TSPRank: Bridging Pairwise and Listwise Methods with a Bilinear Travelling Salesman Model

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ABSTRACT

Traditional Learning-To-Rank (LETOR) approaches, including pairwise methods like RankNet and LambdaMART, often fall short by solely focusing on pairwise comparisons, leading to sub-optimal global rankings. Conversely, deep learning based listwise methods, while aiming to optimise entire lists, require complex tuning and yield only marginal improvements over robust pairwise models. To overcome these limitations, we introduce Travelling Salesman Problem Rank (TSPRank), a hybrid pairwise-listwise ranking method. TSPRank reframes the ranking problem as a Travelling Salesman Problem (TSP), a well-known combinatorial optimisation challenge that has been extensively studied for its numerous solution algorithms and applications. This approach enables the modelling of pairwise relationships and leverages combinatorial optimisation to determine the listwise ranking. This approach can be directly integrated as an additional component into embeddings generated by existing backbone models to enhance ranking performance. Our extensive experiments across three backbone models on diverse tasks, including stock ranking, information retrieval, and historical events ordering, demonstrate that TSPRank significantly outperforms both pure pairwise and listwise methods. Our qualitative analysis reveals that TSPRank's main advantage over existing methods is its ability to harness global information better while ranking. TSPRank's robustness and superior performance across different domains highlight its potential as a versatile and effective LETOR solution. The code and preprocessed data are available at https://github.com/waylonli/TSPRank-KDD2025.

CCS CONCEPTS

Information systems → Learning to rank.

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KEYWORDS

learning-to-rank, pairwise-listwise ranking, travelling salesman problem

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1 INTRODUCTION

Learning to Rank (LETOR) algorithms have become essential in applications such as recommendation systems [16, 30, 36], question answering [10, 15, 27], and information retrieval [2, 9, 34]. These algorithms aim to order a list of ranking entities based on their features, optimising for the most relevant or preferred entities to appear at the top. Recently, LETOR methods have also expanded into other domains, such as stock and portfolio selection [45, 50] and textual ordering [46, 49]. Despite these broader applications of LETOR, latest fundamental work on LETOR still primarily focused on incorporating click data into ranking models and addressing biases introduced by user feedback [20, 21, 33, 54], concentrating on retrieval and recommendation tasks. Limited research has explored general ranking methods across diverse tasks and domains.

Over the past decade, research on LETOR models mainly focuses on pairwise and listwise approaches, while pointwise methods often fail to capture the intricate inter-entity relationships that are essential for accurate ranking. Pairwise methods, such as LambdaMART and RankNet [6], primarily optimise for pairwise comparisons without a holistic view of the entire ranking list, potentially leading to sub-optimal global rankings. Listwise methods optimise the ranking of entire lists directly rather than individuals or pairs. This category includes advanced neural network architectures, particularly adaptations of the Transformer architecture [47], such as Rankformer [9] and SetRank [34]. However, existing work shows that deep learning-based listwise models require complex tuning to achieve marginal gains over robust pairwise models like LambdaMART on information retrieval benchmarks [39]. Therefore, pairwise and listwise methods each have inherent drawbacks and more effective solutions for LETOR have not been exhaustively explored.

Recently, GNNRank successfully used directed graph neural networks to learn listwise rankings from pairwise comparisons [23]. Although their method is not applicable to general LETOR problems, as it requires pre-known pairwise relationships like the outcomes of sports matches, it still suggests a potential approach for LETOR by representing pairwise comparisons as a graph. Inspired by Abend et al., who used combinatorial optimisation techniques to recover the lexical order of recipe pieces [1], we propose Travelling Salesman Problem Rank (TSPRank). This hybrid pairwise-listwise method reframes the ranking problem as a Travelling Salesman Problem (TSP), an NP-hard combinatorial optimisation challenge that seeks the optimal sequence of node visits to minimise total travel cost. In a ranking context, TSPRank aims to find the optimal permutation of ranking entities to maximise the ranking score.

Our main contribution, TSPRank, bridges the gap between pairwise and listwise ranking models through combinatorial optimisation, demonstrating strong robustness across diverse ranking problems. TSPRank simplifies the complex listwise ranking problem into easier pairwise comparisons, thus overcoming the challenges of directly learning listwise rankings in complex data and tasks. It also enhances pairwise methods by incorporating listwise optimisation through a TSP solver. To improve ranking performance, TSPRank can be applied directly as an additional component on embeddings generated from domain-specific backbone models. To our knowledge, it is the first LETOR model to frame the ranking problem as a combinatorial optimisation plus graph representation task. We demonstrate its superior performance across three backbone models on diverse ranking tasks: stock ranking, information retrieval, and historical events ordering, covering both numerical and textual data across multiple domains. We introduce two learning methods for TSPRank: a local method using a pre-defined ground truth adjacency matrix without the TSP solver during training and a global end-to-end method that includes the solver in the training loop for better model-inference alignment. Our empirical analysis visualises the predictions and graph connections to provide insights into TSPRank's effectiveness. We demonstrate that the TSP solver enhances the model's ability to harness global information during ranking and increases tolerance to errors in pairwise comparisons. Additionally, we assess inference latency caused by the combinatorial optimisation solver and suggest potential solutions to mitigate this overhead.

2 BACKGROUND

LETOR algorithms aim to rank entities based on their features. In LETOR, we denote a list of N ranking entities as \mathbf{e} , containing $\{\mathbf{e}_1,\mathbf{e}_2,\ldots,\mathbf{e}_N\}$, with each $\mathbf{e}_i\in\mathbb{R}^d$ where d represents the dimensionality of the feature space. A scoring function $s:\mathbb{R}^d\to\mathbb{R}$ is applied on the entities, which are then ranked in descending order of the $s(\mathbf{e}_i)$ scores. LETOR algorithms are broadly categorised into pointwise, pairwise, and listwise approaches based on their optimisation strategies. Pointwise methods treat ranking as a regression problem, comparing scores $s(\mathbf{e}_i)$ to labels y_i . Models such as OPRF [19], TreeBoost [18], and RankSVM [44], including newer implementations like RankCNN [43], are known for their computational efficiency but may not capture inter-entity relationships adequately.

Pairwise methods focus on the relative comparisons of entity pairs, assessing scores $(s(\mathbf{e}_i), s(\mathbf{e}_i))$ against binary labels y_{ij} , which denote if entity e_i should be ranked higher than e_i . Methods in this category include RankNet [8], LambdaRank [7], and LambdaMART [6]. Listwise methods directly compute scores based on the features of all entities in a list. These methods aim to optimise a listwise objective, comparing the entire set of computed scores $s(\mathbf{e}) \in \mathbb{R}^N$ against a complete set of labels $\mathbf{y} \in \mathbb{R}^N$. To advance this approach, Ai et al. introduced the Deep Listwise Context Model (DLCM) [2]. This model was further refined into general multivariate scoring functions in [3]. Considering that a list of entities can be viewed as a sequence, methodologies from Natural Language Processing (NLP) are applicable to ranking tasks. Notably, the Transformer architecture [47], has been adapted to address listwise ranking challenges, referred to as listwise Transformers in recent work [9, 31, 34-36, 55].

Although listwise ranking methods, primarily neural rankers, have demonstrated their advantages in web search reranking tasks [2, 34], Qin et al. conducted a comprehensive evaluation comparing listwise neural rankers to the gradient-boosted-decision-tree (GBDT)-based pairwise LambdaMART [6, 39]. The results indicated that LambdaMART consistently outperforms listwise rankers across three widely used information retrieval datasets. Furthermore, it was observed that listwise rankers require substantial efforts to achieve only marginal improvements over LambdaMART. Consequently, it is evident that listwise ranking models are not universally applicable solutions and generally lack the robustness needed for broader deployment. This conclusion has also been further validated by Buyl et al. [9].

3 TSPRANK

Directly predicting the listwise order is challenging, as correctly ranking N entities from 1 to N is complex. However, breaking it down into $N \times N$ pairwise comparisons simplifies the task, as each pairwise comparison is more straightforward than the entire listwise ranking. However, a fundamental drawback of pairwise ranking, as highlighted by Cao et al. [11], is that the learning objectives do not focus on minimising the listwise ranking errors. To address this gap and rethink the approach of pairwise ranking, we introduce TSPRank, a novel methodology for position-based ranking problems. This approach integrates listwise optimisation into pairwise comparisons by modelling ranking tasks as TSP. Notably, TSPRank can be applied as an additional component with embeddings generated from domain-specific backbone models to achieve improved ranking performance.

3.1 Ranking As Travelling Salesman Problem

We model the ranking problem as an open-loop Travelling Salesman Problem (TSP). Given a set of entities $\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_N$ and all the pairwise score values $s(\mathbf{e}_i, \mathbf{e}_j)$ indicating the gain of ranking entity \mathbf{e}_j immediately after \mathbf{e}_i , we define a complete graph G=(V,W), where V represents the entities and W represents the pairwise scores between every two entities. Each entity \mathbf{e}_i in the ranking problem corresponds to a city in the TSP. By mapping entities to cities and pairwise scores to weights, we can formulate the ranking

problem as a TSP to find the optimal permutation π . Thus, the objective is to find an optimal open-loop tour π^* of the entities defined in Equation 1 such that the total pairwise score is maximised.

$$\pi^* = \underset{\pi}{\operatorname{argmax}} \sum_{i=1}^{N-1} s(\mathbf{e}_{\pi(i)}, \mathbf{e}_{\pi(i+1)}). \tag{1}$$

The next step is developing a scoring function that accurately models the pairwise relationships between the ranking entities, thereby effectively determining the scores.

3.2 Scoring Model

The scoring model takes a set of ranking entities or their corresponding embeddings $\{\mathbf{e}_1,\mathbf{e}_2,\ldots,\mathbf{e}_N\}$, where each $\mathbf{e}_i\in\mathbb{R}^d$ and d is the dimension of the features or embeddings. It outputs an $N\times N$ weighted adjacency matrix A that represents the pairwise scores of every two entities. The scoring model comprises an optional node encoder and a trainable bilinear model on top.

Encoder. The default encoder used is the Transformer encoder block [47], but it can be replaced with any other encoder suited to the specific task and dataset. Additionally, using an encoder is optional if sufficiently robust backbone models are available.

Trainable Bilinear Model. Given a pair of encoded representations of entities $(\mathbf{e}_i, \mathbf{e}_j)$, the bilinear model computes the pairwise score using the following bilinear form:

$$s(\mathbf{e}_i, \mathbf{e}_j) = \mathbf{e}_i^\mathsf{T} \mathbf{W} \mathbf{e}_j + b, \tag{2}$$

where \mathbf{W} and b are learnable parameters that can be optimised along with the encoder parameters.

The adjacency matrix *A* is constructed as follows:

$$A_{ij} = s(\mathbf{e}_i, \mathbf{e}_j), \text{ for all } i, j \in \{1, \dots, N\},$$
 (3)

where each entry A_{ij} directly corresponds to the computed pairwise comparison score from entity \mathbf{e}_i to entity \mathbf{e}_j .

3.3 Inference

Inference of TSPRank, described in Equation 1, requires solving the open-loop TSP, which is widely recognised as an NP-hard combinatorial optimisation problem. The solution algorithms of the TSP consist of exact algorithms (brunch and bound [37]) and approximation algorithms (ant colony optimisation [52]). Given the scale of the ranking problem and the desired ranking accuracy, we prefer to obtain an exact solution for the TSP rather than an approximate one. Therefore, we formulate the TSP as a Mixed Integer Linear Programming (MILP) problem [40], where the integer variables represent binary decisions on whether a path between two nodes is included in the optimal tour. We then use an MILP optimization solver, such as CPLEX [14] or Gurobi [22], to find the exact optimal solution.

The decision variables are defined as follows:

$$x_{ij} = \begin{cases} 1, & \text{if entity } \mathbf{e}_j \text{ is ranked immediately after } \mathbf{e}_i. \\ 0, & \text{otherwise.} \end{cases}$$
 (4)

We then apply the TSP optimisation problem defined in Appendix A to ensure the result is a single, complete ranking that includes

all entities. This inference process effectively performs listwise optimisation, as it determines the optimal permutation of entities that maximises the overall pairwise ranking score.

4 LEARNING

We introduce two distinct learning methodologies for the TSPRank model outlined in Section 3. The first method is a local approach, focusing exclusively on individual pairwise comparisons during the training phase. The second method is a global, end-to-end approach, incorporating the Gurobi solver directly into the training process, thereby allowing the black-box MILP solver to influence the learning dynamically. Figure 1 illustrates the complete pipeline of the two learning methods as well as the model architecture.

4.1 Local Learning

In the local learning approach, the objective is to understand pairwise consecutive relationships between nodes. The objective is to determine whether entity \mathbf{e}_j should rank one position after \mathbf{e}_i in a given pair of nodes. Therefore, the score $s(\mathbf{e}_i, \mathbf{e}_j)$ is set high if \mathbf{e}_j is supposed to rank consecutively after \mathbf{e}_i , and low otherwise.

To tailor the TSPRank model to ranking scenarios where penalties vary based on the actual positions, we apply a weighted loss. We denote the predicted adjacency matrix A^p from the bilinear model, where $a^p_{ij} \in A^p$ represents the predicted pairwise scores. The target adjacency matrix $A^t = \{a^t_{ij}\}$ is defined such that $a^t_{ij} \in A^t$ equals 1 if \mathbf{e}_j ranks immediately after \mathbf{e}_i , and 0 otherwise. We apply the weighted cross-entropy loss (defined in Equation 5) on each row to identify the next entity $\mathbf{e}_{\pi(i+1)}$ to be ranked given $\mathbf{e}_{\pi(i)}$. The model is trained as a multi-class classification problem, aiming to maximise the probability of $P(\mathbf{e}_{\pi(i+1)} \mid \mathbf{e}_{\pi(i)})$. We weight the loss by the true ranking label y, allowing the penalty to vary according to different ranking positions. Additionally, y can be adjusted to N+1-y depending on whether y represents ascending or descending order.

$$\mathcal{L}_{local}(A^{p}, A^{t}) = -\sum_{i=1}^{N} y_{k} \log \frac{e^{A_{ik}^{p}}}{\sum_{i=1}^{N} e^{A_{ij}^{p}}}, \ k = \arg \max_{j} A_{ij}^{t}.$$
 (5)

4.2 Global Learning

We expect that a globally trained TSPRank model will further enhance the performance as the local learning method focuses solely on pairwise comparisons in isolation during training. Incorporating the TSP solver in the training procedure will better align the model with the inference process. Therefore, we introduce an end-to-end approach. After obtaining the predicted adjacency matrix A^p , defined in Section 4.1, we define the gold decision variable $\mathbf{x}^t = \{x_{ij}^t\}$, where x_{ij}^t is defined as in Equation 4. We aim to train a model to satisfy the margin constraints (Equation 6) for all the possible decision variables \mathbf{x} by minimising the max-margin loss defined in Equation 7. When $\mathbf{x} = \mathbf{x}_t$, the predicted ranking perfectly aligns with the gold ranking, resulting in a loss of zero.

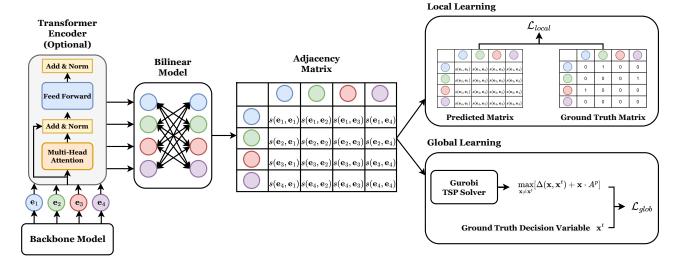


Figure 1: Illustration of TSPRank and the complete pipeline of local and global learning. The pipeline starts with a Transformer Encoder or any embeddings generated from another existing Backbone Model, followed by a Bilinear Model generating pairwise scores to form an Adjacency Matrix. Local learning compares the predicted matrix with the ground truth to calculate the local loss \mathcal{L}_{local} . Global learning uses the max-margin loss \mathcal{L}_{qlob} to incorporate the Gurobi TSP solver during training.

$$\mathbf{x}^t \cdot A^p \ge \mathbf{x} \cdot A^p + \Delta(\mathbf{x}^t, \mathbf{x}), \text{ for all } \mathbf{x},$$
 (6)

$$\mathcal{L}_{glob}(A^p, \mathbf{x}^t) = \max(0, \max_{\mathbf{x} \neq \mathbf{x}^t} [\Delta(\mathbf{x}, \mathbf{x}^t) + \mathbf{x} \cdot A^p] - \mathbf{x}^t \cdot A^p)$$
 (7)

The structured score $\Delta(\mathbf{x}, \mathbf{x}^t)$, defined in Equation 8, aims to enforce a margin for each incorrectly identified edge.

$$\Delta(\mathbf{x}, \mathbf{x}^t) = \sum_{i=1}^{N} \sum_{j=1}^{N} \max(0, x_{ij} - x_{ij}^t).$$
 (8)

This approach eliminates the need to manually define the target adjacency matrix. Instead, it employs the output from the black-box optimiser to directly guide the updates of the model parameters. This methodology not only simplifies the process but also ensures a closer alignment with the solver's procedural dynamics. To accelerate convergence, we integrate a hybrid of local and global loss. Relying solely on the global loss requires significantly more epochs to converge. Therefore, during training, we alternate batches between the global loss and the local loss, ensuring faster and more efficient model convergence.

5 EXPERIMENTAL SETUP

We evaluate TSPRank's effectiveness as a prediction layer integrated into various backbone models. Our goal is to demonstrate that TSPRank enhances performance compared to the original backbone and other general ranking algorithms across different domains. While achieving state-of-the-art (SOTA) performance still depends on the backbone design, TSPRank serves as a component to improve ranking performance. We focus on scenarios where (i) the data contain ordinal ranking labels rather than binary or relevance level labels, and (ii) the complete ranking or at least the top-k entities are important, extending the task's interest beyond merely identifying the top-1 entity. We test our method with three datasets

and backbone models from diverse domains: stock ranking, information retrieval, and historical events ordering. These datasets cover various data modalities, including tabular and textual data. All three tasks can be formulated as presented in Section 3.1. We aim to answer the following research questions (**RQs**):

- RQ1: Does the pairwise-listwise TSPRank outperform the current SOTA general pairwise and listwise ranking methods across different backbone models and datasets?
- RQ2: Does global learning lead to better performance?
- RQ3: Does the pure pairwise method really consistently outperform the deep learning based listwise method across different domains?
- **RQ4**: What are the advantages of hybrid pairwise-listwise TSPRank over other methods?

This section details the experimental setup for each task. All experiments were conducted on a single Nvidia A100 80G GPU.

5.1 Benchmark Models

We benchmark our pairwise-listwise TSPRank model against the original backbone models (if they originally contain a prediction layer), LambdaMART [6], and Rankformer [9], as LambdaMART is still considered the SOTA pairwise ranking method and Rankformer is the SOTA deep learning-based listwise ranking method. The benchmark models chosen include the best pure pairwise and pure listwise methods, which is sufficient to demonstrate the effectiveness of our approach.

In practice, we replace the original prediction layer, which predicts the ranking scores for each entity, with different benchmark models to evaluate the performance achieved by this modification.

5.2 Datasets

Stock Ranking. The task of stock ranking focuses on accurately predicting and ranking stocks according to their anticipated future returns ratio, which aids investors in selecting stocks for investment purposes [17, 41, 53]. We use the dataset¹ introduced by Feng et al. [17], which includes historical trading data from 2013 to 2017 for two significant markets, NASDAQ and NYSE, containing 1026 and 1737 stocks, respectively. We maintain a consistent setting for splitting the data into training, validation, and testing sets over a 3-year, 1-year, and 1-year period.

Information Retrieval. Information retrieval is another critical area where ranking models are extensively applied. The task of information retrieval focuses on accurately ranking documents based on their relevance to a given query, which is crucial for search engines. LambdaMART and Rankformer are both originally proposed for information retrieval task [6, 9]. We use the MQ2008-list² dataset from Microsoft LETOR4.0 [38], a popular benchmark dataset for LETOR algorithms. We acknowledge the existence of more recent information retrieval datasets, but they only provide relevance-level labels without ordinal ranking labels, making them unsuitable for our model evaluation.

Historical Events Ordering. In the final task, we include a textual dataset called "On This Day 2" (OTD2)³ for chronologically ordering historical events. Originally, Honovich et al. constructed this dataset for a regression task to predict the year of occurrence [26]. However, it can also be approached as a ranking task to predict the chronological order of events within a given group of events. The OTD2 dataset, sourced from the "On This Day" website, includes 71,484 events enriched with additional contextual information. Scraped in April 2020, it incorporates recent events and corrections by the site. Preprocessing excluded events before 1 CE and future projections such as "31st predicted perihelion passage of Halley's Comet" in 2061 CE. We follow the 80%/10%/10% train/validation/test split as provided.

5.3 Backbones

Stock Ranking. We use the method by Feng et al. [17] as the backbone model, replacing the prediction layer with different benchmark ranking models. Although other potential methods such as STHAN-SR [42], ALSP-TF [48], and CI-STHPAN [51] have been proposed for stock selection, we do not include them due to the lack of last-state embeddings needed to integrate TSPRank, unavailability of source code, or reproducibility issues. Since our primary goal is to demonstrate TSPRank as a versatile ranking approach rather than achieving SOTA results on a single dataset, this selection of backbone is sufficient to validate our model's performance.

Information Retrieval. Given that the features in the MQ2008-list are encoded using a combination of BM25 and TF-IDF methods, we treat BM25 and TF-IDF as the backbone models and use these encoded features as embeddings.

Historical Events Ordering. Concatenating event titles and information can result in contexts spanning thousands of tokens. Therefore, we use the <code>text-embedding-3-small^4</code> embeddings from OpenAI as the backbone model, which supports up to 8191 tokens. Our goal is not to achieve SOTA performance but to ensure a fair comparison. The small version (<code>text-embedding-3-small</code>) with 1536 dimensions, compared to the large version's 3072 dimensions (<code>text-embedding-3-large</code>), is more computationally efficient and sufficient for our purposes.

5.4 Technical Setup

Stock Ranking. Considering that TSPRank specialises in smallscale ranking problems, we implement rankings within individual sectors, categorising stocks into groups based on their sectors. We exclude all sector groups containing three or fewer stocks and remove stocks with unidentified sector information. Detailed descriptions of the sector-specific grouping are provided in Appendix E. For the benchmarking process, we use outputs from the relational embedding layer introduced by Feng et al. [17], replacing the original prediction layer with the other benchmark models. This modification enables us to assess the extent to which transitioning from a point-wise (original model) to pairwise, listwise, and our hybrid approaches can enhance performance. All benchmark models and TSPRank with local learning are trained for 100 epochs for each sector, as 100 epochs are sufficient for the benchmark models to converge. We find that TSPRank with global learning generally requires more epochs to converge; therefore, TSPRank-global is trained for an additional 50 epochs to ensure convergence. Other hyperparameters are specified in Appendix B. For LambdaMART, we use 10,000 trees since previous experiments indicated that Rankformer failed to outperform LambdaMART with this configuration [9]. We choose the widely-used XGBoost⁵ [12] implementation of LambdaMART, especially due to the performance enhancements in its version 2.0.

Information Retrieval. In the MQ2008-list dataset, a query might contain over 1,000 documents, resulting in a graph that is too large for the TSP solver to handle efficiently. Therefore, we focus on a reranking or post-reranking stage. Specifically, we extract the top 10 and top 30 documents for each query to conduct two separate experiments. This approach allows us to manage the computational complexity while still evaluating the effectiveness of TSPRank in a realistic ranking scenario. We use similar hyperparameters as in the stock ranking task but increase the number of transformer layers in both Rankformer and TSPRank to four, as we do not use any pretrained embeddings here. To ensure fairness, we also follow the 5-fold cross-validation setup as provided by Microsoft.

Historical Events Ordering. We randomly allocate the events into ranking groups and train the ranking models to predict the ground truth order of occurrences within these groups. We test with group sizes of 10, 30 and 50 for fair comparisons. For each group size, we generate the group allocations using five different random seeds and report the average performance to mitigate the effects of random group allocation. Regarding the models, we observed overfitting

 $^{^{1}}https://github.com/fulifeng/Temporal_Relational_Stock_Ranking/$

 $^{^2} https://www.microsoft.com/en-us/research/project/letor-learning-rank-information-retrieval/letor-4-0/$

³https://github.com/ltorroba/machine-reading-historical-events

⁴https://platform.openai.com/docs/guides/embeddings

 $^{^5} https://xgboost.readthedocs.io/en/latest/tutorials/learning_to_rank.html$

with Rankformer and TSPRank when including the transformer block, even with a 0.5 dropout rate. This is likely due to the strong representational power of the contextual embedding and the relatively small size of the OTD2 dataset compared to other NLP corpora. Consequently, we retained only the scoring network in Rankformer and the trainable bilinear model in TSPRank, integrating them directly with the *text-embedding-3-small* embeddings. This setting not only prevents overfitting but also ensures similar model sizes. Other hyperparameters are specified in Appendix B. We remove the weights in the weighted loss function for TSPRank-Local here since all events should be weighted equally without any additional requirements in this task.

5.5 Evaluation

Stock Ranking. Given that our task encompasses both ranking and stock selection functionalities, we employ both traditional ranking metrics and financial performance metrics in our evaluation. For ranking effectiveness, we use the Mean Average Precision at K (MAP@K), which evaluates the precision of the top *K* ranked stocks by averaging the precision scores at each relevant stock position. We also use Kendall's Tau, defined as: $\tau = \frac{(C-D)}{\frac{1}{2}n(n-1)}$, where C is the number of concordant pairs (pairs of entities that are in the same order in both predicted and ground truth rankings), D is the number of discordant pairs (pairs of entities that are in different orders in the rankings), and *n* is the total number of entities being ranked. Kendall's Tau is a correlation coefficient that measures the ordinal association between two ranked lists. This is suitable in our case, where we need to assess the similarity between the predicted rankings and the ground-truth rankings. Furthermore, to assess the financial impact of the rankings, we simulate trading activities by predicting the rankings of all individual stocks in every sector for the next trading day t + 1 on trading day t. This simulation is consistent with the one presented by Feng et al. [17]. We then rank these stocks, hold the top k stocks S_k , and sell them on trading day t+1. The price of stock i on day t is denoted as $p_i^{(t)}$ per share. The cumulative Investment Return Ratio (IRR) and Sharpe Ratio (SR) are defined in Equation 9, where R_p is the return of the portfolio, R_f is the risk-free rate, and σ is the standard deviation:

$$IRR^{k} = \sum_{i \in S^{k}} \frac{p_{i}^{(t)} - p_{i}^{(t-1)}}{p_{i}^{(t-1)}}, SR = \frac{E(R_{p} - R_{f})}{\sigma(R_{p})}.$$
 (9)

Information Retrieval. We evaluate the performance of our models using several well-established ranking metrics: Normalized Discounted Cumulative Gain (NDCG) at various cutoff levels (3, 5, 10), Mean Reciprocal Rank (MRR), and Kendall's tau. NDCG measures a document's usefulness based on its position in the result list, with higher positions receiving more weight. On the other hand, MRR assesses the rank position of the first relevant document, calculated as the average of the reciprocal ranks of the first relevant document for each query. The formula for MRR is defined by MRR = $\frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\mathrm{rank}_i}$, where |Q| is the total number of queries and rank i is the rank position of the first relevant document for the i-th query.

Historical Events Ordering. We report the Kendall's Tau, MRR, Exact Match (EM) of ordering, and the Root Mean Square Error (RMSE) of the predicted and ground truth rankings. EM is defined as the ratio of the number of events whose predicted order exactly matches the ground truth order to the total number of events, formulated as: EM = $\frac{\# \text{ correctly ordered events}}{\# \text{ events}}$.

6 RESULTS

The aggregated results for all benchmark models on the stock ranking dataset are presented in Table 1. These results represent the average performance across 50 sectors in the NASDAQ market and 70 sectors in the NYSE market, excluding sectors with three or fewer stocks as outlined in the experimental setup. Detailed results for each individual sector are provided in Appendix E. The results on the MQ2008-list retrieval dataset are shown in Table 2. A 5-fold cross-validation was performed, with detailed results for each fold provided in Appendix F. Lastly, the results on OTD2 for historical events ordering are presented in Table 3, with complete results for different random group allocations provided in Appendix G.

The results highlight the comparisons among three types of models: pairwise (LambdaMART), listwise (Rankformer), and our pairwise-listwise method (TSPRank).

Better Performance of Pairwise-Listwise Method Across Diverse Tasks (RQ1). Our pairwise-listwise method, TSPRank-Global, demonstrates outstanding robustness and superior performance across diverse datasets and domains. For instance, on the NAS-DAQ stock ranking dataset (Table 1), TSPRank-Global achieves a Kendall's Tau of 0.0447, significantly surpassing both LambdaMART (0.0071) and Rankformer (0.0110). Similarly, on the NYSE dataset (Table 1), TSPRank-Global attains a Kendall's Tau of 0.0422, outperforming LambdaMART (0.0054) and Rankformer (0.0181). Both TSPRank-Local and TSPRank-Global also consistently achieve higher IRR and SR, yielding improved financial performance. The model's robustness is further evidenced by its consistent top performance across other datasets. For example, in the MQ2008-list (Table 2), TSPRank-Global leads with NDCG@10 scores of 0.8884 for the top 10 documents and 0.7631 for the top 30 documents, indicating superior ranking accuracy, despite a minor difference in Kendall's Tau compared to Rankformer (around 0.01 to 0.02). Additionally, TSPRank-Global achieves top performance in the historical events ordering task (Table 3), regardless of the group size (10, 30, and 50).

TSPRank Can Be Extra Component Upon Embeddings For Boosting The Performance. In the stock ranking and ordering tasks for historical events, we directly deployed TSPRank on the stock embeddings and text embeddings. As demonstrated, TSPRank effectively serves as an additional component on embeddings, significantly enhancing ranking performance. This capability allows TSPRank to have broader applications across various domains.

Stronger Robustness Towards Number of entities. TSPRank-Global also shows greater robustness concerning the number of entities compared to the pure pairwise LambdaMART and listwise Rankformer. As evidenced by the MQ2008 (Table 2) results, the gap between LambdaMART and Rankformer narrows as the number of documents increases from 10 to 30, with the NDCG@3 score difference between these two methods reducing from -0.0387 to -0.0146.

Market	Model	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
	Feng et al. + MLP (Original)	0.0093	0.1947	0.5341	0.1690	0.2366	0.9881	0.3253	0.1892	0.9682	0.5871
	Feng et al. + LambdaMART	0.0071	0.0310	-0.0873	0.1539	0.0340	0.0445	0.3144	0.0505	0.2678	0.5858
NASDAQ	Feng et al. + Rankformer	0.0110	0.2257	0.5464	0.1620	0.2857	1.1245	0.3216	0.2309	1.0943	0.5860
	Feng et al. + TSPRank-Local	0.0291	0.5353	1.2858	0.1658	0.4416	1.7401	0.3297	0.2537	1.2623	0.5932
	Feng et al. + TSPRank-Global	0.0447	0.7849	1.7471	0.1633	0.5224	2.0359	0.3364	0.2937	1.4331	0.5999
	Feng et al. + MLP (Original)	0.0162	0.4170	1.0755	0.1791	0.2574	1.2367	0.2841	0.2257	1.3186	0.4649
	Feng et al. + LambdaMART	0.0054	0.1005	0.1367	0.1307	0.0732	0.4192	0.2592	0.1063	0.6882	0.4574
NYSE	Feng et al. + Rankformer	0.0181	0.2924	0.9113	0.1535	0.2701	1.2890	0.2758	0.2515	1.4200	0.4651
	Feng et al. + TSPRank-Local	0.0313	0.5012	1.5710	0.1424	0.3974	1.9735	0.2756	0.2788	1.6662	0.4680
	Feng et al. + TSPRank-Global	0.0422	0.4787	1.4552	0.1392	0.3889	1.9976	0.2756	0.2816	1.7350	0.4732

Table 1: Performance comparison of Feng et al., LambdaMART, Rankformer, and TSPRank on the NASDAQ and NYSE stock ranking dataset, averaged across all filtered sectors.

				Top 10					Top 30		
Model	Type	NDCG@3	NDCG@5	NDCG@10	MRR	τ	NDCG@3	NDCG@5	NDCG@10	MRR	τ
LambdaMART	Pairwise	0.6833	0.7222	0.8707	0.4259	0.1474	0.7340	0.7298	0.7403	0.3617	0.2372
Rankformer	Listwise	0.7220	0.7565	0.8865	0.4661	0.2317	0.7486	0.7470	0.7596	0.3732	0.2834
TSPRank-Local	Pairwise-Listwise	0.6858	0.7213	0.8719	0.4266	0.1544	0.7189	0.7240	0.7362	0.3206	0.2054
TSPRank-Global	Pairwise-Listwise	0.7281	0.7585	0.8884	0.4861	0.2212	0.7582	0.7558	0.7631	0.3895	0.2647

Table 2: Evaluation of LambdaMART, Rankformer, and TSPRank on MQ2008-list information retrieval dataset for top 10 and top 30 documents.

Group Size			1	.0				30			50			
Model	Type	<i>τ</i> ↑	ЕМ↑	MRR ↑	RMSE↓	$\tau \uparrow$	ЕМ↑	MRR ↑	RMSE ↓	<i>τ</i> ↑	ЕМ↑	MRR ↑	RMSE ↓	
te-3-small + LambdaMART	Pairwise	0.6297	0.3008	0.7554	1.993	0.5929	0.1064	0.6122	5.969	0.6000	0.0639	0.5596	9.618	
te-3-small + Rankformer	Listwise	0.6190	0.2899	0.7361	1.998	0.5859	0.0921	0.4911	5.973	0.5724	0.0527	0.3526	10.069	
te-3-small + TSPRank-Local	Pairwise-Listwise	0.5658	0.2856	0.7679	2.296	0.5095	0.0873	0.5739	6.930	0.4713	0.0460	0.3949	12.084	
te-3-small + TSPRank-Global	Pairwise-Listwise	0.6301	0.3350	0.7936	2.057	0.6302	0.1384	0.7300	5.770	0.6207	0.0871	0.6618	9.602	

Table 3: Evaluation of LambdaMART, Rankformer, and TSPRank on OTD2 dataset for historical events ordering for group sizes of 10, 30, and 50. "te-3-small" stands for "text-embedding-3-small".

Similarly, in historical events ordering (Table 3), LambdaMART and Rankformer's performance fluctuates more significantly with group size changes. This is evident from the varying differences in their Kendall's Tau and MRR compared to those of TSPRank-Global. Conversely, TSPRank-Global consistently performs well regardless of group size, maintaining top performance across most metrics.

Global Learning Outperforms Local Learning (RQ2). As evidenced by the performance of TSPRank-Global compared to TSPRank-Local on MQ2008 and OTD2. For example, on the OTD2 dataset (Table 3), TSPRank-Global achieves a Kendall's Tau of 0.6301, 0.6302, 0.6207 for the three different group sizes, compared to TSPRank-Local's 0.5658, 0.5095, and 0.4713. These results suggest that the end-to-end global optimisation approach of TSPRank-Global aligns more effectively with overall optimisation goals, whereas the non-end-to-end method may not perfectly align with global optimisation by the TSP solver.

LambdaMART Does Not Always Outperform Deep Learning Based Ranking Algorithm (RQ3). Although Qin et al. suggests that GBDT models, such as LambdaMART, generally outperform deep learning models on standard information retrieval datasets [39], our results indicate that this is not always the case in other contexts. As demonstrated in Table 1, within the domain-specific

scenario of stock ranking, LambdaMART shows markedly poorer performance. Specifically, LambdaMART achieves a Kendall's Tau of 0.0071 on NASDAQ and 0.0054 on NYSE, trailing behind Rankformer (0.0110 and 0.0181) and TSPRank-Global (0.0447 and 0.0422). Table 2 further validates this observation. In both the top 10 and top 30 document settings, LambdaMART consistently underperforms Rankformer and TSPRank-Global when adapting to ordinal ranking labels across all metrics. These results underscore that while LambdaMART performs well with binary relevance labels or relevance levels labels, it is not always the optimal choice for recovering complete rankings.

Overall, TSPRank's success suggests that combining pairwise and listwise approaches helps the model capture the relative ordering of entities and the overall ranking structure. This dual focus likely contributes to its superior performance across various datasets and metrics, making it versatile and powerful.

7 VISUALISATION ANALYSIS

As mentioned before, our pairwise-listwise TSPRank addresses both the lack of listwise optimisation in pairwise LambdaMART and the robustness issues in listwise Rankformer, which arise from attempting to predict the complete rankings directly. To empirically validate this and answer **RQ4** (the advantages of hybrid pairwise-listwise TSPRank over other methods), we conducted another experiment on the OTD2 dataset, chosen because of the better interpretability provided by text. We arbitrarily sample three events each from the US, UK, and China, ensuring that the events within each country occurred at least 50 years apart (detailed in Table 4). We then use the pretrained LambdaMART, Rankformer, and TSPRank-Global from the experiments described in Section 5 to predict the rankings for this constructed group. We visualise the predictions given by the three rankers in Figure 2. Both the pairwise LambdaMART and pairwise-listwise TSPRank-Global successfully recover the intra-country event order, correctly identifying the relative order within the same colour group. However, the listwise Rankformer incorrectly predicts that "US-2" occurs earlier than "US-1".

Although LambdaMART successfully recovers the intra-country event order, it makes mistakes in the overall ranking, particularly failing to recover the correct order of ["US-1", "UK-1", "CN-1"] and ["US-3", "UK-3", "CN-3"], validating its weaker ability for listwise ranking optimisation. In contrast, TSPRank accurately recovers most orders, with only a minor error between "US-2" and "UK-2", which only have a 30-year gap (1934 and 1904).

We also visualise the intra-country connections using the adjacency matrix predicted by TSPRank's bilinear model in Figure 3, omitting cross-country connections for clarity. As highlighted in red, the direct comparison between "US-1" and "US-3" is incorrect since s(US-1, US-3) should be higher than s(US-3, US-1), but the model fails in this case. However, as shown in Figure 2, TSPRank still correctly places "US-1" at position 3 and "US-3" at position 8. This indicates that the model benefits from the cross-country connections and the listwise optimisation provided by the TSP solver. This makes the model more tolerant to errors or uncertainties in pairwise comparisons, as the listwise optimisation ensures that the highest-scoring permutation is selected. We provide additional examples in Appendix C to further validate this observation.

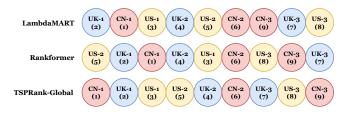


Figure 2: Visualisation of predictions by LambdaMART, Rankformer, and TSPRank-Global on the constructed group. Numbers in parentheses indicate the true ranking.

8 INFERENCE LATENCY

Incorporating a combinatorial optimisation solver is known to cause additional computational overhead, which can impact the inference latency. Therefore, we compare the average inference time per ranking group for TSPRank and Rankformer on the OTD2 historical events ordering dataset. The experimental setup and detailed results are provided in Appendix D.

We observe that the inference time for TSPRank increases exponentially with the number of ranking entities, primarily due

Event Title	Year	Rank	Label
1st US store to install electric lights, Philadelphia	1878	3	US-1
1st sitting US President to visit South America, FDR in Colombia	1934	5	US-2
75th US Masters Tournament, Augusta National GC: Charl Schwartzel of South Africa birdies the final 4 holes to win his first major title, 2 strokes ahead of Australian pair Adam Scott and Jason Day	2011	8	US-3
Charles Watson-Wentworth, 2nd Marquess of Rockingham, becomes Prime Minister of Great Britain	1782	2	UK-1
1st main line electric train in UK (Liverpool to Southport)	1904	4	UK-2
UK Terrorism Act 2006 becomes law	2006	7	UK-3
A Mongolian victory at the naval Battle of Yamen ends the Song Dynasty in China	1279	1	CN-1
US Senate rejects China People's Republic membership to UN	1953	6	CN-2
China's Hubei province, the original center of the coronavirus COVID-19 outbreak eases restrictions on travel after a nearly two-month lockdown	2020	9	CN-3

Table 4: Event titles in the constructed group. Labels indicate the order of occurrence within each country, e.g., "US-1" denotes the earliest event in the US within the group.

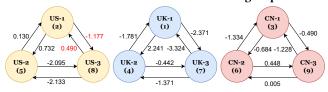


Figure 3: Illustration of the intra-country pairwise comparison graph. Edges between pairs of events from different countries are omitted for clarity. Scores highlighted in red indicate errors in the pairwise prediction for TSPRank-Global.

to the discrete TSP solver. When the group size reaches 100, the solver consumes approximately 99.8% of the inference time, while the encoding time remains similar to that of Rankformer. Therefore, TSPRank is more suitable for small-scale ranking problems with fewer than 30 entities, where its inference time is comparable to Rankformer. It is also advantageous in scenarios where TSPRank's performance improvements outweigh the increased latency. Solvers like Gurobi are efficient for small TSP graphs. However, exact solutions for larger graphs require specialised techniques, such as the Concorde TSP Solver⁶, which uses cutting-plane algorithms and a branch-and-bound approach to solve graphs with up to 85,900 nodes [4]. Beyond exact solvers, heuristic algorithms like the Christofides–Serdyukov algorithm [13] and the Lin–Kernighan–Helsgaun heuristic [24, 25, 32] are also used.

Moreover, recent advances in neural networks have enabled the use of deep learning to approximate the TSP reward function, employing reinforcement learning to solve the problem [5, 28, 29]. While we do not delve deeply into the various TSP solutions in this paper, we demonstrate that inference latency stems from the TSP solver and discuss potential enhancements for reducing inference latency and tackling large-scale ranking problems.

 $^{^6} https://www.math.uwaterloo.ca/tsp/concorde/index.html\\$

9 CONCLUSION

This study introduces TSPRank, a novel pairwise-listwise approach for position-based ranking tasks, by modelling them as the Travelling Salesman Problem (TSP). We present two learning methods for TSPRank, integrating listwise optimization into pairwise comparisons to address the limitations of traditional pure pairwise and listwise ranking models. TSPRank's application to diverse backbone models and datasets, including stock ranking, information retrieval, and historical events ordering, demonstrates its superior performance and robustness. Key findings include TSPRank's ability to outperform existing models such as LambdaMART and Rankformer across multiple datasets and various metrics. Furthermore, TSPRank's capability to function as an additional component on embeddings suggests its versatility and potential for broader applications across different domains.

Our empirical analysis reveals that TSPRank's superior performance is due to the discrete TSP solver's ability to more effectively utilise listwise information. It also enhances TSPRank's tolerance to uncertainties in pairwise comparisons by ensuring the selection of the highest-scoring permutation. Future work could explore the use of alternative TSP solvers and further enhancements to the Gurobi solver to reduce inference latency and improve scalability.

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A TSP OPTIMISATION PROBLEM

Ranking entity \mathbf{e}_j immediately after entity \mathbf{e}_i is analogous to travelling from city i to city j. Let N be the total number of entities to be ranked and z_i variables to represent the number of entities ranked before entity i. The MILP formulation of the TSPRank inference is as follows:

$$\min_{x_{ij}} \quad \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} a_{ij} x_{ij} \tag{10}$$

$$s.t. \quad \sum_{j=1, j\neq i}^{N} x_{ij} \le 1 \quad \text{ for all } i$$
 (11)

$$\sum_{i=1, i \neq j}^{N} x_{ij} \le 1 \quad \text{ for all } j$$
 (12)

$$\sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} x_{ij} = N - 1 \tag{13}$$

$$z_i + 1 \le z_j + N(1 - x_{ij})$$
 $i, j = 2, ..., N, i \ne j$ (14)

$$z_i \ge 0 \quad i = 2, \dots, N \tag{15}$$

Constraints (11) and (12) ensure that each entity has at most one predecessor and one successor in the ranking, expressed as 2N-2 linear inequalities. Constraint (13) ensures that the total number of pairwise comparisons is exactly N-1. These constraints ensure that the selected set of pairwise comparisons forms a valid ranking sequence. Constraints (14) and (15) introduce variables z to eliminate multiple separate sequences and enforce that there is a single, complete ranking that includes all entities.

B HYPERPARAMETERS SETTING

The hyperparameters are specified in Table 5. In the table, several abbreviations are used for conciseness and clarity:

- **lr**: Learning rate, which controls the step size during the optimization process.
- tf layer: Number of transformer layers, indicating the depth of the transformer model.
- tf nheads: Number of attention heads, which specifies the number of parallel attention mechanisms within the transformer layer.
- **tf dim_ff**: Dimensionality of the feed-forward network within the transformer layer.

C ADDITIONAL VISUALISATION EXAMPLES

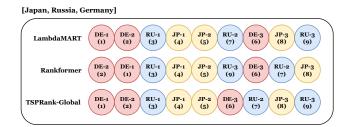
We further construct three more groups using events from different countries. The event titles, labels, and true rankings are provided in Table 6. The visualisation of the models' predictions are shown in Figure 4. We observe similar patterns to those discussed in Section 7.

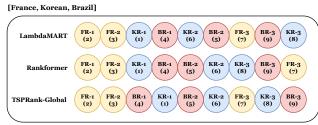
D LATENCY ANALYSIS DETAILS

We conduct an inference time analysis on a standalone device with an AMD Ryzen 7 5800X 8-Core CPU and an Nvidia RTX 4070 Super GPU. Using the standalone device instead of the one used for training is to avoid interference from other running jobs on the shared computing node.

Dataset	Hyperparameter	Value	Model
	n_estimators	10^{4}	
	loss_fn	rank:pairwise	LambdaMART
All Tasks	eval_metric	auc	Lambuawaki
	early_stopping	50	
	loss	OrdinalLoss [9]	Rankformer
	lr	1e-4	
	weight_decay	1e-5	
Stocks	tf layer	1	Rankformer, TSPRank
Stocks	tf nheads	8	Kalikitililei, 13f Kalik
	tf dim_ff	128	
	batch_size	128	
	lr	1e-4	
	weight_decay	1e-5	
MQ2008	tf layer	4	Rankformer, TSPRank
MQ2008	tf nheads	8	Kanktormer, 15FKank
	tf dim_ff	128	
	batch size	64	
	lr	1e-4	
Historical Events	weight_decay	1e-5	Dankfama TCDDank
riistorical Events	tf dim_ff	0	Rankformer, TSPRank
	batch size	32	

Table 5: Hyperparameters for LambdaMART model across different tasks: Stock Ranking, MQ2008, and Historical Events Ordering.





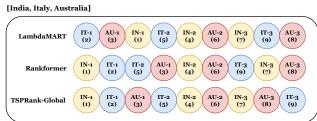


Figure 4: Visualisation of the model predictions on additional groups. Numbers in parentheses indicate the true ranking.

Figure 5 illustrates the average inference time in seconds per ranking group for TSPRank and Rankformer on the OTD2 historical events ordering dataset, with an input dimensionality of 1536. We provide the inference times for various group sizes: 5, 10, 30, 50, and 100.

Group	Event Title	Year	Rank	Label
	Japanese immigration to Brazil begins when 781 people arrive in Santos aboard the Kasato-Maru ship	1908	4	JP-1
	Passenger ship Lurline sends radio signal of sighting Japanese war fleet	1941	5	JP-2
	A reactor at the Fukushima Daiichi nuclear power plant melts and explodes and releases radioactivity into the atmosphere a	2011	8	JP-3
	day after Japan's earthquake.			
1	The State Bank of the Russian Empire is established.	1860	3	RU-1
	"Mirror", Russian film directed by Andrei Tarkovsky, starring Margarita Terekhova and Ignat Daniltsev, is released	1975	7	RU-2
	Russian city Moscow begins a city-wide lockdown after 4 hours notice due to coronavirus COVID-19	2020	9	RU-3
	Albrecht II of Habsburg becomes king of Germany	1438	1	DE-1
	Magdeburg in Germany seized by forces of the Holy Roman Empire under earl Johann Tilly, most inhabitants massacred, one	1631	2	DE-2
	of the bloodiest incidents of the Thirty Years' War			
	The cult classic "One Million Years B.C.", starring Raquel Welch, is released 1st in West Germany	1966	6	DE-3
	French King Charles VIII occupies Florence	1494	2	FR-1
	1st steamboat, Pyroscaphe, 1st run in France	1783	3	FR-2
	Francois Mitterrand becomes president of France	1981	7	FR-3
	The Hangul alphabet is published in Korea	1446	1	KR-1
2	Korea is divided into North and South Korea along the 38th parallel	1945	6	KR-2
	North Korea blocks a South Korean supply delegation from the Kaesong joint industrial zone	2013	8	KR-3
	Bahia Independence Day: the end of Portuguese rule in Brazil, with the final defeat of the Portuguese crown loyalists in the	1823	4	BR-1
	province of Bahia			
	Belo Horizonte, the first planned city of Brazil, founded	1897	5	BR-2
	Brazilian court blocks President Michel Temer from abolishing Renca, which would open parts of the Amazon to mining	2017	9	BR-3
	Indian Mutiny against rule by the British East India Company begins with the revolt of the Sepoy soldiers in Meerut	1857	1	IN-1
	Gandhi supports the African People's Organisations resolution to declare the Prince of Wales day of arrival in South Africa a	1910	4	IN-2
	day of mourning, in protest against the South Africa Acts disenfranchisement of Indians, Coloureds and Africans			
	Bomb attack on train in Assam India (27 soldiers killed)	1995	7	IN-3
3	1st Italian Parliament meets at Turin	1860	2	IT-1
	King Victor Emmanuel III of Italy abdicates and is succeeded by his son Umberto II who reigns for only 34 days before the	1946	5	IT-2
	monarchy is abolished			
	Storms in Italy kill at least 11 with 75% of Venice flooded and two tornadoes striking Terracina	2018	9	IT-3
	Edmund Barton is elected Prime Minister in Australia's first parliamentary election	1901	3	AU-1
	Australian Championships Women's Tennis: Beryl Penrose wins her only Australian singles title; beats Thelma Coyne Long	1955	6	AU-2
	6-4, 6-3			
	Cricket World Cup, Melbourne (MCG): Australia defeats fellow host New Zealand by 7 wickets to win their 5th title; Player of	2015	8	AU-3
	Series: Mitchel Starc			

Table 6: Three additionally constructed groups using events from different countries.

The comparison shows that the inference time for TSPRank increases exponentially with the number of ranking entities in a group. This increase is primarily due to the discrete TSP solver, as indicated by the overlapping blue and red lines. The blue line represents the time taken by the TSP solver, while the red line shows the total inference time for a ranking group. When the group size reaches 100, approximately 99.8% of the inference time is consumed by the solver. The encoding time from the input to the adjacency matrix remains similar to that of Rankformer (purple).

E COMPLETE STOCKS RANKING RESULTS FOR SECTORS

Table 7 to 16 presents the comprehensive results for each sector in NASDAQ and NYSE after filtering.

F MQ2008 COMPLETE RESULTS

Table 17 presents the detailed performance results on the MQ2008 dataset across different folds.

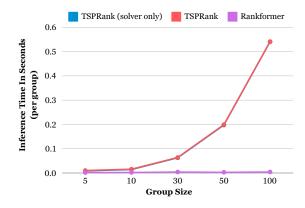


Figure 5: Mean inference time per ranking group for TSPRank and Rankformer on OTD2 across group sizes of 5, 10, 30, 50, and 100. The blue (TSPRank solver only) and red (TSPRank) lines overlap with minor differences.

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Computer Manufacturing	5	-0.0521	-0.3767	-1.2666	0.1857	0.1037	0.5894	0.4529	0.2167	1.3724	1.0000
Transportation Services	5	-0.0185	-0.3402	-1.1114	0.1941	0.2663	1.2239	0.4590	0.1263	0.7757	1.0000
Medical/Dental Instruments	17	0.0227	-0.1845	-0.2096	0.1055	0.2604	1.2060	0.1519	0.3940	2.0538	0.1922
Property-Casualty Insurers	19	0.0044	-0.3242	-0.5479	0.1055	-0.1942	-0.4679	0.2075	-0.2643	-1.0239	0.2131
Medical Specialities	5	-0.0101	-0.0157	0.0948	0.1814	0.0702	0.4433	0.4902	-0.0402	-0.1500	1.0000
Biotechnology: Biological Products (No Diagnostic Substances)	12	0.0288	0.5664	1.1922	0.1224	0.7839	2.1772	0.2253	0.4882	1.7150	0.3138
Telecommunications Equipment	16	-0.0046	-0.6169	-1.1101	0.1646	-0.2057	-0.4332	0.1718	-0.1449	-0.4478	0.2132
Medical/Nursing Services	6	0.0507	1.0367	1.8435	0.1688	0.7042	2.3042	0.4062	0.4471	1.8070	0.7530
Water Supply	9	0.0131	0.2849	1.0457	0.1561	0.2404	1.1933	0.2417	0.2146	1.1336	0.4176
Real Estate Investment Trusts	8	-0.0084	-0.0165	-0.0359	0.1055	0.0948	0.8628	0.2625	0.0099	0.1480	0.4738
Business Services	17	0.0130	0.4041	1.1789	0.1266	0.2231	1.1491	0.1589	0.3422	1.7452	0.1987
Major Pharmaceuticals	29	0.0008	0.2889	0.7399	0.0970	0.7151	1.4622	0.1273	0.4020	1.2343	0.1419
Farming/Seeds/Milling	6	0.0227	0.1512	0.7310	0.1688	-0.0104	0.0358	0.3945	0.0634	0.4711	0.7495
Industrial Specialties	11	0.0346	2.0118	4.1591	0.1224	0.7883	2.8012	0.2304	0.4046	2.0223	0.3336
Air Freight/Delivery Services	6	-0.0014	-0.0397	0.0735	0.1899	-0.0147	0.0708	0.3680	0.0704	0.4319	0.7407
Electrical Products	13	-0.0202	-0.2313	-0.6316	0.0675	-0.0352	-0.0250	0.1517	0.0833	0.5303	0.2264
Television Services	8	-0.0054	-0.0664	-0.0262	0.1224	-0.1397	-0.4674	0.2876	-0.0528	-0.1493	0.4848
Investment Bankers/Brokers/Service	18	0.0195	1.5618	3.0264	0.1899	0.2890	1.8445	0.2187	0.2075	1.3520	0.2438
Catalog/Specialty Distribution	7	0.0210	-0.0168	0.1895	0.1814	0.5484	1.8405	0.3354	0.4288	1.8188	0.5961
Savings Institutions	20	0.0460	0.5287	1.5253	0.1181	0.3299	1.5116	0.1646	0.2436	1.2962	0.1981
Other Consumer Services	9	0.0079	-0.0556	0.3305	0.2532	-0.2156	-0.6957	0.2904	-0.0076	0.0782	0.4044
Auto Parts:O.E.M.	6	-0.0104	-0.1260	-0.1430	0.2152	-0.1427	-0.5708	0.3638	0.0074	0.1431	0.7229
Trucking Freight/Courier Services	11	0.0265	0.6905	1.5795	0.1772	0.4522	1.4994	0.2501	0.5216	1.8957	0.3417
Radio And TV Broadcasting And Communications Equipment	10	-0.0055	0.1535	0.5546	0.0970	0.0259	0.2365	0.2168	0.2805	1.2102	0.3377
Biotechnology: Electromedical & Electrotherapeutic Apparatus	5	0.0513	1.1212	2.2247	0.2532	0.8664	2.9716	0.5070	0.3760	1.9405	1.0000
Home Furnishings	8	0.0303	-0.1578	-0.3445	0.1308	0.1396	0.6085	0.2752	0.1764	0.8462	0.4762
Major Chemicals	7	-0.0118	-0.3026	-0.8089	0.1730	0.0614	0.3825	0.3291	0.0943	0.6049	0.5455
Other Specialty Stores	8	0.0027	0.4400	1.1201	0.1561	-0.1071	-0.3697	0.2623	0.0242	0.2259	0.4928
Computer Software: Programming, Data Processing	7	-0.0118	-0.1717	-0.2653	0.2363	0.4192	1.6818	0.3425	0.2852	1.5359	0.5278
Restaurants	20	-0.0264	-0.4583	-1.2790	0.0464	-0.0233	0.0328	0.1416	-0.0919	-0.3906	0.1653
Automotive Aftermarket	6	0.0059	0.0265	0.2472	0.1646	0.1734	0.9593	0.3872	0.2190	1.3142	0.7483
Investment Managers	5	0.0092	0.2662	1.3199	0.2236	0.1422	0.9601	0.4869	0.0976	0.7306	1.0000
Oil Refining/Marketing	6	-0.0132	-0.2807	-1.0433	0.2785	0.1007	0.5836	0.3687	0.1559	0.9894	0.6879
Real Estate	7	0.0226	0.3281	1.2869	0.1857	0.2733	1.6266	0.3202	0.2303	1.5590	0.6019
Apparel	8	-0.0081	0.0019	0.2242	0.1308	0.3005	1.1491	0.2600	0.1953	0.9464	0.4672
Oil & Gas Production	6	-0.0036	-0.1716	-0.3582	0.1730	-0.3052	-1.1493	0.3697	-0.2423	-0.8614	0.7456
Computer Communications Equipment	5	-0.0025	0.8757	1.9336	0.2152	0.2596	1.3220	0.4681	0.0383	0.3025	1.0000
Clothing/Shoe/Accessory Stores	8	-0.0153	-0.1938	-0.2218	0.1730	-0.2163	-0.4854	0.2675	-0.0573	-0.0205	0.4725
Commercial Banks	5	0.0034	0.0180	0.1952	0.1561	0.2602	1.4412	0.5117	0.1656	0.9570	1.0000
Hospital/Nursing Management	5	-0.0244	0.0170	0.3074	0.2278	0.1864	0.9844	0.4473	0.2216	1.3716	1.0000
Banks	5	0.0689	0.4518	1.8758	0.2194	0.3074	1.6594	0.5326	0.0939	0.6403	1.0000
Professional Services	6	0.0350	-0.2014	-0.6058	0.1646	0.2080	1.1435	0.3901	0.1859	1.1313	0.7501
Packaged Foods	7	0.0162	-0.0081	0.1270	0.1688	-0.0930	-0.4279	0.3333	-0.0692	-0.3715	0.5875
Metal Fabrications	12	-0.0010	-0.1004	-0.1038	0.1392	0.1738	0.8350	0.2014	0.2037	1.0968	0.2687
Diversified Commercial Services	6	0.0294	0.0471	0.3382	0.2658	0.5017	2.1019	0.4004	0.2662	1.5863	0.7258
Computer peripheral equipment	6	0.0434	0.3923	1.0476	0.2110	0.2852	1.2401	0.4163	0.2432	1.3341	0.7431
Steel/Iron Ore	7	0.0250	0.6945	1.8428	0.1814	0.4356	1.7598	0.3472	0.1355	0.7523	0.5850
Hotels/Resorts	5	0.0471	0.9652	2.2147	0.2405	1.2521	4.3657	0.5136	0.8753	3.8558	1.0000
Biotechnology: In Vitro & In Vivo Diagnostic Substances	5	0.0126	0.3358	0.9351	0.1857	0.5339	1.9262	0.4754	0.4424	2.1666	1.0000
Electronic Components	8	0.0081	0.5326	1.3140	0.1350	0.7561	2.3124	0.2850	0.7520	2.7036	0.4646
Average	9.12	0.0094	0.1947	0.5341	0.1690	0.2366	0.9881	0.3254	0.1892	0.9682	0.5871

Table 7: Performance of baseline model proposed in [17] on NASDAQ

G OTD2 COMPLETE RESULTS

Table 18 shows the detailed performance results on the OTD2 dataset with five different random group allocations.

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Biotechnology: Laboratory Analytical Instruments	5	0.0244	0.9165	2.6132	0.2447	0.5556	3.2469	0.4930	0.4553	3.1498	1.0000
Diversified Commercial Services	9	0.0315	1.9463	2.2132	0.2827	1.0483	2.8712	0.3033	0.7726	2.9765	0.3992
Other Specialty Stores	11	-0.0083	-0.2757	-0.4046	0.1350	0.1972	0.7898	0.2220	0.2008	0.9486	0.3136
Investment Managers	18	0.0147	1.2026	3.1766	0.1224	0.7153	3.3275	0.1547	0.5711	3.2101	0.2090
Electrical Products	13	0.0021	0.2232	0.7774	0.1266	0.1747	0.9553	0.1699	0.2038	1.2445	0.2505
Major Pharmaceuticals Other Pharmaceuticals	18 5	0.0083 0.0420	-0.1707 0.7478	-0.0414 2.6057	0.1730 0.2700	-0.1365 0.2195	-0.3281 1.2131	0.2218 0.4916	-0.0340 0.1719	-0.0488 1.0601	0.2218 1.0000
Automotive Aftermarket	10	0.0420	0.7478	0.8903	0.2700	0.2193	0.7936	0.4916	0.1719	0.5851	0.3680
Precious Metals	11	-0.0163	0.6813	1.6358	0.0717	0.1310	0.7730	0.2117	0.0238	0.2233	0.3088
Publishing	5	0.0151	-0.4553	-1.1204	0.2743	-0.1287	-0.3477	0.4744	-0.1218	-0.5510	1.0000
Military/Government/Technical	11	0.0094	0.3709	1.3192	0.1013	0.2765	1.3624	0.1962	0.1733	1.0585	0.3280
Business Services	22	0.0371	0.8236	2.3041	0.0633	0.5385	2.6426	0.1423	0.6044	3.6581	0.1825
Packaged Foods	16	0.0130	0.0371	0.3576	0.1055	0.2376	1.1822	0.1892	0.2100	1.2396	0.2425
Life Insurance	17	0.0316	0.4408	1.1822	0.1730	0.3049	1.3894	0.1927	0.4008	2.1153	0.2161
Power Generation	15	-0.0011	-0.2409	-1.1783	0.1181	0.0223	0.2317	0.1723	0.0708	0.6655	0.2197
Clothing/Shoe/Accessory Stores	15	0.0175	1.9787	2.2021	0.1097	0.3421	0.9112	0.1711	0.1680	0.6053	0.2362
Medical Specialities	11	0.0526	0.2179	0.7375	0.2194	0.5787	2.5074	0.2525	0.4993	2.7790	0.3406
Property-Casualty Insurers	30	0.0192	0.2673	0.7250	0.1561	0.0009	0.1354	0.1425	0.0476	0.3467	0.1597
Accident & Health Insurance	5 7	-0.0143 0.0286	0.4029 0.5901	1.0810	0.2785 0.2110	0.4239 0.0935	2.0508 0.7004	0.4489 0.3469	0.2645 0.0952	1.7726 0.7942	1.0000 0.5747
Farming/Seeds/Milling Engineering & Construction	5	0.0286	-0.4365	2.1545 -0.4714	0.3080	-0.0482	0.7004	0.3469	-0.0339	-0.0130	1.0000
Aerospace	9	0.0120	0.0075	0.2826	0.2110	0.2362	1.0729	0.2651	0.3670	1.9615	0.3881
Industrial Specialties	9	0.0000	1.0994	1.8806	0.2110	0.4923	1.9735	0.2031	0.3469	1.9804	0.3838
Specialty Insurers	6	0.0311	0.4101	2.1419	0.2236	0.3361	2.9795	0.3976	0.3112	3.1113	0.7424
Major Chemicals	29	0.0367	2.0708	1.9914	0.0591	0.8546	2.3885	0.1067	0.7252	2.8721	0.1438
Integrated oil Companies	19	0.0051	-0.1042	-0.0241	0.1181	0.2789	1.1388	0.1840	0.2697	1.2332	0.2238
Air Freight/Delivery Services	8	0.0255	-0.1557	0.0996	0.2152	0.2922	1.1280	0.3223	0.1947	1.0094	0.4667
Auto Parts:O.E.M.	18	0.0028	0.0070	0.1948	0.1308	0.0986	0.5461	0.1505	0.1639	0.8894	0.1828
Metal Fabrications	23	-0.0221	-0.2684	-0.7043	0.0802	-0.1461	-0.4471	0.1493	-0.0714	-0.2014	0.1765
Professional Services	11	0.0264	0.3941	1.4152	0.1181	0.4917	2.3416	0.1934	0.4289	2.3950	0.3339
Consumer Electronics/Appliances	6	0.0177	0.0551	0.3653	0.2152	0.2219	1.5692	0.3870	0.1651	1.4599	0.7282
Fluid Controls	7	0.0054	0.4329	1.2246	0.1899	0.0558	0.3530	0.3397	0.1384	0.7871	0.5731
Other Consumer Services Steel/Iron Ore	17 9	0.0035 0.0161	0.2075 1.3380	0.6701 1.9147	0.1350 0.1730	-0.0566 0.7475	-0.0291 1.9947	0.1894 0.2719	0.0480 0.2903	0.3380 1.1482	0.2213 0.4063
Oil/Gas Transmission	6	0.0161	0.1326	0.7732	0.1730	0.7473	1.7503	0.2719	0.2903	1.5104	0.4063
Plastic Products	6	0.0337	0.1520	1.8102	0.2068	0.2107	1.1718	0.4048	0.1032	1.6670	0.7250
Agricultural Chemicals	7	-0.0338	-0.0122	0.0616	0.1308	-0.0179	0.0328	0.3043	0.0169	0.1883	0.5500
Containers/Packaging	9	0.0532	0.3567	1.6435	0.1857	0.4655	2.9107	0.2787	0.3857	2.8297	0.4273
Water Supply	7	0.0738	0.7212	1.9706	0.2489	0.6259	2.6691	0.3610	0.5509	2.8809	0.6004
Finance: Consumer Services	20	-0.0260	0.2587	0.9367	0.1097	0.3842	1.5753	0.1486	-0.0273	-0.0406	0.1818
Commercial Banks	21	0.0054	0.2928	1.1736	0.1055	0.4938	2.5922	0.1517	0.4329	2.4692	0.1838
Medical/Dental Instruments	12	0.0329	0.7236	2.3267	0.1477	0.7127	3.6677	0.2138	0.4851	3.0057	0.3029
Computer Software: Prepackaged Software	11	0.0123	-0.2829	-0.3307	0.1941	0.2058	0.8394	0.2593	0.3625	1.6677	0.3238
Oil Refining/Marketing	9	-0.0159	0.1866	0.6283	0.2447	-0.0744	-0.1300	0.2857	-0.1153	-0.5105	0.3784
Hotels/Resorts	10	0.0259	0.7732	3.1388	0.1350	0.5796	3.2348	0.2466	0.4231	2.9367	0.3681
Restaurants Department/Specialty Retail Stores	7 8	-0.0202	-0.0501	-0.0017	0.1899	-0.1252	-0.5018	0.3136	-0.0738	-0.3704	0.5521
Marine Transportation	14	-0.0060 -0.0003	-0.1601 0.6801	-0.1885 1.3866	0.1603 0.1603	-0.0338 -0.0446	0.0994 0.0176	0.3261 0.2203	-0.0367 0.1103	-0.0017 0.5606	0.4595 0.2719
EDP Services	11	0.0025	0.4429	1.0640	0.1899	0.0527	0.3354	0.2445	0.0562	0.3661	0.2719
Hospital/Nursing Management	10	-0.0374	0.5054	0.9916	0.1941	-0.0250	0.1177	0.2586	0.0100	0.1850	0.3317
Savings Institutions	6	0.0412	0.5441	2.1445	0.2236	0.3033	1.9788	0.4058	0.1754	1.4319	0.7565
Investment Bankers/Brokers/Service	13	-0.0064	0.2290	0.8349	0.1181	-0.0216	-0.0215	0.1873	0.0205	0.2107	0.2678
Meat/Poultry/Fish	5	-0.0151	-0.2439	-0.6973	0.2743	0.0403	0.3354	0.4512	0.0990	0.8471	1.0000
Beverages (Production/Distribution)	12	0.0239	0.2351	1.0409	0.1013	0.2266	1.5338	0.2250	0.2515	1.9701	0.2991
Homebuilding	16	0.0310	1.6988	3.3707	0.1603	0.9321	3.4975	0.1765	1.0189	4.3494	0.2300
Shoe Manufacturing	5	0.0429	1.4649	1.9803	0.2658	0.4093	1.3059	0.5056	0.3139	1.3117	1.0000
Construction/Ag Equipment/Trucks	6	0.0423	0.5257	1.4138	0.1772	0.5199	2.0191	0.3840	0.4947	2.1520	0.7582
Real Estate	13	0.0009	-0.0317	-0.0225	0.0759	0.1550	1.0338	0.1716	0.1310	1.0304	0.2399
Package Goods/Cosmetics	10	-0.0003	-0.0312	0.0688	0.1477	0.0314	0.2598	0.2396	0.2293	1.3812	0.3537
Oilfield Services/Equipment	8	0.0162	-0.1475	-0.2068	0.1772	-0.3710	-1.2420	0.3026	-0.3021	-1.2370	0.4645
Paper Mining & Quarrying of Nanmatallia Minarala (Na Fuela)	8	0.0141	0.6179	1.8996	0.2405	0.2799	1.4098	0.3134	0.1059	0.6770	0.4843
Mining & Quarrying of Nonmetallic Minerals (No Fuels) Railroads	6 10	0.0468 -0.0005	-0.0296 0.4472	0.1624 1.7451	0.2954 0.1477	0.0354 0.3417	0.2772 1.6340	0.4271 0.2414	0.0090 0.2757	0.1427 1.6390	0.7184 0.3544
Home Furnishings	8	0.0309	0.3454	1.1039	0.1477	0.2405	1.0716	0.2414	0.2737	1.0300	0.3344
Apparel	10	-0.0188	-0.5308	-1.3461	0.2023	0.2403	0.4380	0.3136	0.1563	0.7771	0.4656
Office Equipment/Supplies/Services	9	0.0418	0.4468	1.4524	0.1646	-0.0953	-0.3830	0.2329	-0.0194	-0.0141	0.3381
Forest Products	5	0.0311	0.9493	2.0567	0.2785	0.5285	2.1856	0.4836	0.3948	1.9793	1.0000
Auto Manufacturing	9	0.0282	0.5113	1.4388	0.2152	0.1761	0.9958	0.2564	0.3446	2.0070	0.4000
Services-Misc. Amusement & Recreation	6	0.0787	0.8940	2.7186	0.2616	0.5470	3.0031	0.4278	0.3861	2.8966	0.7456
Semiconductors	5	0.0361	1.1884	2.5332	0.2489	0.4766	1.9157	0.4909	0.3035	1.5702	1.0000

Table 8: Performance of baseline model proposed in [17] on NYSE

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Computer Manufacturing	5	0.0143	-0.0477	0.0634	0.2658	0.1977	1.0821	0.4838	0.1648	1.0999	1.0000
Transportation Services	5	0.0303	-0.3902	-1.3876	0.2405	-0.3105	-1.6243	0.4913	0.0701	0.4840	1.0000
Medical/Dental Instruments	17	0.0164	1.2784	2.6419	0.0591	0.2390	1.0163	0.1275	0.0349	0.2789	0.1781
Property-Casualty Insurers	19	0.0438	-0.4535	-0.9007	0.1392	-0.2711	-1.1097	0.1636	-0.2591	-1.3919	0.1832
Medical Specialities	5	0.0286	-0.3505	-0.5935	0.2321	-0.3086	-1.5448	0.5000	-0.1143	-0.6432	1.0000
Biotechnology: Biological Products (No Diagnostic Substances)	12	0.0167	-0.5780	-0.9332	0.1224	-0.3050	-1.1125	0.1941	-0.1622	-0.6921	0.2982
Telecommunications Equipment	16	-0.0026	-0.7386	-1.5655	0.1435	-0.4117	-1.4491	0.1535	-0.3187	-1.4648	0.1932
Medical/Nursing Services	6	-0.0149	-0.0497	-0.0130	0.2110	0.1909	0.7797	0.3657	0.1880	0.9182	0.7504
Water Supply	9	0.0138	-0.2709	-0.4976	0.1181	0.2231	1.0461	0.2353	0.2432	1.2927	0.4097
Real Estate Investment Trusts	8	0.0090	-0.3951	-2.2191	0.1139	-0.0881	-0.5507	0.2759	-0.0085	-0.0022	0.4790
Business Services	17	0.0134	0.7775	1.8770	0.0759	0.1112	0.5812	0.1421	0.2183	1.2653	0.2053
Major Pharmaceuticals	29	-0.0131	-0.3425	-0.1044	0.0633	0.1920	0.6252	0.1113	0.2564	0.8491	0.1307
Farming/Seeds/Milling	6	0.0070	-0.2211	-0.6017	0.1435	-0.0610	-0.2920	0.3863	0.0426	0.3586	0.7456
Industrial Specialties	11	0.0141	1.9566	3.0194	0.0844	1.2322	4.2824	0.1960	0.8835	4.1077	0.3188
Air Freight/Delivery Services	6	-0.0120	-0.0647	-0.0398	0.1603	-0.1099	-0.4199	0.3741	-0.0872	-0.3385	0.7380
Electrical Products	13	0.0040	0.2195	0.7759	0.0802	-0.0645	-0.2118	0.1458	-0.0673	-0.3283	0.2409
Television Services	8	0.0048	-0.4989	-1.9251	0.1097	-0.3301	-1.6766	0.2724	-0.2817	-1.6943	0.4904
Investment Bankers/Brokers/Service	18	0.0049	-0.4233	-1.4110	0.1435	-0.4133	-2.8575	0.1620	-0.2782	-2.1985	0.1965
Catalog/Specialty Distribution	7	0.0018	0.0361	0.3542	0.1392	0.4392	1.4817	0.3129	0.3009	1.3728	0.5969
Savings Institutions	20	0.0073	-0.5940	-2.4198	0.0380	-0.2556	-1.3820	0.0956	-0.1932	-1.1429	0.1436
Other Consumer Services	9	0.0184	-0.5178	-1.9858	0.1688	-0.2258	-1.0093	0.2571	-0.0715	-0.3173	0.4181
Auto Parts: O.E.M.	6	0.0048	0.1345	0.5066	0.1730	0.0763	0.4337	0.3884	-0.0166	0.0164	0.7414
Trucking Freight/Courier Services	11	0.0228	0.0093	0.2164	0.1519	0.0257	0.2385	0.2135	0.0142	0.1851	0.3134
Radio And TV Broadcasting And Communications Equipment	10	-0.0251	1.3940	2.4058	0.1139	0.5622	1.8837	0.2053	0.4707	1.9249	0.3386
Biotechnology: Electromedical & Electrotherapeutic Apparatus	5	-0.0219	0.3264	1.1313	0.1646	0.5856	2.5303	0.4655	0.3959	2.0268	1.0000
Home Furnishings	8	0.0183	-0.7652	-2.4810	0.1308	-0.4145	-1.7633	0.2893	-0.2704	-1.3645	0.4916
Major Chemicals	7	0.0006	0.4466	1.4170	0.1308	-0.1249	-0.6651	0.3113	-0.1602	-0.9885	0.5976
Other Specialty Stores	8	-0.0114	-0.6167	-2.5278	0.1392	-0.3897	-2.4056	0.2696	-0.2322	-1.4418	0.4623
Computer Software: Programming, Data Processing	7	-0.0158	0.1778	0.6673	0.2025	0.0463	0.3354	0.3059	0.1507	0.9838	0.5630
Restaurants	20	-0.0096	-0.3113	-1.1495	0.0675	-0.2282	-1.0070	0.1078	-0.1540	-0.7702	0.1484
Automotive Aftermarket	6	-0.0081	-0.1409	-0.4848	0.1646	0.0733	0.4952	0.3854	0.0569	0.4265	0.7266
Investment Managers	5	-0.0412	-0.0107	0.1591	0.1899	0.0263	0.2434	0.4667	0.0409	0.3532	1.0000
Oil Refining/Marketing	6	0.0112	0.6837	1.9976	0.1266	0.2552	1.4019	0.3999	0.0009	0.0929	0.7491
Real Estate	7	0.0113	0.2837	1.1850	0.1181	0.1146	0.7490	0.3291	0.2638	1.7563	0.5990
Apparel	8	-0.0267	-0.1962	-0.4159	0.1435	-0.2422	-1.1042	0.2485	-0.3126	-1.7706	0.4580
Oil & Gas Production	6	-0.0177	0.0560	0.3511	0.1603	-0.1765	-0.4981	0.3704	-0.2671	-1.0112	0.7382
Computer Communications Equipment	5	0.0395	0.3573	1.1938	0.2405	0.1316	0.8054	0.5035	0.0113	0.1607	1.0000
Clothing/Shoe/Accessory Stores	8	0.0252	-0.5559	-1.6409	0.1519	-0.5269	-2.1383	0.2799	-0.3526	-1.4378	0.4914
Commercial Banks	5	0.0580	-0.1046	-0.2805	0.2236	0.0350	0.2759	0.4944	0.3320	0.7075	1.0000
Hospital/Nursing Management	5	0.0092	-0.0562	-0.0759	0.2405	0.1333	0.7221	0.4655	0.1142	0.9918	1.0000
Banks	5	0.0059	-0.2917	-1.6896	0.2025	-0.1515	-0.9863	0.4880	0.1027	0.6914	1.0000
Professional Services	6	0.0188	-0.5588	-2.1915	0.1224	-0.4077	-2.9101	0.3978	0.0101	0.1476	0.7492
Packaged Foods	7	0.0154	1.0455	2.4185	0.1224	0.2836	1.3385	0.3228	-0.0336	-0.1327	0.7492
Metal Fabrications	12	0.0134	1.4819	2.5295	0.1088	0.2830	2.9503	0.3228	0.2094	1.0487	0.3923
Diversified Commercial Services	6	0.0239	-0.5072	-1.6332	0.1139	-0.0854	-0.3199	0.1934	0.2094	1.3537	0.7200
Computer peripheral equipment	6	0.0546	1.0655	2.2080	0.2321	0.1955	0.9741	0.3924	0.2212	0.9538	0.7455
Steel/Iron Ore	7	0.0546	-0.2630	-0.6538	0.1983	-0.0995	-0.3004	0.4048	-0.0112	0.9538	0.7455
Hotels/Resorts	5	-0.0235	-0.2630	-0.6558	0.1688	0.2568	1.2714	0.3380	0.6803	3.0630	1.0000
Biotechnology: In Vitro & In Vivo Diagnostic Substances	5 5	0.0454	-0.1496 -0.2929	-0.41//	0.2152	0.2568	2.0998	0.4735	0.8803	1.9659	1.0000
	8		0.5785								
Electronic Components		-0.0312		1.3210	0.1603	0.5248	1.9204	0.2548	0.3378	1.5919	0.4711
Average	9.12	0.0071	0.0310	-0.0873	0.1539	0.0340	0.0445	0.3144	0.0505	0.2678	0.5858

Table 9: Complete result table for LambdaMART on NASDAQ.

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Biotechnology: Laboratory Analytical Instruments	5	0.0000	0.6418	3.0829	0.1899	0.4841	3.4649	0.4970	0.4841	3.4492	1.0000
Diversified Commercial Services	9	0.0128	1.5345	2.2816	0.1983	0.6707	2.3281	0.2647	0.4743	2.2261	0.4146
Other Specialty Stores	11	0.0016	-0.4049	-0.7317	0.1435	-0.2758	-0.8344	0.2161	-0.1138	-0.3821	0.3255
Investment Managers Electrical Products	18 13	0.0280 0.0080	-0.0565	-0.0769 -0.2386	0.0970	0.2047 -0.0166	1.1636 -0.0226	0.1484	0.3683 0.0685	2.2241	0.1888 0.2450
Major Pharmaceuticals	18	0.0080	-0.0764 0.7983	1.4109	0.1055 0.1308	0.1837	0.8006	0.1578 0.1835	0.0683	0.5614 0.6883	0.2430
Other Pharmaceuticals	5	-0.0143	-0.0489	-0.0297	0.2025	-0.0429	-0.1446	0.4712	0.1293	0.8351	1.0000
Automotive Aftermarket	10	0.0268	0.3631	1.0532	0.0886	-0.0249	0.0486	0.2075	-0.0197	0.0353	0.3614
Precious Metals	11	0.0147	-0.2612	-0.9794	0.1139	-0.2128	-1.0622	0.2063	0.0052	0.1263	0.3314
Publishing	5	0.0479	-0.0885	-0.1322	0.2447	-0.0158	0.0293	0.5084	-0.1535	-0.7639	1.0000
Military/Government/Technical	11	-0.0206	0.3135	1.2221	0.1181	0.2572	1.3468	0.1880	0.2948	1.7646	0.2961
Business Services	22	0.0118	-0.2033	-1.0205	0.0844	-0.3400	-2.8763	0.1045	-0.2780	-2.4584	0.1312
Packaged Foods	16	0.0146	-0.0450	-0.0991	0.0675	-0.1055	-0.6338	0.1153	-0.0492	-0.3276	0.1915
Life Insurance	17	0.0013	0.4844	2.2569	0.0338	0.9186	5.5226	0.1235	0.7000	4.8547	0.1734
Power Generation Clothing/Shoe/Accessory Stores	15 15	0.0001 -0.0152	0.4149 -0.3638	1.4183 -1.1112	0.1055 0.0802	0.1330 -0.5180	1.0341 -2.2291	0.1486 0.1378	0.0962 -0.4522	0.9612 -1.8764	0.2192 0.1949
Medical Specialities	11	0.0163	0.1157	0.9983	0.0549	0.0511	0.5236	0.2002	0.0434	0.4638	0.3105
Property-Casualty Insurers	30	-0.0150	-0.3339	-1.8750	0.0253	-0.2293	-1.7631	0.0539	-0.1881	-1.6600	0.0851
Accident &Health Insurance	5	0.0193	0.0647	0.3770	0.2658	0.1197	0.8376	0.4862	0.2289	1.5754	1.0000
Farming/Seeds/Milling	7	0.0210	-0.2092	-1.0287	0.1730	-0.0773	-0.5290	0.3408	-0.0765	-0.6195	0.5825
Engineering & Construction	5	-0.0286	-0.6108	-1.9237	0.2236	-0.3614	-1.7340	0.4709	-0.0749	-0.2026	1.0000
Aerospace	9	0.0138	-0.0585	-0.0292	0.1435	0.2664	1.3216	0.2480	0.2080	1.3286	0.4100
Industrial Specialties	9	-0.0093	0.2417	0.7658	0.1308	0.3355	1.7741	0.2419	0.4916	2.9676	0.3970
Specialty Insurers	6	0.0132	0.0248	0.2510	0.1772	0.1812	1.7888	0.3905	0.1476	1.5814	0.7401
Major Chemicals	29	-0.0014	0.9222	2.1943	0.0633	0.2557	1.3246	0.0759	0.2242	1.4245	0.1104
Integrated oil Companies Air Freight/Delivery Services	19 8	0.0107	0.1442	0.6068	0.1181 0.1603	0.2332	1.1554	0.1397	0.2060	1.1236	0.1846
Auto Parts:O.E.M.	18	0.0123 -0.0036	0.5049 0.3236	1.8273 1.1766	0.1603	-0.0349 0.3508	-0.0056 1.5749	0.3019 0.1041	-0.0296 0.4035	-0.0516 1.9846	0.4711 0.1615
Metal Fabrications	23	0.0044	0.3230	0.7621	0.0844	0.3308	1.6071	0.1041	0.4033	1.3637	0.1329
Professional Services	11	-0.0002	0.0308	0.2546	0.1392	0.1195	0.7118	0.2135	0.1413	0.9830	0.3149
Consumer Electronics/Appliances	6	0.0244	0.4636	1.7942	0.1899	0.3072	2.2109	0.3929	0.1913	1.7115	0.7528
Fluid Controls	7	0.0094	-0.2719	-0.7571	0.1435	0.0033	0.1266	0.3298	0.0295	0.2601	0.5846
Other Consumer Services	17	0.0155	-0.1323	0.0756	0.1097	-0.2485	-0.9130	0.1418	-0.0400	-0.0941	0.1920
Steel/Iron Ore	9	0.0121	0.1835	0.5921	0.1266	0.2446	0.8770	0.2471	0.2832	1.1043	0.4234
Oil/Gas Transmission	6	-0.0165	0.0695	0.5316	0.1477	0.1606	1.4076	0.3868	0.1223	1.2065	0.7418
Plastic Products	6	-0.0003	-0.1394	-0.2104	0.1814	0.0448	0.3587	0.3715	0.2178	1.5464	0.7333
Agricultural Chemicals	7 9	0.0262	-0.1353	-0.3462	0.1561	0.1867	0.9687	0.3371	0.0902 0.2204	0.6374	0.5874
Containers/Packaging Water Supply	7	0.0100 0.0302	0.4112 -0.3861	2.4134 -1.7638	0.1013 0.1814	0.2591 -0.1310	2.1785 -0.6964	0.2278 0.3469	0.2204	1.9453 0.1464	0.4089 0.5939
Finance: Consumer Services	20	0.0096	0.9553	2.8125	0.0422	0.5232	2.5844	0.1184	0.2217	1.4814	0.1665
Commercial Banks	21	0.0075	0.1036	0.5447	0.0506	0.4271	2.3475	0.1055	0.4649	3.0711	0.1418
Medical/Dental Instruments	12	0.0127	-0.2963	-1.7528	0.1139	-0.2316	-2.0540	0.1707	-0.2241	-2.1604	0.2663
Computer Software: Prepackaged Software	11	0.0120	-0.4054	-1.0410	0.0802	-0.0426	-0.0959	0.1878	0.0912	0.6130	0.3252
Oil Refining/Marketing	9	0.0049	-0.4859	-1.2104	0.0759	-0.2478	-1.1750	0.2351	-0.2189	-1.3731	0.4055
Hotels/Resorts	10	-0.0106	-0.1800	-0.6967	0.1224	-0.0396	-0.1907	0.2023	0.1254	0.9986	0.3454
Restaurants	7	-0.0126	-0.4359	-2.0032	0.1519	-0.0917	-0.5576	0.3139	-0.0712	-0.4825	0.5702
Department/Specialty Retail Stores	8	0.0051	0.0043	0.2435	0.1857	-0.1060	-0.1541	0.3040	-0.1186	-0.3509	0.4650
Marine Transportation	14	0.0335	-0.2724	-0.6564	0.0970	-0.2722	-1.0105	0.1756	-0.1424	-0.6389	0.2513
EDP Services	11 10	-0.0057 0.0193	-0.1577 4.2295	-0.4264 3.5191	0.1055 0.1097	0.1571 0.8279	0.9432 2.2462	0.1845 0.2389	0.2683 0.5408	1.5957 1.9074	0.2959 0.3636
Hospital/Nursing Management Savings Institutions	6	0.0193	-0.0950	-0.5292	0.1097	0.0393	0.3589	0.4001	0.0866	0.7941	0.7442
Investment Bankers/Brokers/Service	13	-0.0240	0.2734	1.0000	0.0802	0.0255	0.2335	0.1606	-0.0393	-0.1499	0.2442
Meat/Poultry/Fish	5	-0.0135	-0.0616	-0.1277	0.2363	0.1429	1.0507	0.4669	0.1074	0.9181	1.0000
Beverages (Production/Distribution)	12	0.0299	-0.1384	-0.6496	0.0802	-0.0516	-0.3698	0.1929	-0.0390	-0.3551	0.2900
Homebuilding	16	0.0151	-0.2566	-1.3115	0.0759	0.0165	0.1893	0.1428	0.0038	0.1021	0.2014
Shoe Manufacturing	5	0.0361	-0.3162	-0.5245	0.2236	-0.1060	-0.2621	0.5164	0.2378	1.0544	1.0000
Construction/Ag Equipment/Trucks	6	-0.0373	0.1895	0.7694	0.1857	0.3942	1.5671	0.3788	0.4011	1.8141	0.7335
Real Estate	13	-0.0286	-0.6280	-3.5603	0.0802	-0.3128	-2.2656	0.1423	-0.1233	-0.9755	0.2367
Package Goods/Cosmetics	10	-0.0092	-0.0532	-0.0795	0.1013	0.1455	1.1054	0.2028	0.1955	1.6992	0.3396
Oilfield Services/Equipment	8	-0.0315	-0.2869	-0.8246	0.1181	-0.4142	-1.9334	0.2386	-0.3447	-1.6829	0.4587
Paper Mining & Occupating of Nonmotellia Minerale (No Finale)	8	0.0141	-0.2248	-0.8357	0.1266	-0.1451	-0.7288	0.2860	0.0000	0.0900	0.4747
Mining & Quarrying of Nonmetallic Minerals (No Fuels) Railroads	6 10	0.0389 -0.0085	2.0392 0.1485	4.2855 0.6666	0.1730 0.1055	0.5500 0.1695	2.5453 1.0637	0.3837 0.1922	0.1273 0.1236	0.8274 0.9389	0.7666 0.3336
Home Furnishings	8	0.0165	-0.3182	-0.7994	0.1055	-0.0887	-0.3797	0.1922	-0.0377	-0.1389	0.3336
Apparel	10	-0.0281	-0.3182	-0.7994	0.1477	-0.1056	-0.3244	0.2792	0.0245	0.2272	0.3297
Office Equipment/Supplies/Services	9	0.0301	0.1822	0.7178	0.1392	-0.0653	-0.1916	0.2836	-0.0758	-0.3325	0.4270
Forest Products	5	-0.0185	0.0951	0.5010	0.1983	0.2182	1.1585	0.4662	0.3766	1.8965	1.0000
Auto Manufacturing	9	-0.0187	0.1151	0.5711	0.1055	0.0523	0.4158	0.2260	0.0694	0.5413	0.3996
Services-Misc. Amusement & Recreation	_										
	6	0.0182	-0.2761	-1.3759	0.1899	0.0169	0.1929	0.4046	0.1916	1.5817	0.7536
Semiconductors Average			-0.2761 -0.4208 0.1005	-1.3759 -1.7579 0.1367	0.1899 0.1730 0.1307	0.0169 -0.0284 0.0732	0.1929 -0.0098 0.4192	0.4046 0.4759 0.2593	0.1916 0.4026 0.1063	1.5817 2.0180 0.6882	0.7536 1.0000 0.4574

Table 10: Complete result table for LambdaMART on NYSE.

Sector	Stocks		IDD 01	CD C1	MAROI	IDD 02	SR@3	MAP@3	IRR@5	CDOL	MAP@5
	5	τ 0.0244	IRR@1	SR@1	MAP@1	IRR@3				SR@5	
Computer Manufacturing		-0.0244	-0.0458	0.0585	0.2110	0.2554	1.1537	0.4627	0.2167	1.3724	1.0000
Transportation Services	5	-0.0193	-0.3402	-1.1114	0.1941	0.2787	1.2932	0.4557	0.1263	0.7757	1.0000
Medical/Dental Instruments	17	0.0492	0.1590	0.6044	0.1055	0.6454	2.2254	0.1592	0.6764	2.7925	0.2023
Property-Casualty Insurers	19	0.0136	0.1661	0.6221	0.0928	-0.0236	0.0176	0.1306	-0.1705	-0.7351	0.1768
Medical Specialities	5	0.0336	-0.0239	0.1681	0.2405	0.2459	1.1755	0.4768	-0.0402	-0.1500	1.0000
Biotechnology: Biological Products (No Diagnostic Substances)	12	0.0395	1.4993	2.0935	0.1519	1.4277	3.3088	0.2429	0.5337	1.8510	0.3092
Telecommunications Equipment	16	-0.0179	-0.7585	-1.6430	0.1688	-0.2981	-0.7723	0.1779	-0.1275	-0.3238	0.2197
Medical/Nursing Services	6	-0.0311	0.1104	0.4698	0.1561	0.3651	1.4513	0.3659	0.3374	1.5209	0.7409
Water Supply	9	0.0574	0.4483	1.3802	0.2068	0.5629	2.3886	0.2843	0.3641	1.8486	0.4219
Real Estate Investment Trusts	8	-0.0132	0.0069	0.1270	0.0844	-0.0191	-0.0712	0.2595	-0.0638	-0.4460	0.4922
Business Services	17	0.0253	0.4529	1.0647	0.1392	0.5424	1.9924	0.1655	0.6901	2.8825	0.2158
Major Pharmaceuticals	29	0.0079	-0.1586	-0.0520	0.0506	0.3816	0.8635	0.1174	0.5645	1.3108	0.1410
Farming/Seeds/Milling	6	0.0216	0.3578	1.1610	0.1899	0.1054	0.6186	0.3685	0.1074	0.7423	0.7387
Industrial Specialties	11	0.0355	2.0407	2.9100	0.0886	1.1427	3.4837	0.2028	0.8774	3.5009	0.3327
Air Freight/Delivery Services	6	0.0008	0.0305	0.2780	0.1983	-0.0337	-0.0015	0.3706	0.0795	0.4713	0.7377
Electrical Products	13	0.0238	0.7368	1.5589	0.0675	0.5567	1.8610	0.1782	0.7503	2.7229	0.2683
Television Services	8	-0.0102	-0.1655	-0.3784	0.1266	-0.1655	-0.5383	0.2979	-0.1354	-0.5403	0.4825
Investment Bankers/Brokers/Service	18	0.0182	0.9022	2.0099	0.1688	0.1769	1.1874	0.2114	0.1941	1.2786	0.2410
Catalog/Specialty Distribution	7	0.0354	0.2672	0.7606	0.1435	0.7167	1.8853	0.3401	0.5044	1.9389	0.5866
Savings Institutions	20	0.0530	0.5454	1.5980	0.1224	0.2679	1.2659	0.1615	0.2020	1.1164	0.1943
Other Consumer Services	9	-0.0166	-0.0931	-0.2221	0.1055	0.1196	0.7069	0.2257	0.1118	0.7043	0.3956
Auto Parts:O.E.M.	6	0.0345	-0.1027	-0.3203	0.1055	-0.0189	0.0618	0.3987	-0.0246	-0.0228	0.7652
Trucking Freight/Courier Services	11	0.0244	0.4114	0.9919	0.1899	0.4502	1.3182	0.2658	0.4701	1.4809	0.3332
Radio And Television Broadcasting And Communications Equipment	10	0.0109	-0.0742	-0.1502	0.0633	0.1295	0.7907	0.1845	-0.0134	0.0003	0.3628
Biotechnology: Electromedical & Electrotherapeutic Apparatus	5	0.0107	1.1587	2.2743	0.2532	0.1253	3.0769	0.5075	0.3760	1.9405	1.0000
Home Furnishings	8	0.0490	-0.2161	-0.4893	0.2332	-0.0517	-0.0146	0.2785	0.0614	0.3821	0.4723
Major Chemicals	7	-0.0138	-0.2516	-0.4893	0.1433	0.1080	0.5532	0.2783	0.0866	0.5661	0.4723
*	8	-0.0138	-0.2316	-0.6296		-0.2925	-0.7834	0.3317	-0.0670	-0.1054	0.4397
Other Specialty Stores					0.2110						
Computer Software: Programming, Data Processing	7	-0.0158	-0.1693	-0.2412	0.2194	0.1802	0.8314	0.3338	0.3037	1.6221	0.5186
Restaurants	20	-0.0124	-0.3350	-0.8094	0.0380	0.1699	0.7861	0.1470	0.1158	0.6462	0.1718
Automotive Aftermarket	6	0.0675	0.9524	2.4494	0.2489	0.3451	1.5889	0.4456	0.2365	1.3197	0.7386
Investment Managers	5	-0.0479	-0.0173	-0.0278	0.1308	0.0694	0.4809	0.4447	0.0976	0.7306	1.0000
Oil Refining/Marketing	6	-0.0177	-0.2807	-1.0433	0.2785	0.0871	0.5231	0.3664	0.1192	0.7835	0.6866
Real Estate	7	0.0346	0.0248	0.2712	0.1435	0.3611	1.8716	0.3226	0.3814	2.2677	0.6013
Apparel	8	-0.0126	-0.1179	-0.4358	0.1055	-0.0198	0.0517	0.2583	0.1292	0.7542	0.4581
Oil & Gas Production	6	-0.0317	-0.3547	-0.9233	0.1688	-0.3303	-1.1890	0.3507	-0.3033	-1.1135	0.7115
Computer Communications Equipment	5	0.0084	1.4289	2.4003	0.2405	0.3316	1.4066	0.4632	0.0383	0.3025	1.0000
Clothing/Shoe/Accessory Stores	8	-0.0123	-0.3926	-0.7858	0.1435	-0.1718	-0.3006	0.2778	-0.0946	-0.1198	0.4774
Commercial Banks	5	0.0008	0.2494	0.8646	0.2236	0.2425	1.0891	0.4749	0.1656	0.9570	1.0000
Hospital/Nursing Management	5	0.0168	0.4520	1.3993	0.2194	0.5566	2.6969	0.5056	0.2216	1.3716	1.0000
Banks	5	0.0975	0.4188	1.6950	0.2194	0.3821	1.9376	0.5333	0.0939	0.6403	1.0000
Professional Services	6	0.0367	-0.1459	-0.4075	0.1646	0.2578	1.3598	0.3896	0.2896	1.7259	0.7525
Packaged Foods	7	0.0262	-0.0358	0.0393	0.1561	0.0106	0.1580	0.3479	0.0664	0.4664	0.5737
Metal Fabrications	12	0.0107	0.8319	1.7550	0.1266	0.3500	1.3203	0.2131	0.4291	1.7411	0.2848
Diversified Commercial Services	6	0.0451	0.1541	0.5682	0.2743	0.5603	2.3008	0.4030	0.3485	2.0433	0.7311
Computer peripheral equipment	6	0.0076	0.2860	0.8418	0.2152	0.4543	1.7633	0.3826	0.3222	1.6209	0.7227
Steel/Iron Ore	7	-0.0190	-0.2737	-0.9245	0.1097	-0.1345	-0.4884	0.2989	-0.0798	-0.2852	0.5987
Hotels/Resorts	5	-0.0109	0.5641	2.9180	0.1646	0.9370	3.6587	0.4780	0.8753	3.8558	1.0000
Biotechnology: In Vitro & In Vivo Diagnostic Substances	5	-0.0151	0.9486	2.0263	0.2110	0.4172	1.5755	0.4665	0.4424	2.1666	1.0000
Electronic Components	8	-0.0069	0.3731	1.0121	0.1392	0.7566	2.3061	0.2789	0.6594	2.3433	0.4611
Average	9.12	0.0110	0.2257	0.5464	0.1620	0.2857	1.1245	0.3216	0.2309	1.0943	0.5860
Twerage	7.16	0.0110	0.2237	3.3 104	0.1020	0.2037	1.12 13	0.5210	0.2307	1.0713	0.5000

Table 11: Complete result table for Rankformer on NASDAQ.

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Biotechnology: Laboratory Analytical Instruments	5	-0.0025	0.6902	2.1537	0.1983	0.5843	3.4616	0.4698	0.4553	3.1498	1.0000
Diversified Commercial Services	9	0.0367	1.4739	1.9763	0.2405	1.0969	2.9188	0.3043	0.8108	3.0485	0.4004
Other Specialty Stores	11	0.0059	-0.1341	-0.0301	0.1519	0.3229	1.1175	0.2370	0.0706	0.4060	0.3223
Investment Managers	18	0.0376	0.7707	2.4018	0.1139	0.6134	3.1095	0.1526	0.5251	3.1464	0.2086
Electrical Products	13	0.0253	0.5033	1.4703	0.1097	0.1957	1.1061	0.1695	0.3724	2.1064	0.2651
Major Pharmaceuticals Other Pharmaceuticals	18 5	0.0117 -0.0034	-0.1838 0.3746	-0.0680 1.4293	0.1772 0.2405	-0.1492 0.1998	-0.3752 1.1667	0.2199 0.4583	0.0132 0.1719	0.1763 1.0601	0.2236 1.0000
Automotive Aftermarket	10	0.0421	0.3740	0.6239	0.2403	0.1499	0.9958	0.4383	0.1719	0.9409	0.3905
Precious Metals	11	-0.0154	-0.2354	-0.4765	0.1646	-0.1428	-0.5177	0.1969	-0.0027	0.0953	0.3068
Publishing	5	-0.0160	0.0131	0.1672	0.1013	-0.0435	-0.1085	0.4831	-0.1218	-0.5510	1.0000
Military/Government/Technical	11	0.0274	0.3260	1.0909	0.1181	0.2801	1.3298	0.1887	0.2861	1.5777	0.3309
Business Services	22	0.0470	0.5503	1.6952	0.0675	0.6726	3.2061	0.1472	0.6842	4.0307	0.1781
Packaged Foods	16	0.0202	0.0653	0.4200	0.1097	0.3028	1.2772	0.1920	0.2975	1.5563	0.2549
Life Insurance	17	0.0321	0.7816	1.8057	0.1814	0.3132	1.4290	0.1920	0.3749	1.9991	0.2148
Power Generation Clothing/Shoe/Accessory Stores	15 15	0.0293 0.0225	0.0506 0.6554	0.3164 1.1923	0.1097 0.0759	0.1053 0.1537	0.7563 0.5621	0.1774 0.1535	0.1561 0.1204	1.3379 0.5030	0.2333 0.2334
Medical Specialities	11	0.0223	0.0334	0.5023	0.2236	0.5825	2.4361	0.1333	0.1204	3.0334	0.2334
Property-Casualty Insurers	30	0.0222	0.3422	0.8457	0.1561	0.0831	0.4595	0.1430	0.0884	0.5538	0.1626
Accident &Health Insurance	5	0.0160	0.2131	1.1893	0.1899	0.2929	1.9963	0.4965	0.2645	1.7726	1.0000
Farming/Seeds/Milling	7	0.0458	0.7947	2.8643	0.2110	0.1444	0.9477	0.3516	0.0944	0.7830	0.5795
Engineering & Construction	5	-0.0177	-0.0470	-0.0562	0.1857	0.0668	0.4253	0.4752	-0.0339	-0.0130	1.0000
Aerospace	9	0.0070	0.0075	0.2826	0.2110	0.2110	0.9805	0.2700	0.3692	1.9613	0.3847
Industrial Specialties	9	0.0233	0.5945	1.2360	0.1814	0.4902	1.9122	0.2867	0.4382	2.3662	0.3906
Specialty Insurers	6 29	0.0266 0.0385	0.2417	1.9522	0.1772	0.2524	2.3140	0.4182	0.1542 0.9413	1.5739	0.7641
Major Chemicals Integrated oil Companies	19	0.0030	0.7861 -0.1368	2.3038 -0.1112	0.0506 0.1181	0.9033 0.3038	2.5378 1.2159	0.1083 0.1861	0.9413	3.3278 1.2721	0.1439 0.2256
Air Freight/Delivery Services	8	-0.0264	-0.1159	-0.4758	0.1224	0.0035	0.1200	0.2447	0.0342	0.2842	0.5034
Auto Parts:O.E.M.	18	0.0093	-0.0773	-0.1814	0.0169	0.1225	0.6453	0.1027	0.2304	1.2174	0.1590
Metal Fabrications	23	0.0315	0.4166	1.2780	0.0464	0.2232	1.1539	0.0748	0.3343	1.8060	0.1225
Professional Services	11	0.0424	0.3269	1.2574	0.0928	0.7564	3.3393	0.2011	0.4197	2.2984	0.3334
Consumer Electronics/Appliances	6	0.0143	-0.0331	-0.0448	0.2236	0.1965	1.3905	0.3849	0.1815	1.6288	0.7276
Fluid Controls	7	0.0046	0.2013	0.8376	0.1308	0.0164	0.1977	0.3425	0.1301	0.7341	0.5530
Other Consumer Services	17 9	0.0112	-0.1938	-0.3318	0.1055	0.0592	0.3613	0.1786	0.0714	0.4484	0.2146
Steel/Iron Ore Oil/Gas Transmission	6	0.0063 0.0429	0.4187 0.0450	0.9607 0.3377	0.1308 0.1772	0.4679 0.1682	1.4640 1.3444	0.2604 0.4004	0.3296 0.1402	1.2657 1.2989	0.4055 0.7125
Plastic Products	6	0.0445	0.5481	1.7984	0.1772	0.2097	1.1128	0.4119	0.2402	1.6555	0.7280
Agricultural Chemicals	7	-0.0274	-0.1482	-0.5050	0.1139	0.0579	0.3661	0.3099	0.0235	0.2252	0.5530
Containers/Packaging	9	0.0560	0.3614	1.6604	0.1857	0.4993	3.0729	0.2811	0.4182	3.0827	0.4291
Water Supply	7	0.0434	0.3842	1.2216	0.2321	0.4928	2.1438	0.3462	0.5040	2.6645	0.5847
Finance: Consumer Services	20	0.0222	-0.0371	0.0167	0.0928	0.3712	1.6133	0.1367	0.3801	1.8747	0.1840
Commercial Banks	21	0.0191	0.1958	0.9104	0.0759	0.2458	1.3927	0.1327	0.2432	1.5127	0.1786
Medical/Dental Instruments Computer Software: Prepackaged Software	12 11	0.0359 0.0051	0.9956 0.3920	3.0300 1.8192	0.1139 0.0802	0.7530 0.3935	3.7000 2.3690	0.2131 0.1770	0.6578 0.3880	3.9586 2.4915	0.3012 0.2962
Oil Refining/Marketing	9	-0.0131	-0.0392	0.2148	0.0302	-0.0582	-0.0842	0.1770	-0.1034	-0.4494	0.2702
Hotels/Resorts	10	0.0302	0.5783	2.1517	0.1603	0.4510	2.6568	0.2363	0.4765	3.1656	0.3614
Restaurants	7	-0.0250	-0.0055	0.1315	0.1941	-0.1752	-0.7641	0.3181	-0.0880	-0.4705	0.5514
Department/Specialty Retail Stores	8	-0.0093	-0.0487	-0.6587	0.1181	0.0553	0.4820	0.2581	0.1323	0.9452	0.5083
Marine Transportation	14	-0.0028	0.3115	0.8296	0.1561	-0.0475	0.0074	0.2211	0.1118	0.5671	0.2705
EDP Services	11	0.0016	0.3955	0.9938	0.1857	0.2148	0.8664	0.2482	0.0830	0.4807	0.3157
Hospital/Nursing Management	10	0.0094	0.3321	1.0789	0.1139	0.0799	0.4927	0.2016	0.0709	0.4200	0.3503
Savings Institutions Investment Bankers/Brokers/Service	6 13	0.0233	0.5687 0.2942	2.2148 1.0115	0.1983 0.1181	0.2700 0.0082	1.7638 0.1411	0.4015 0.1854	0.1603 0.0205	1.3813 0.2107	0.7545 0.2678
Meat/Poultry/Fish	5	-0.0003	-0.2439	-0.6973	0.2743	0.0082	0.6218	0.4543	0.0203	0.8471	1.0000
Beverages (Production/Distribution)	12	0.0192	0.1427	0.6925	0.1055	0.2875	1.9098	0.2288	0.2508	1.9447	0.2990
Homebuilding	16	0.0415	1.1992	2.3832	0.1139	0.9380	3.1958	0.1707	1.1283	4.2944	0.2342
Shoe Manufacturing	5	0.0387	0.8778	1.4294	0.2110	0.5701	1.6533	0.5089	0.3139	1.3117	1.0000
Construction/Ag Equipment/Trucks	6	0.0457	0.7575	1.8814	0.1730	0.4618	1.8972	0.3821	0.5135	2.2277	0.7643
Real Estate	13	0.0035	-0.0317	-0.0225	0.0759	0.1757	1.1769	0.1742	0.1773	1.3251	0.2446
Package Goods/Cosmetics	10	0.0098	-0.0312	0.0688	0.1477	0.0474	0.3356	0.2410	0.2505	1.5186	0.3546
Oilfield Services/Equipment Paper	8	-0.0069 0.0150	-0.4508 0.6198	-0.9192 1.8548	0.2321 0.2152	-0.1833 0.3067	-0.5156 1.4751	0.2717 0.3050	-0.2205 0.0984	-0.8215 0.6318	0.4629 0.4842
Mining & Quarrying of Nonmetallic Minerals (No Fuels)	6	0.0130	-0.0299	0.1618	0.2152	0.0305	0.2549	0.3030	-0.0001	0.0318	0.4842
Railroads	10	-0.0109	0.4033	1.3568	0.1266	0.2680	1.2789	0.2410	0.2466	1.4833	0.3504
Home Furnishings	8	0.0336	0.2567	0.8786	0.1899	0.2967	1.3483	0.3080	0.1965	1.0645	0.4663
Apparel	10	0.0079	0.2067	0.8641	0.1055	0.1946	0.9773	0.2025	0.3079	1.4040	0.3496
Office Equipment/Supplies/Services	9	-0.0390	-0.3344	-1.2649	0.0844	-0.3280	-1.6894	0.2274	-0.2768	-1.5305	0.3900
Forest Products	5	0.0664	0.9244	2.0120	0.2532	0.7321	2.7681	0.5052	0.3948	1.9793	1.0000
Auto Manufacturing	9	0.0252	0.0875	0.4246	0.2025	0.1577	0.9115	0.2520	0.3126	1.8921	0.3949
Services-Misc. Amusement & Recreation Semiconductors	6 5	0.0602 0.0378	0.5462 0.7516	2.0205 1.9347	0.1857 0.2236	0.4993 0.4438	2.8017 1.8223	0.4308 0.4859	0.3038 0.3035	2.2588 1.5702	0.7432 1.0000
Average	10.97	0.0378	0.7316	0.9113	0.2236	0.4438	1.2890	0.4839	0.3033	1.4200	0.465
	10.77	0.0101	0.2724	0.7113	0.1333	0.2701	1.2070	0.2730	0.2313	1.7200	0.103

Table 12: Complete result table for Rankformer on NYSE.

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Computer Manufacturing	5	0.0345	0.1128	0.6215	0.1983	0.3465	2.3286	0.5059	0.2167	1.3724	1.0000
Transportation Services	5	0.0008	0.4351	1.2510	0.2489	0.2339	1.1572	0.4838	0.1263	0.7757	1.0000
Medical/Dental Instruments	17	0.0090	0.5775	1.9145	0.0802	0.4503	2.3065	0.1254	0.4129	2.3442	0.1809
Property-Casualty Insurers	19	0.0194	-0.0452	0.1845	0.1013	0.0247	0.2305	0.1751	0.0401	0.2988	0.1967
Medical Specialities	5	0.0303	-0.0239	0.1681	0.2405	0.0473	0.3352	0.4930	-0.0402	-0.1500	1.0000
Biotechnology: Biological Products (No Diagnostic Substances)	12	0.0186	2.4685	2.9704	0.1688	1.0795	3.2313	0.2117	0.4928	1.8969	0.3013
Telecommunications Equipment	16	0.0312	0.2872	0.9428	0.0675	0.0301	0.2521	0.1292	0.1160	0.6588	0.2023
Medical/Nursing Services	6	0.0345	0.6698	1.5659	0.1688	0.7648	2.4595	0.3915	0.3438	1.4557	0.7572
Water Supply	9	0.0392	0.4756	1.4303	0.2110	0.4821	2.1976	0.2785	0.3584	1.8276	0.4219
Real Estate Investment Trusts	8	0.0063	0.1655	1.0105	0.1392	0.1347	1.1262	0.2818	0.0755	0.6959	0.4834
Business Services	17	0.0268	1.6051	2.4223	0.1603	0.9827	3.3542	0.1798	0.7203	3.4705	0.2180
Major Pharmaceuticals	29	0.0147	1.7511	2.5307	0.0380	1.1160	2.4861	0.0649	0.7787	2.4209	0.0850
Farming/Seeds/Milling	6	0.0479	0.2494	0.8739	0.2152	0.2853	1.4940	0.4044	0.0968	0.6758	0.7522
Industrial Specialties	11	0.0219	1.4803	2.9657	0.0844	0.9133	2.7340	0.2220	0.7123	2.9349	0.3298
Air Freight/Delivery Services	6	0.0165	0.5981	1.5902	0.1772	0.1919	0.8855	0.4121	0.0617	0.3960	0.7350
Electrical Products	13	0.0139	0.7310	2.2919	0.1055	0.3622	1.6007	0.1772	0.4157	1.8738	0.2609
Television Services	8	0.0318	-0.0302	0.0737	0.1181	0.0519	0.3379	0.3061	-0.0576	-0.1870	0.5070
Investment Bankers/Brokers/Service	18	0.0366	0.0700	0.3793	0.1055	0.4111	2.0910	0.1343	0.5326	3.0702	0.1857
Catalog/Specialty Distribution	7	0.0474	1.0474	1.6694	0.1730	0.9757	2.4631	0.3209	0.6368	2.3162	0.6066
Savings Institutions	20	0.0341	0.4459	1.3907	0.1266	0.3911	1.7948	0.1472	0.2374	1.2924	0.1919
Other Consumer Services	9	0.0327	-0.0204	0.1423	0.1350	0.3638	1.6126	0.2714	0.1654	0.8493	0.4181
Auto Parts:O.E.M.	6	0.0205	0.1364	0.5079	0.2278	0.0853	0.4936	0.4083	-0.0303	-0.0533	0.7472
Trucking Freight/Courier Services	11	0.0236	1.2633	1.9697	0.1941	0.8822	2.3363	0.2698	0.4234	1.4514	0.3321
Radio And TV Broadcasting And Communications Equipment	10	0.0020	0.6117	1.1721	0.1097	0.5461	1.8837	0.2218	0.2672	1.3208	0.3429
Biotechnology: Electromedical & Electrotherapeutic Apparatus	5	0.0336	0.3490	1.3161	0.2152	0.6316	2.6888	0.4892	0.3760	1.9405	1.0000
Home Furnishings	8	0.0255	-0.5294	-0.9480	0.1772	-0.0071	0.1231	0.2902	0.0675	0.4162	0.4921
Major Chemicals	7	0.0386	0.0550	0.3581	0.1266	0.2015	1.0694	0.3293	0.1306	0.8491	0.6094
Other Specialty Stores	8	0.0666	0.6364	2.0735	0.1266	0.9138	3.1965	0.3033	0.1963	1.0324	0.5221
Computer Software: Programming, Data Processing	7	0.0470	0.7064	2.3288	0.1814	0.6583	3.4336	0.3305	0.3598	2.1732	0.6190
Restaurants	20	0.0077	0.1668	0.6579	0.0506	0.1775	0.9692	0.0942	0.1184	0.7246	0.1443
Automotive Aftermarket	6	0.0328	0.3689	1.2364	0.2025	0.3357	1.7185	0.3999	0.2355	1.3734	0.7544
Investment Managers	5	0.0471	-0.0055	0.1115	0.2110	0.0272	0.2449	0.5087	0.0976	0.7306	1.0000
Oil Refining/Marketing	6	0.0317	0.5765	1.6158	0.2532	0.3921	1.8925	0.4154	0.1472	0.9318	0.7284
Real Estate	7	0.0454	0.0186	0.2540	0.1350	0.4378	2.0464	0.3376	0.3771	2.2129	0.5996
Apparel	8	0.0366	0.9977	1.9552	0.1688	0.4962	1.6474	0.3054	0.3216	1.4747	0.4992
Oil & Gas Production	6	0.0160	-0.3752	-1.0564	0.1519	-0.0738	-0.0969	0.3826	-0.2398	-0.8349	0.7308
Computer Communications Equipment	5	0.0168	0.8553	2.3743	0.2785	0.2458	1.1800	0.4777	0.0383	0.3025	1.0000
Clothing/Shoe/Accessory Stores	8	0.0582	0.0546	0.3739	0.1477	0.1752	0.6443	0.3064	0.1487	0.6079	0.5038
Commercial Banks	5	0.0361	0.0714	0.4419	0.1603	0.4664	2.2140	0.5415	0.1656	0.9570	1.0000
Hospital/Nursing Management	5	0.0076	0.4818	1.7654	0.2321	0.4274	2.4203	0.4794	0.2216	1.3716	1.0000
Banks	5	0.0227	0.2333	1.0907	0.2194	0.1565	0.9575	0.5002	0.0939	0.6403	1.0000
Professional Services	6	0.0625	0.6336	2.1653	0.2194	0.3393	1.7894	0.4255	0.2238	1.3882	0.7533
Packaged Foods	7	0.0262	-0.0920	-0.1460	0.1730	-0.0812	-0.3737	0.3474	-0.0810	-0.4288	0.5873
Metal Fabrications	12	0.0157	0.1418	0.6525	0.0464	0.4426	1.7620	0.1650	0.1618	0.8427	0.2879
Diversified Commercial Services	6	0.0501	0.6682	2.4055	0.1899	0.5824	2.4056	0.4144	0.1631	1.0603	0.7604
Computer peripheral equipment	6	0.0199	1.3021	2.2781	0.1857	0.7407	2.5088	0.3971	0.2258	1.2091	0.7362
Steel/Iron Ore	7	0.0510	0.9485	1.9659	0.2068	0.3539	1.4568	0.3633	0.1541	0.8421	0.5944
Hotels/Resorts	5	0.0168	2.2934	3.7945	0.2869	1.1013	4.1555	0.4829	0.8753	3.8558	1.0000
Biotechnology: In Vitro & In Vivo Diagnostic Substances	5	0.0252	0.4688	1.5839	0.2068	0.8971	3.0465	0.4845	0.4424	2.1666	1.0000
Electronic Components	8	0.0234	0.6777	1.6029	0.1435	0.8915	2.7138	0.2949	0.5627	2.2689	0.4826
Average	9.12	0.0291	0.5353	1.2858	0.1658	0.4416	1.7401	0.3297	0.2537	1.2623	0.5932
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Table 13: Complete result table for TSPRank with local training on NASDAQ.

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Biotechnology: Laboratory Analytical Instruments	5	0.0403	0.5598	2.6040	0.2236	0.5557	3.3714	0.5270	0.4553	3.1498	1.0000
Diversified Commercial Services	9	0.0411	2.4720	2.5039	0.2954	1.0517	3.0297	0.3104	0.8197	3.1495	0.4093
Other Specialty Stores	11	0.0227	0.0245	0.2376	0.0717	0.6322	1.8056	0.2046	0.4220	1.6928	0.3128
Investment Managers	18	0.0117	1.0477	3.4502	0.0886	0.6783	3.7383	0.1346	0.3774	2.6299	0.1689
Electrical Products	13	0.0218	0.4920	1.4221	0.1181	0.2664	1.3944	0.1587	0.3098	1.7686	0.2540
Major Pharmaceuticals Other Pharmaceuticals	18 5	0.0306 0.0092	-0.1847 0.4138	-0.0638 1.5458	0.1814 0.2405	0.3830 0.3732	1.4800 1.9308	0.1917 0.4695	0.2538 0.1719	1.4076 1.0601	0.2024 1.0000
Automotive Aftermarket	10	0.0092	0.4158	1.4042	0.2403	0.3732	1.1375	0.2370	0.1719	0.6515	0.3820
Precious Metals	11	0.0319	0.0474	0.3216	0.0844	0.3152	1.3579	0.1988	0.2239	1.1337	0.3240
Publishing	5	0.0277	-0.1257	-0.7956	0.1519	0.0233	0.2224	0.5159	-0.1218	-0.5510	1.0000
Military/Government/Technical	11	0.0371	0.4694	1.4329	0.1266	0.4552	1.9754	0.2239	0.3242	1.8900	0.3363
Business Services	22	0.0333	0.3364	1.1996	0.0464	0.5007	2.9498	0.1036	0.4044	2.9889	0.1477
Packaged Foods	16	0.0406	0.1458	0.5813	0.0928	0.2060	1.0524	0.1685	0.1690	1.0981	0.2349
Life Insurance	17	0.0239	0.0882	0.6505	0.0211	0.2186	1.7630	0.0924	0.2678	1.9882	0.1652
Power Generation	15	0.0353	0.3675	2.5478	0.0591	0.3169	2.3796	0.1531	0.2577	2.3831	0.2139
Clothing/Shoe/Accessory Stores	15	0.0379	2.3676	2.2979	0.1097	0.9053	1.9437	0.1742	0.4445	1.3033	0.2438
Medical Specialities	11	0.0343	0.7813	2.8202	0.1224	0.5672	3.3380	0.2140	0.4546	3.0373	0.3194
Property-Casualty Insurers Accident &Health Insurance	30 5	0.0075 0.0244	0.0193 0.3087	0.2590 1.8361	0.1266 0.1519	0.1917 0.3655	0.9142 2.0095	0.1240 0.5082	0.1814 0.2645	1.0815 1.7726	0.1435 1.0000
Farming/Seeds/Milling	7	0.0244	0.3846	1.5380	0.1319	0.1224	0.8832	0.3364	0.2643	1.0892	0.5915
Engineering & Construction	5	0.0345	0.1577	0.7986	0.1561	0.2455	1.1889	0.5277	-0.0339	-0.0130	1.0000
Aerospace	9	0.0247	0.7391	1.9837	0.1308	0.5730	2.8210	0.2447	0.4335	2.6282	0.4132
Industrial Specialties	9	0.0156	0.4662	1.8216	0.0928	0.5138	2.5086	0.2639	0.3418	2.0486	0.4138
Specialty Insurers	6	0.0518	0.3274	1.8225	0.2068	0.3344	3.0660	0.3997	0.2600	2.6415	0.7428
Major Chemicals	29	0.0202	0.7541	2.2509	0.0549	0.5005	2.7419	0.0898	0.5291	3.3371	0.1152
Integrated oil Companies	19	0.0167	0.9524	2.2709	0.0886	0.7087	2.8509	0.1526	0.3655	2.0313	0.1893
Air Freight/Delivery Services	8	0.0177	0.4120	1.2900	0.1561	0.4939	2.1393	0.3075	0.2120	1.0822	0.4611
Auto Parts:O.E.M.	18	0.0392	0.2733	0.9433	0.1139	0.1944	0.9760	0.1296	0.3378	1.7314	0.1898
Metal Fabrications	23	0.0090	0.4761	3.1351	0.0169	0.3988	2.1217	0.0830	0.1986	1.1345	0.1143
Professional Services	11	0.0415	0.4349	1.4948	0.1646	0.6978	3.2171	0.2356	0.6156	3.2783	0.3452
Consumer Electronics/Appliances Fluid Controls	6 7	0.0272 0.0474	0.1768 0.8668	0.8642 1.9553	0.2194 0.2194	0.3083 0.4234	2.0561 1.9204	0.4058 0.3397	0.0786 0.3069	0.7728 1.6782	0.7263 0.6052
Other Consumer Services	17	0.0179	0.5385	1.3441	0.0717	0.2641	1.2278	0.1350	0.5152	2.2771	0.1867
Steel/Iron Ore	9	0.0231	0.7430	1.3593	0.1435	0.5142	1.6196	0.2548	0.3780	1.4982	0.4237
Oil/Gas Transmission	6	0.0322	0.2737	1.7428	0.1519	0.2241	2.0204	0.3973	0.1256	1.2338	0.7301
Plastic Products	6	0.0838	0.5736	2.0377	0.2068	0.5182	3.0642	0.4416	0.4475	3.2359	0.7683
Agricultural Chemicals	7	0.0226	0.1401	1.3763	0.0844	0.0105	0.1532	0.3488	-0.0051	0.0369	0.6279
Containers/Packaging	9	0.0385	0.6422	2.6688	0.2110	0.4324	2.8012	0.2700	0.3217	2.6081	0.4249
Water Supply	7	0.0570	0.3788	1.2039	0.1983	0.3926	2.0605	0.3439	0.4456	2.4154	0.6084
Finance: Consumer Services	20	0.0160	0.9140	2.1926	0.0970	0.4886	2.4532	0.1188	0.1702	1.2730	0.1705
Commercial Banks	21	0.0188	0.0495	0.7665	0.0169	0.1185	1.1677	0.0546	0.1436	1.4201	0.0947
Medical/Dental Instruments	12	0.0101	0.7262	3.7107	0.1013	0.5041	3.1897	0.1854	0.2896	1.9492	0.2843
Computer Software: Prepackaged Software	11 9	0.0342 0.0240	0.3481 0.8635	1.5806 2.6404	0.0928 0.1603	0.6486 0.1772	3.3962	0.1925 0.2635	0.4644 -0.0090	2.7707 0.0016	0.3269 0.4166
Oil Refining/Marketing Hotels/Resorts	10	0.0240	0.8493	3.3624	0.1603	0.1772	1.1876 2.1728	0.2833	0.3277	2.3952	0.3793
Restaurants	7	0.0654	0.6800	2.9722	0.1131	0.2561	1.9646	0.3556	0.0743	0.6134	0.6355
Department/Specialty Retail Stores	8	0.0213	0.2109	0.7823	0.1561	0.1482	0.7635	0.2872	0.0783	0.5165	0.4944
Marine Transportation	14	0.0413	0.3574	0.9199	0.1519	0.3326	1.4241	0.1847	0.3045	1.6041	0.2481
EDP Services	11	0.0313	0.5444	1.1215	0.2447	0.4464	1.7959	0.2302	0.2479	1.2955	0.3362
Hospital/Nursing Management	10	0.0296	0.4994	1.5208	0.0928	0.4827	1.5102	0.2201	0.3523	1.2736	0.3718
Savings Institutions	6	0.0238	0.0890	0.5546	0.1857	0.2552	1.7050	0.4058	0.1622	1.4018	0.7484
Investment Bankers/Brokers/Service	13	0.0301	0.1306	0.6194	0.1139	0.3248	1.6569	0.1985	0.2423	1.3841	0.2842
Meat/Poultry/Fish	5	0.0244	0.3557	1.7454	0.1350	0.2320	1.7939	0.5115	0.0990	0.8471	1.0000
Beverages (Production/Distribution)	12	0.0224	0.1657	0.7928	0.1055	0.2767	1.8955	0.2189	0.3159	2.6596	0.2953
Homebuilding	16	0.0198	1.2634	2.6371	0.1139	1.1338	4.2467	0.1624	0.8278	3.7611	0.2217
Shoe Manufacturing	5	0.0412 0.0389	0.6360	1.1819	0.2110	0.5264 0.5174	1.6604	0.5075	0.3139 0.5055	1.3117 2.1878	1.0000 0.7595
Construction/Ag Equipment/Trucks Real Estate	6 13	0.0389	0.5224 0.5298	1.4423 1.8985	0.1730 0.1097	0.3496	2.1491 2.1786	0.3830 0.1953	0.3528	2.1878	0.7595
Package Goods/Cosmetics	10	0.0401	0.5845	1.4541	0.1730	0.4727	2.1772	0.2637	0.2672	1.7438	0.3694
Oilfield Services/Equipment	8	0.0285	-0.1387	-0.4397	0.0928	-0.0712	-0.2511	0.2520	-0.1750	-0.7463	0.5034
Paper	8	0.0297	0.8200	2.5088	0.2194	0.4023	1.8222	0.3010	0.2678	1.4775	0.4899
Mining & Quarrying of Nonmetallic Minerals (No Fuels)	6	0.0490	0.4848	1.1827	0.3080	0.1191	0.6274	0.4039	0.0349	0.2884	0.7267
Railroads	10	0.0199	0.4851	1.4619	0.1350	0.4577	2.4256	0.2414	0.3471	2.0814	0.3683
Home Furnishings	8	0.0198	0.3184	1.0925	0.1899	0.2273	1.0715	0.2979	0.1034	0.6607	0.4743
Apparel	10	0.0177	0.2459	0.9315	0.0970	0.1652	0.8444	0.2199	0.2379	1.2735	0.3689
Office Equipment/Supplies/Services	9	0.0385	0.1088	0.5265	0.1392	0.1758	0.9885	0.2579	-0.0792	-0.3433	0.4275
Forest Products	5	0.0521	0.8712	1.9437	0.2363	0.6435	2.6611	0.5234	0.3948	1.9793	1.0000
Auto Manufacturing	9	0.0460	0.5626	1.7120	0.2068	0.4137	2.4364	0.2571	0.3849	2.3002	0.4122
Services-Misc. Amusement & Recreation	6	0.0585	0.5954	2.6355	0.1772	0.5220	3.4206	0.4334	0.3573	2.7303	0.7524
Semiconductors	5	0.0429	0.6257	2.3595	0.1519	0.5468	2.3792	0.5202	0.3035	1.5702	1.0000
Average	10.97	0.0313	0.5012	1.5710	0.1424	0.3974	1.9735	0.2756	0.2788	1.6662	0.4680

Table 14: Complete result table for TSPRank with local training on NYSE.

Computer Manufacturing 5 0.0462 0.7131 2.6391 0.1941 0.4412 2.6858 0.5063 0.2167 1.3724 1	1.0000
	1.0000
	1.0000
	0.1898
	0.1896
·	1.0000
	0.3079
A A	0.1929
Medical/Nursing Services 6 0.0406 0.2231 0.8829 0.1857 0.5104 2.0530 0.4067 0.3734 1.6074 0	0.7533
	0.4305
Real Estate Investment Trusts 8 0.0606 0.2353 1.3346 0.1266 0.2303 1.6356 0.2996 0.1188 1.0167 0	0.5047
Business Services 17 0.0327 0.9827 2.0224 0.0886 0.4924 2.0209 0.1296 0.5139 2.5909 0	0.1958
Major Pharmaceuticals 29 0.0150 1.3801 1.7649 0.0844 1.1300 2.4818 0.0928 0.6112 1.9240 0	0.1143
Farming/Seeds/Milling 6 0.0557 0.3764 1.2830 0.2152 0.1955 1.0461 0.4126 0.1064 0.7187 0	0.7526
Industrial Specialties 11 0.0219 0.8028 1.9248 0.1013 1.1003 3.2369 0.2295 0.6864 2.9025 0	0.3320
Air Freight/Delivery Services 6 0.0182 0.1825 0.6729 0.1646 0.3296 1.3477 0.4015 0.0836 0.4943 0	0.7340
Electrical Products 13 0.0237 1.3353 2.4725 0.0970 0.8455 2.7356 0.1866 0.5791 2.3875 0	0.2745
Television Services 8 0.0552 0.8375 2.4448 0.1941 0.3247 1.4238 0.3315 0.0965 0.5797 0	0.5135
Investment Bankers/Brokers/Service 18 0.0392 1.2698 3.2572 0.0802 0.9476 2.9791 0.1796 0.6891 3.1783 0	0.2325
Catalog/Specialty Distribution 7 0.0486 2.0857 2.9492 0.1435 0.6505 1.9303 0.3586 0.3549 1.4601 0	0.6089
	0.1627
· ·	0.4193
	0.7706
	0.3295
e e	0.3792
· · ·	1.0000
	0.5008
	0.6400
	0.5228
	0.6468
	0.1650
	0.7566
	1.0000
	0.7240
	0.7240
· · · · · · · · · · · · · · · · · · ·	
**	0.5303
	0.7624 1.0000
1	
	0.5028
	1.0000
	1.0000
	1.0000
	0.7574
e a constant of the constant o	0.5915
	0.2896
	0.7675
	0.7476
	0.5988
	1.0000
6,	1.0000
ı.	0.5051
Average 9.12 0.0447 0.7849 1.7471 0.1633 0.5224 2.0359 0.3364 0.2937 1.4331 0	0.5999

Table 15: Complete result table for TSPRank with global training on NASDAQ.

Sector	Stocks	τ	IRR@1	SR@1	MAP@1	IRR@3	SR@3	MAP@3	IRR@5	SR@5	MAP@5
Biotechnology: Laboratory Analytical Instruments	5	0.0454	0.5059	2.8110	0.1983	0.4805	3.2350	0.5251	0.4553	3.1498	1.0000
Diversified Commercial Services	9	0.0287	0.6134	1.6824	0.1603	0.7515	2.5416	0.2771	0.5597	2.3811	0.4168
Other Specialty Stores	11	0.0426	0.4883	1.1274	0.1266	0.7789	2.1611	0.2180	0.4915	1.7811	0.3265
Investment Managers	18	0.0319	0.8985	3.0370	0.0844	0.5710	2.9765	0.1282	0.5072	3.0107	0.1797
Electrical Products	13	0.0364	0.5099	1.8447	0.1097	0.3411	1.9502	0.1793	0.3041	1.8406	0.2766
Major Pharmaceuticals Other Pharmaceuticals	18 5	0.0484 0.0462	0.3468	0.8992	0.1392 0.2743	0.5776 0.3309	2.5628 1.6992	0.1620 0.4883	0.3553 0.1719	2.0901	0.2052 1.0000
Automotive Aftermarket	10	0.0462	0.4623 0.3244	1.6864 1.1962	0.2743	0.3309	0.9214	0.4883	0.1719	1.0601 0.7006	0.3639
Precious Metals	11	0.0370	0.8095	2.1805	0.1200	0.1897	2.6943	0.2344	0.1202	2.0062	0.3355
Publishing	5	0.0504	-0.1658	-0.1896	0.2869	-0.0292	0.0094	0.4887	-0.1218	-0.5510	1.0000
Military/Government/Technical	11	0.0340	0.0927	0.4890	0.1477	0.2599	1.5451	0.2105	0.2256	1.6561	0.3416
Business Services	22	0.0314	0.7742	2.5470	0.0886	0.6654	3.7382	0.1331	0.5076	3.6890	0.1686
Packaged Foods	16	0.0275	0.0566	0.3738	0.0970	0.2547	1.5930	0.1460	0.2264	1.7117	0.2216
Life Insurance	17	0.0325	0.9913	2.8119	0.0886	0.2141	1.4321	0.1486	0.2798	2.0832	0.1960
Power Generation	15	0.0410	-0.0439	-0.0996	0.0675	0.1298	1.1274	0.1535	0.1802	1.5840	0.2119
Clothing/Shoe/Accessory Stores	15	0.0456	1.2433	1.6214	0.1055	0.6930	1.5866	0.1737	0.3455	1.1032	0.2485
Medical Specialities	11	0.0271	0.4398	1.7652	0.0802	0.5340	3.1256	0.1995	0.4774	3.0575	0.3153
Property-Casualty Insurers	30	0.0142	0.2757	0.8266	0.0886	0.2229	1.2077	0.0879	0.1546	1.0534	0.1065
Accident &Health Insurance	5	0.0286	0.1709	1.0124	0.1435	0.2999	1.9586	0.5124	0.2645	1.7726	1.0000
Farming/Seeds/Milling Engineering & Construction	7 5	0.0310 0.0437	0.1738 0.2857	0.8761 1.1477	0.1814 0.1519	0.2130 0.3424	1.4021 1.2229	0.3345 0.5270	0.0954 -0.0339	0.7925 -0.0130	0.5989 1.0000
Engineering & Construction Aerospace	9	0.0437	0.2857	2.4841	0.1319	0.3424	2.5592	0.5270	0.3839	2.5218	0.4233
Industrial Specialties	9	0.0411	0.6488	0.6053	0.1392	0.4342	2.5392	0.2632	0.3839	2.5218	0.4233
Specialty Insurers	6	0.0346	0.1339	2.9815	0.1361	0.3912	3.5052	0.4156	0.2610	2.5276	0.7635
Major Chemicals	29	0.0742	0.4391	1.3614	0.2521	0.5311	2.4851	0.4130	0.4246	2.4869	0.1054
Integrated oil Companies	19	0.0298	0.5355	1.4804	0.0759	0.3828	1.8127	0.1322	0.2732	1.6078	0.1797
Air Freight/Delivery Services	8	0.0354	0.8190	2.0955	0.1857	0.4494	2.0238	0.2972	0.2071	1.1508	0.4734
Auto Parts:O.E.M.	18	0.0282	0.6774	2.4992	0.0844	0.2974	1.6579	0.1238	0.2797	1.5649	0.1822
Metal Fabrications	23	0.0315	1.1879	2.4235	0.1266	0.3417	1.4612	0.1414	0.2625	1.3513	0.1663
Professional Services	11	0.0516	1.2433	2.7674	0.1350	0.3915	2.0929	0.2042	0.3667	2.1894	0.3435
Consumer Electronics/Appliances	6	0.0434	0.0869	0.5293	0.1730	0.2392	1.6402	0.3926	0.1074	0.9977	0.7422
Fluid Controls	7	0.0458	0.7086	3.1057	0.1857	0.3542	1.9654	0.3476	0.2994	1.8719	0.6313
Other Consumer Services	17	0.0284	0.2415	0.7103	0.1055	0.0138	0.1909	0.1676	0.3256	1.6478	0.2158
Steel/Iron Ore	9	0.0238	0.9439	1.6691	0.1181	0.3774	1.2905	0.2536	0.3934	1.5161	0.4125
Oil/Gas Transmission	6	0.0580	0.3785	1.7910	0.1772	0.2577	2.1271	0.4144	0.1777	1.6504	0.7406
Plastic Products	6 7	0.0726 0.0618	0.3942 0.0953	1.6841 0.5161	0.1646 0.1266	0.5777 0.2795	3.5004 1.5774	0.4369 0.3643	0.3581 0.0391	2.5870 0.3648	0.7513 0.6268
Agricultural Chemicals Containers/Packaging	9	0.0018	0.0613	0.5496	0.1200	0.3036	2.4296	0.3043	0.0391	2.6423	0.4258
Water Supply	7	0.0570	0.4097	1.4196	0.2025	0.8891	3.7332	0.3591	0.4585	2.5417	0.6079
Finance: Consumer Services	20	0.0433	0.5376	2.0062	0.0886	0.2829	1.6800	0.1111	0.2882	2.0748	0.1659
Commercial Banks	21	0.0217	0.5504	2.0888	0.0802	0.5011	2.9425	0.1217	0.3375	2.5244	0.1625
Medical/Dental Instruments	12	0.0313	0.1891	1.0436	0.0759	0.4168	2.7722	0.1833	0.4027	2.8406	0.2830
Computer Software: Prepackaged Software	11	0.0261	0.7705	2.1522	0.0844	0.6469	3.1697	0.2011	0.4349	2.3852	0.3323
Oil Refining/Marketing	9	0.0593	0.7053	2.2314	0.1224	0.3295	1.6251	0.2555	0.1965	1.2611	0.4422
Hotels/Resorts	10	0.0402	0.1859	0.9010	0.1181	0.5225	3.0131	0.2403	0.4942	3.4102	0.3747
Restaurants	7	0.0682	0.1222	0.6333	0.1561	0.0546	0.4712	0.3378	0.1528	1.1004	0.6384
Department/Specialty Retail Stores	8	0.0555	0.3472	1.0299	0.1519	0.2370	0.9831	0.2977	0.2523	1.1683	0.5081
Marine Transportation	14	0.0361	0.5846	1.4050	0.1392	0.2815	1.3936	0.1765	0.2895	1.6238	0.2451
EDP Services	11	0.0468	0.6478	1.7467	0.1224	0.2712	1.2282	0.2332	0.2565	1.3250	0.3540
Hospital/Nursing Management	10	0.0399	0.0487	0.3412	0.0464	0.3271	1.2364	0.2157	0.2169	0.9386	0.3695
Savings Institutions	6	0.0546	-0.0320	-0.0924	0.1561	0.2396	1.9658	0.4027	0.1941 0.2408	1.7806	0.7720
Investment Bankers/Brokers/Service	13 5	0.0233 0.0723	0.1814 0.1941	0.7968 1.0074	0.1139 0.2068	0.2372 0.2952	1.2043 1.8236	0.1967 0.5122	0.2408	1.3483 0.8471	0.2689 1.0000
Meat/Poultry/Fish Beverages (Production/Distribution)	12	0.0723	0.1941	1.4588	0.2068	0.2932	2.8449	0.3122	0.0990	2.9831	0.2874
Homebuilding	16	0.0433	1.2737	2.8299	0.0970	1.0350	3.6869	0.1629	1.0061	4.1459	0.2241
Shoe Manufacturing	5	0.0630	2.4099	2.3840	0.2700	0.6841	1.9317	0.5136	0.3139	1.3117	1.0000
Construction/Ag Equipment/Trucks	6	0.0445	1.1036	2.3375	0.1899	0.5665	2.0795	0.4158	0.3165	1.4641	0.7446
Real Estate	13	0.0218	0.3852	1.8531	0.0464	0.3056	2.0952	0.1261	0.2149	1.7090	0.2573
Package Goods/Cosmetics	10	0.0684	0.5788	2.1845	0.1392	0.4712	2.9352	0.2482	0.3153	2.2773	0.3878
Oilfield Services/Equipment	8	0.0453	0.1043	0.5019	0.1181	0.0309	0.2552	0.2832	-0.0842	-0.2748	0.5072
Paper	8	0.0654	0.1922	0.8538	0.1392	0.3425	1.7754	0.3228	0.2166	1.2878	0.5110
Mining & Quarrying of Nonmetallic Minerals (No Fuels)	6	0.0535	0.0412	0.2960	0.1561	0.2562	1.2813	0.4196	0.0165	0.1869	0.7555
Railroads	10	0.0324	0.0023	0.1227	0.0928	0.3475	2.1375	0.2307	0.1976	1.4698	0.3561
Home Furnishings	8	0.0360	0.5031	1.2453	0.2110	0.3288	1.5796	0.3073	0.2074	1.2672	0.4880
Apparel	10	0.0296	0.0734	0.4790	0.0759	0.3282	1.8800	0.1871	0.3780	2.1074	0.3702
Office Equipment/Supplies/Services	9	0.0479	-0.1323	-0.2453	0.1477	0.1893	0.9815	0.2722	-0.0432	-0.1300	0.4131
Forest Products	5	0.0639	0.9512	2.0830	0.2616	0.6872	2.6944	0.5047	0.3948	1.9793	1.0000
Auto Manufacturing	9	0.0451	0.4649	1.6525	0.1392	0.3408	2.0907	0.2628	0.2689	1.7380	0.4230
Services-Misc. Amusement & Recreation	6	0.0345	0.4000	1.4716	0.2236	0.4410	2.7912	0.4051	0.3083	2.4364	0.7499
Semiconductors	5 10.07	0.0571	0.9888	2.7414	0.2068	0.4380	1.9950	0.5087	0.3035	1.5702	1.0000
Average	10.97	0.0422	0.4787	1.4552	0.1392	0.3889	1.9976	0.2756	0.2816	1.7350	0.4732

Table 16: Complete result table for TSPRank with global training on NYSE.

		Lan	ıbdaMART				Ra	nkformer				TSP	Rank-Local				TSPI	Rank-Global		
	NDCG@3	NDCG@5	NDCG@10	MRR	Tau	NDCG@3	NDCG@5	NDCG@10	MRR	τ	NDCG@3	NDCG@5	NDCG@10	MRR	Tau	NDCG@3	NDCG@5	NDCG@10	MRR	τ
Fold										Top	p 10									
Fold 1	0.6867	0.7180	0.8702	0.4060	0.1330	0.7218	0.7504	0.8832	0.4280	0.2083	0.6837	0.7227	0.8699	0.3956	0.1346	0.7224	0.7606	0.8883	0.4895	0.2174
Fold 2	0.6651	0.7052	0.8631	0.4379	0.1117	0.7057	0.7469	0.8809	0.4784	0.2045	0.6671	0.7031	0.8668	0.4655	0.1193	0.7162	0.7472	0.8838	0.4706	0.1940
Fold 3	0.6904	0.7337	0.8755	0.4286	0.1782	0.7442	0.7743	0.8968	0.4984	0.2651	0.6936	0.7326	0.8735	0.4153	0.1813	0.7341	0.7678	0.8927	0.4883	0.2444
Fold 4	0.6702	0.7180	0.8657	0.4248	0.1406	0.7082	0.7504	0.8814	0.4413	0.2345	0.6930	0.7247	0.8749	0.4662	0.1655	0.7227	0.7519	0.8847	0.4932	0.2192
Fold 5	0.7043	0.7361	0.8791	0.4324	0.1734	0.7301	0.7605	0.8904	0.4844	0.2459	0.6915	0.7232	0.8742	0.3905	0.1714	0.7483	0.7651	0.8926	0.4887	0.2311
Average	0.6833	0.7222	0.8707	0.4259	0.1474	0.7220	0.7565	0.8865	0.4661	0.2317	0.6858	0.7213	0.8719	0.4266	0.1544	0.7287	0.7585	0.8884	0.4861	0.2212
										Top	p 30									
Fold 1	0.7284	0.7244	0.7410	0.3563	0.2392	0.7214	0.7221	0.7411	0.3535	0.2497	0.7151	0.7230	0.7401	0.3096	0.2515	0.7587	0.7504	0.7604	0.3685	0.2616
Fold 2	0.7097	0.7088	0.7225	0.3564	0.2061	0.7501	0.7466	0.7598	0.3896	0.2970	0.7189	0.7240	0.7362	0.3206	0.2054	0.7521	0.7534	0.7587	0.3945	0.2725
Fold 3	0.7481	0.7397	0.7463	0.3750	0.2409	0.7641	0.7638	0.7665	0.3860	0.2932	0.7288	0.7304	0.7426	0.3061	0.2444	0.7703	0.7612	0.7637	0.4190	0.2686
Fold 4	0.7386	0.7357	0.7421	0.3754	0.2443	0.7271	0.7292	0.7465	0.3526	0.2591	0.7223	0.7233	0.7368	0.3483	0.2294	0.7547	0.7558	0.7635	0.3833	0.2545
Fold 5	0.7453	0.7406	0.7495	0.3456	0.2554	0.7803	0.7733	0.7841	0.3841	0.3178	0.7122	0.7235	0.7425	0.2997	0.2435	0.7550	0.7583	0.7693	0.3820	0.2675
Average	0.7340	0.7298	0.7403	0.3617	0.2372	0.7486	0.7470	0.7596	0.3732	0.2834	0.7195	0.7248	0.7396	0.3169	0.2348	0.7582	0.7558	0.7631	0.3895	0.2649

Table 17: Complete results on MQ2008-list for information retrieval.

		Lambo	daMART			Rank	former			TSPRa	nk-Local			0.6285 0.3275 0.8038 0.6344 0.3400 0.7997 0.6304 0.3339 0.7751 0.6226 0.3310 0.7903 0.6347 0.3428 0.7993 0.6301 0.3350 0.7936 0.6334 0.1378 0.7356 0.6348 0.1351 0.7510 0.6312 0.1419 0.6895 0.6290 0.1349 0.7242 0.6227 0.1423 0.7498 0.6302 0.1384 0.7300 0.6179 0.0821 0.6632 0.6189 0.0834 0.6604 0.6169 0.0901 0.6347 0.6231 0.0886 0.6731		
								Group	Size 10							
Allocation	τ ↑	ЕМ↑	MRR ↑	RMSE ↓	$\tau \uparrow$	ЕМ↑	MRR ↑	RMSE ↓	τ ↑	ЕМ↑	MRR ↑	RMSE ↓	τ ↑	ЕМ↑	MRR ↑	RMSE ↓
1	0.6456	0.3043	0.7813	1.904	0.6269	0.2801	0.7542	1.962	0.5632	0.2909	0.7703	2.369	0.6285	0.3275	0.8038	2.060
2	0.5834	0.2739	0.7504	2.144	0.6196	0.2924	0.7509	2.007	0.5664	0.2682	0.7918	2.226	0.6344	0.3400	0.7997	2.047
3	0.6343	0.3018	0.7534	1.963	0.6144	0.2874	0.7162	2.017	0.5568	0.2917	0.7489	2.356	0.6304	0.3339	0.7751	2.063
4	0.6252	0.3051	0.7431	1.992	0.6123	0.2935	0.7264	2.022	0.5533	0.2632	0.7363	2.274	0.6226	0.3310	0.7903	2.082
5	0.6008	0.2862	0.7538	2.086	0.6217	0.2962	0.7328	1.984	0.5891	0.3138	0.7924	2.255	0.6347	0.3428	0.7993	2.035
Average	0.6297	0.3008	0.7554	1.993	0.6190	0.2899	0.7361	1.998	0.5658	0.2856	0.7679	2.296	0.6301	0.3350	0.7936	2.057
	Group Size 30															
1	0.5947	0.1066	0.6334	5.948	0.5872	0.0905	0.4825	5.945	0.5026	0.0886	0.5416	6.957	0.6334	0.1378	0.7356	5.729
2	0.5882	0.1013	0.6102	6.047	0.5868	0.0880	0.4927	5.980	0.5256	0.0867	0.6039	6.714	0.6348	0.1351	0.7510	5.728
3	0.5856	0.1135	0.6288	6.071	0.5834	0.0930	0.5059	5.984	0.5116	0.0860	0.5677	6.9300	0.6312	0.1419	0.6895	5.748
4	0.6030	0.1013	0.6062	5.838	0.5863	0.0925	0.4826	5.970	0.5043	0.0873	0.6162	7.0420	0.6290	0.1349	0.7242	5.790
5	0.5930	0.1091	0.5822	5.943	0.5858	0.0967	0.4917	5.986	0.5036	0.0879	0.5401	7.0070	0.6227	0.1423	0.7498	5.857
Average	0.5929	0.1064	0.6122	5.969	0.5859	0.0921	0.4911	5.973	0.5095	0.0873	0.5739	6.930	0.6302	0.1384	0.7300	5.770
								Group	Size 50							
1	0.6074	0.0672	0.5694	9.476	0.5717	0.0543	0.3857	10.084	0.4700	0.0460	0.3961	12.149	0.6179	0.0821	0.6632	9.645
2	0.6072	0.0658	0.5418	9.437	0.5747	0.0523	0.3211	10.012	0.4907	0.0463	0.3514	11.693	0.6189	0.0834	0.6604	9.601
3	0.5973	0.0625	0.5435	9.681	0.5741	0.0523	0.3516	10.040	0.4573	0.0404	0.3529	12.406	0.6169	0.0901	0.6347	9.650
4	0.5989	0.0611	0.5581	9.627	0.5710	0.0541	0.3706	10.086	0.4688	0.0481	0.3617	11.994	0.6231	0.0886	0.6731	9.575
5	0.5891	0.0627	0.5852	9.870	0.5705	0.0505	0.3342	10.122	0.4697	0.0490	0.5122	12.179	0.6268	0.0915	0.6774	9.537
Average	0.6000	0.0639	0.5596	9.618	0.5724	0.0527	0.3526	10.069	0.4713	0.0460	0.3949	12.084	0.6207	0.0871	0.6618	9.602

Table 18: Complete results on OTD2 for historical events ordering.