficiency vs. effectiveness trade-off. Accuracy is not the metric we are targeting for the classifier. Our goal is in fact to maximise the recall over *Continue* documents, without hindering precision. To this end, we fine tune a filtering threshold on the probability of belonging to class *Continue* predicted by the classifier. By varying this threshold, we can find the sweet spot between precision and recall. Finally, the position of the sentinel s impacts on the accuracy of the classifier and on the efficiency of the LEAR framework. Early sentinels generate less reliable partial document scores/ranks (due to the limited number of trees) potentially harming the classifier accuracy. On the other hand, they may produce large speedups thanks to the amount of tree traversals avoided. In the experimental section we investigate different sentinel points.

# 3 EXPERIMENTS

Datasets. The datasets used for experiments are MSN-1<sup>4</sup> (Fold 1) and Istella<sup>5</sup>. The MSN-1 one consists of 31,351 queries and 136 features extracted from 3,771,125 query-document pairs, while the Istella dataset is composed of 33,018 queries and 220 features extracted from 10,454,629 query-document pairs. They thus differ in the average number of documents per query, ranging from the 120 of MSN-1 to the 317 of Istella. The query-document pairs in both datasets are labeled with relevance judgments ranging from 0 (irrelevant) to 4 (perfectly relevant). Istella comes with about 96% of non-relevant documents and a normal distribution among the relevant ones centered on label 2, while MSN-1 shows a power law distribution with 51% of non-relevant documents. Both the datasets are split in four partitions with sizes 60%-20%-5%-15%: the first partition is used to train the  $\lambda$ -MART ranking model; the second for hyper-parameter tuning of  $\lambda$ -Mart; the binary classifier is trained on the second partition and fine-tuned on the third; finally, the fourth partition is used as test set to evaluate the efficiency and effectiveness of the ensemble and the EE strategies considered.

**Ranking models**. The reference ranking models were trained with  $\lambda$ -Mart. Indeed, we used the LightGBM implementation<sup>6</sup>, and finetuning hyper-parameters by maximizing NDCG@10 and using a

bayesian approach as provided by HyperOpt<sup>7</sup>. The number of trees was limited at 1,500 and tuned with 100 iterations for early stopping. The resulting ensembles have 1,047 and 1,469 trees for MSN-1 and Istella, respectively. Each tree has up to 64 leaves.

**Competitor algorithm.** We evaluate LEAR against the EPT heuristic strategy. For EPT we used  $k_s = 15$  and proximity thresholds p ranging from 0.3 (more aggressive EE) to 0.8 (more conservative EE), with a step size of 0.1.

**LEAR binary classifier**. As previously discussed, we use a forest of 10 trees to detect *Continue/Exit* documents. We used top-15 results ranked by the full ensemble to determine the document in the two classes. The model was trained by optimizing the logistic loss and using the same implementation framework of  $\lambda$ -MART (LightGBM + HyperOpt). We also performed feature importance analysis on query-document features. The resulting models employs 54 features for MSN-1 and 118 for Istella. Finally, in all tests for LEAR we used different choices of confidence classifier thresholds, ranging from 0.1 (more conservative EE) to 0.7 (more aggressive EE), with steps of 0.1. Note that the effect of these thresholds is similar to the one modeled by parameter *p* in EPT.

Assessing the efficiency. We assess the efficiency of LEAR and EPT using QuickScorer (QS) [6, 10], the state-of-the-art algorithm for scoring ensembles of regression trees. We extend QS by introducing the computation of early exit strategies (both LEAR and EPT) at a given sentinel during the scoring process. All the results reported hereinafter consider the total latency of the process, i.e., the time needed to score the documents with the  $\lambda$ -Mart model plus the time needed to compute the early exit strategy. Our extended QS is implemented in C++.

#### 3.1 Performance of LEAR classifier

Table 2 reports the precision and recall performance of the LEAR classifier. LEAR exhibits a very large recall for the Continue class of 97% and 99% on the MSN-1 and Istella datasets, respectively. Therefore, the classifier is able to identify nearly all documents that should continue the forest traversal because they are likely to be included into the top-k results. Having such a large recall on the Continue class is necessary for a high-quality final ranking. The second objective of the classifier is to minimize the number of false positives, i.e., the number of Exit documents incorrectly classified as Continue, as they do not contribute to the final top-k results and only increase the overall evaluation cost. In this regard, the recall on the Exit class is 82% for MSN-1 and 91% for Istella, which are pretty good results given the large amount of documents which we expect to prune. These results were achieved with a sentinel s = 50, by thresholding the classifier's predicted probability at 50%. In the following subsection, we investigate the impact on performance of these two tuning parameters.

Figure 1 reports the feature importance analysis of the binary classifier including the rank- and score-based features made available at the sentinel. Notably, the document rank and the document score at the sentinel (red bars) are the first and fourth most important features, thus largely contributing to the classification accuracy.

 $<sup>^4</sup> http://research.microsoft.com/en-us/projects/mslr/\\$ 

<sup>&</sup>lt;sup>5</sup>http://blog.istella.it/istella-learning-to-rank-dataset/

 $<sup>^6</sup>https://github.com/microsoft/LightGBM\\$ 

<sup>&</sup>lt;sup>7</sup>https://github.com/hyperopt/hyperopt

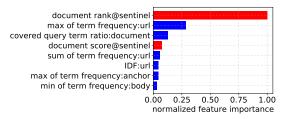


Figure 1: Feature importance analysis.

Table 2: LEAR Precision and Recall figures.

Class	MSN-1		Istella		
	Precision	Recall	Precision	Recall	
Exit	1.00	0.82	1.00	0.91	
Continue	0.33	0.97	0.25	0.99	

# 3.2 Efficiency/effectiveness trade-off

We compare the performance of LEAR against EPT by evaluating the efficiency/effectiveness trade-offs for the MSN-1 dataset. The two plots in Figure 2 show the impact of the two strategies on: *i*) the final ranking quality, evaluated in terms of reduction of NDCG@10 compared to the reference  $\lambda$ -MART model (y-axis), and ii) the speedup derived from the reduced number of documents to be scored through the full ensemble (x-axis). Specifically, each plot reports three curves, each corresponding to the performance of the method when applied at a given sentinel, i.e., after 50, 100, and 200 trees of the  $\lambda$ -MART model. For each sentinel, the curve reports the different efficiency/effectiveness trade-offs obtained by varying the confidence/proximity threshold for LEAR/EPT, respectively. The two plots allow us to easily identify the sentinel with the best efficiency/effectiveness trade-off, i.e., the line dominating the others in terms of final ranking quality and achieved speedup. Figure 2 (a) shows that the best choice for LEAR is to put the sentinel after the 50-th tree. In this setting, LEAR achieves no effectiveness degradation with a speedup of up to 3× for small values of the confidence threshold (up to 0.3).

Note the this result exactly corresponds to that of  $\mathrm{EE}_{ideal}$ , reported in Table 1 as the best possible result to which EPT can tend. By increasing the LEAR confidence threshold, the EE strategy becomes more aggressive. This translates to higher speedups at the cost of higher degradation of the ranking quality. Similarly, Figure 2 (b) reports the same analysis for EPT by varying the proximity

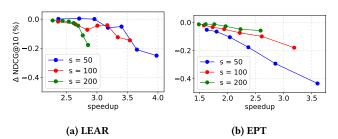


Figure 2: Efficiency-effectiveness trade-offs of LEAR and EPT by varying the sentinel on the MSN-1 dataset.

threshold. Here, the best trade-offs are achieved at 200 trees. In this setting, results show no quality degradation with speedups of up to 1.75× by using proximity thresholds higher than 0.6. From that point, in correspondence of lower proximity values, EPT starts degrading ranking quality with a maximum loss observed of -0.05% in correspondence to a speedup of about 2.6×. On the MSN-1 dataset, LEAR and EPT thus show their best results by using sentinels placed at different points of the ensemble. We also tested the two methods on the Istella dataset. We do not report the plots due to space constraints. Results on Istella show that the best performance of the two methods are achieved at 100 trees. We conclude the analysis by reporting a direct comparison of the best sentinel placements of the two methods in Figure 3. Figure 3 (a) provide such a comparison on the MSN-1 dataset. It clearly show the superiority of LEAR with respect to EPT. Indeed, the former method outperforms the latter by margin, providing much higher speed-ups when keeping fixed the effectiveness degradation or, conversely, providing higher effectiveness at the same speed-up ratio. Figure 3 (b) shows the same comparison on Istella, where LEAR still outperforms EPT in terms of trade-offs despite a reduced margin. To conclude, we experimentally show that our ML-based solution for early exit additive ranking ensembles is able to achieve better efficiency-effectiveness trade-offs than previous state-of-the-art heuristics.

# 4 CONCLUSION

We have discussed LEAR, an effective ML-based technique to speedup document ranking employing additive ensembles of regression trees. LEAR forces documents to early exit the ensemble if they are unlikely to be ranked among the final top-k results. Experiments on two public datasets showed that LEAR achieves speedups larger than  $5\times$  with a negligible loss of NDCG@10 (< 0.05%). Results also showed that it remarkably outperforms the state-of-the-art document-level EE heuristics. As future work, we intend to investigate the integration in the LEAR framework of query-level early exit strategies.

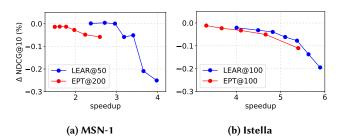


Figure 3: Efficiency-effectiveness trade-offs of the best LEAR against the best EPT on the MSN-1 and Istella datasets.

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