Enhancing Cross-Sectional Currency Strategies by Ranking Refinement with Transformer-based Architectures

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ABSTRACT
The performance of a cross-sectional currency strategy depends crucially on accurately ranking instruments prior to portfolio construction. While this ranking step is traditionally performed using heuristics, or by sorting outputs produced by pointwise regression or classification models, Learning to Rank algorithms have recently presented themselves as competitive and viable alternatives. Despite improving ranking accuracy on average however, these techniques do not account for the possibility that assets positioned at the extreme ends of the ranked list – which are ultimately used to construct the long/short portfolios – can assume different distributions in the input space, and thus lead to sub-optimal strategy performance. Drawing from research in information retrieval that simultaneously enjoys widespread adoption across various commercial applications [25, 32, 39]. While there are numerous studies directed at developing better LTR algorithms and demonstrating their superiority over traditional baselines on US equities.

 CCS CONCEPTS
• Information systems → Learning to rank; • Computing methodologies → Neural networks; • Applied computing → Economics.

KEYWORDS
learning to rank, neural networks, machine learning, information retrieval, foreign exchange markets, quantitative finance

1 INTRODUCTION
Cross-sectional strategies are a popular trading style, with numerous works in academic finance documenting technical variations and their use across different asset classes [5]. Unlike time-series methods which adopt a narrow, longitudinal focus and trade individual assets independently [29], cross-sectional strategies cover a broader slate of instruments and typically involve buying assets with the highest expected returns (Winners) while simultaneously selling those with the lowest (Losers). The classical cross-sectional momentum (CSM) of [20] for instance, was originally applied to equities and assumes the persistence of returns – trading some top segment of stocks against an equally-sized bottom segment after ranking them by returns over the past 12-months. Here we focus on the foreign exchange (FX) market which relative to equities is more liquid, and enjoys larger trading volumes as well as lower transaction costs [27].

The confluence of these factors, and the fact that participants are typically professional investors, raises the bar for generating consistent excess returns over time [27].

Along with the proliferation of machine learning, numerous cross-sectional strategies incorporating advanced prediction techniques such as [18, 19, 21] have been developed. While the regression and classification models utilised by these frameworks can accurately produce mean estimates of future returns, they do not explicitly account for the crucial expected order of returns – which is the key driver of trading performance for these strategies. Addressing this deficiency, [35] propose a novel class of cross-sectional strategies that use LTR (Learning to Rank) algorithms and demonstrate their superiority over traditional baselines on US equities.

At its core, LTR involves the use of machine learning to train models to perform ranking tasks [24]. This is an active area of research within information retrieval that simultaneously enjoys widespread adoption across various commercial applications [25, 32, 39]. While there are numerous studies directed at developing better LTR algorithms, one particular branch concentrates on ranking refinement or re-ranking1. These approaches (for e.g. [2, 31, 44]) generally model the mutual interactions across items contained in an already-ranked list in order to produce another scoring function that is then used to refine the same list. In [2], the authors borrow from the idea of pseudo relevance models and propose to represent each query with its associated top-ranked documents, or local ranking context. They develop the DLCM (Deep Listwise Context Model) that learns a local context embedding by encoding the features

1We will use the terms “ranking refinement” and “re-ranking” interchangeably.
of the top documents obtained by an initial sort, and use this to improve LTR systems under a re-ranking framework. Recognising the limitations of the recurrent neural network (RNN) architecture (i.e., information decay that worsens with encoding distance) at the core of the DLCM, [34] and [31] propose Transformer-based [41] models. By incorporating positional embeddings, [34] further show that this new model is suitable for re-ranking and report significant improvements over DLCM.

In this work, we use the Transformer-based framework employed by [34] for ranking refinement: With an existing set of rankings supplied by a standard LTR algorithm, we cast our problem in the supervised learning setting utilised by LTR. Next, we concretely evaluate our re-ranked results against a mix of the original LTR model and conventional benchmarks. On a set of 31 currency pairs, we demonstrate how the performance profile of the currency CSM strategy can be enhanced by re-ranking.

2 RELATED WORKS

2.1 Cross-sectional Currency Momentum

Momentum strategies can be classified as being either time-series or cross-sectional. In time-series momentum, which was first proposed by [29], an instrument’s trading rule relies only on previous returns. With cross-sectional momentum (CSM), the relative performance of assets is the essence of the strategy—after ranking securities based on some scoring model, the long/short portfolios are constructed by trading the extremes (e.g. top and bottom deciles) of the ranked list. Since [20], which demonstrate the profitability of this strategy on US equities, the literature has been galvanised by a broad spectrum of works—ranging from technical refinements spanning varying levels of sophistication [5, 19, 21, 33] to reports documenting the ubiquity of momentum in different asset classes and markets [13, 15–17, 23, 38]. Unlike the extensive works focused on equity momentum, currency momentum is centred on the time-series of individual currency pairs and is often cast as “technical trading rules” for which [28] provides a broad overview. While studies such as [9, 36] offer evidence of CSM being profitable in FX markets, their results involve trading a narrow cross-section in involving only major pairs and lack a unifying analysis that explains their returns. [27] addresses this research gap and also demonstrate that portfolios constructed by trading the winner/loser segments (analogous to [20] in the equity literature) can generate high unconditional excess returns. The work in [5] adopts a more sophisticated approach by using volatility-scaled moving-average convergence divergence (MACD) indicators as inputs. Beyond this and unlike the comparatively abundant work on equity momentum, we find little published in terms of constructing currency CSM portfolios.

2.2 Learning to Rank

Learning to Rank (LTR) is an active research area within information retrieval focusing on developing models that learn how to sort lists of objects in order to maximise utility. Its prominence grew in parallel with the accessibility of modern computing hard- and software, and its algorithms utilise sophisticated architectures that allow it to learn in a data-driven manner—unlike their predecessors such as BM25 [37] and LMIR [36] which require no training but which instead need handcrafting and explicit design [24]. We point the interested reader to [25] for a comprehensive overview.

Given the widespread adoption of LTR across numerous applications such as search engines, e-commerce [39] and entertainment [32], there is motivation both in academia and industry to develop better models. For example, one broad set of studies propose query-specific ranking which attempts to improve accuracy by modelling query-specific feature distributions. While conceptually appealing, this is infeasible due to cost and generalisation issues arising from a potentially infinite number of possible queries [2]. To get around this intractability, [10] learn ranking models for separate queries during training and combine relevant ones based on the similarity between test and training queries.

Another related direction that is known as re-ranking or ranking refinement concentrates on improving the initial ranking via the extracted features embedded within items. This is paralleled by the well-known pseudo relevance feedback method [22, 43] in language modelling. In the LTR context, these features are typically mutual interactions—either across an entire list of objects which is the approach used by [31, 34] or some subset of it as per [2]. The new scoring function that is subsequently constructed encodes these cross-item dependencies into its input space. [2] for instance propose the Deep Listwise Context Model (DLCM) for LTR which use an RNN with gated recurrent units to perform encoding. With this setup, they simultaneously tackle the earlier intractability issue by modelling and using the local ranking context of test queries on the fly. A major drawback with RNN-based approaches however, is that the encoded feature information degrades with encoding distance. Motivated by Transformer [41] architectures as a workaround, [31] and [34] utilise an adapted variant—exploiting both the self-attention mechanism that learns the inter-item dependencies without any decay of information over encoding distance, as well as the encoding procedure that allows for parallelisation [31]. By incorporating positional encodings, [34] demonstrates that this modification allows the model to perform re-ranking.

Surveying the LTR-related literature on finance, we note that published works such as [35, 40, 42] apply a single layer of ranking and make no further attempts to refine the sorted outputs. Given the comparative advantages of the Transformer-based architecture used by [31, 34] for re-ranking, we adopt their model and demonstrate that additional gains can be extracted in the context of the currency CSM strategy. We apply this model to refine the outputs produced by LambdaMART [8] and ListNet [11]—which are both well known and performant LTR algorithms—and concretely evaluate their re-ranked performance against a mixture of the original LTR algorithms and traditional baselines.

3 PROBLEM DEFINITION

For a given portfolio of currencies that is rebalanced daily, the returns for a cross-sectional momentum (CSM) strategy at day $t$ can be expressed as follows:

$$ r_{CSM}^{t+1} = \sum_{i=1}^{n} \frac{X_t(i)}{\sigma_t(i)} \sigma_t(i)$$

### Note

We use the terms 'currency CSM' and 'cross-sectional currency momentum' interchangeably.
where \( r_{t,t+1}^{CSM} \) denotes the realised portfolio returns going from day \( t \) to \( t+1 \), \( n \) refers to the number of currency pairs in the portfolio and \( \chi_{t}^{(i)} \in \{-1, 0, 1\} \) signifies the cross-sectional momentum signal or trading rule for pair \( i \). The annualised target volatility \( \sigma_{tgt} \) is set at 15% and asset returns are scaled with \( \sigma_{t}^{(i)} \) which is an estimator for ex-ante daily volatility. For simplicity we use a rolling exponentially weighted standard deviation with a 63-day span on daily returns for \( \sigma_{t}^{(i)} \), and note that other sophisticated methods such as GARCH [7] can be employed.

The flow diagrams in Figure 1 provides a high-level overview of the CSM strategy pipeline under both LTR and Ranking Refinement frameworks. Under the former, an LTR\(^3\) scoring function \( f \) computes scores before passing the results into separate Ranking and Selection components. With Re-ranking however, an additional refinement step that seeks to improve the accuracy of the ranking index vector \( Z^X \) is introduced prior to Selection. In the next section, we formalise the Ranking Refinement problem setting.

### 3.1 Ranking Refinement Formulation

The goal of improving the accuracy of an initial ranked list of currency instruments by re-ranking is essentially a Learning to Rank problem. Given this, we begin with a training set \( \Psi = \{(x, y) \in \mathbb{R}_n^m \times \mathbb{R}_n^m\} \). Here, \( x = \{x_1, \ldots, x_n\} \) is a list of \( n \) currency instruments, and each \( x_i \in x \) is a feature vector for currency \( i \). Additionally, \( y \) is an accompanying vector of decile portfolio labels for the following day, and \( C \) is our universe of tradable currencies. Given the LTR objective of learning a scoring function \( f(\cdot; \Theta) : \mathbb{R}_n^m \rightarrow \mathbb{R}_n^m \), we achieve this by minimising the empirical loss:

\[
\mathcal{L}(f) = \frac{1}{|\Psi|} \sum_{(x,y) \in \Psi} t(y, f(x))
\]

and note that \( f \) is parameterised by \( \Theta \) and \( t(\cdot) \) is a loss function. Ranking refinement, which can be thought of as a special case of LTR, uses an \( m \)-sized list \( x = \{x_1, \ldots, x_m\} \) obtained after an initial round of ranking where each \( x_i \in x \) as before. Additionally, [34] and [31] set \( m = n \) and re-rank the entire list, while others such as [2] use \( m < n \) and instead focus on refining the top \( m \) segment of the original list.

Referring to Equation 2, we note that algorithms that are used in both the initial and re-ranking scenarios are differentiated by their choice of \( f \) and \( t \). In this work, we use the Transformer-based architecture proposed by [34] as \( f \) for ranking refinement, set \( t \) as the listwise loss, and concentrate on re-ranking some \( m < n \) top/bottom ranked currency instruments to form corresponding long/short portfolios.

### 4 RANKING REFINEMENT MODEL

In this section, we explain the Ranking Refinement model as applied to improving long positions and note that the refining procedure is similar for shorts. Presented with an initial list of \( m \) top-retrieved currencies produced by a standard LTR algorithm, we want to learn a scoring function that refines this list by incorporating information across items. We next discuss key components of our model that allow this to be accomplished.

#### 4.1 Model Inputs

Inputs comprise of a list of \( m \) currencies \( x \) after an initial round of ranking by a standard LTR algorithm.

##### 4.1.1 Positional Encodings

To exploit the information about relative positions contained in the initial sort, we add positional encodings to the input embeddings that have passed through a first round of sort. While [41] propose both fixed and learnable positional encodings to encode item order in a list, we use the former which is given as:

\[
PE_{(pos_{2i})} = \sin\left(\frac{pos}{10000^{((2i)/d_{model})}}\right)
\]

\[
PE_{(pos_{2i+1})} = \cos\left(\frac{pos}{10000^{((2i)/d_{model})}}\right)
\]

where \( pos \) denotes the item’s position, \( i \) is an element belonging to an embedding dimension index.

#### 4.2 Encoder Layer

The Encoder layer facilitates learning higher-order representations of items in the list, and it accomplishes this by employing the attention mechanism and a feed-forward network alongside various techniques such as dropouts, residual connections and layer normalisation. A schematic of a single encoder layer is shown on the left of Figure 2.

##### 4.2.1 Self-Attention Mechanism

This is the key component in the Transformer architecture that allows representations of items to be
constructed. While there are different ways of computing attention (e.g. [3, 26]), we use the form known as Scaled Dot-Product:

$$\text{Att}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_{\text{model}}}} \right) V$$

(5)

where $Q$ is a query matrix of dimension $d_{\text{model}}$ that contains all items in the list, $K$ and $V$ are respectively the key and value matrices, and lastly $\frac{1}{\sqrt{d_{\text{model}}}}$ is a scaling factor to mitigate issues arising from small gradients in the softmax operator.

The model’s capacity to learn representations can be further enhanced by ensembling multiple attention modules in what [41] refers to as multi-head attention:

$$\text{MHA}(Q, K, V) = \text{concat}(\text{head}_1, ..., \text{head}_h)W^O$$

(6)

$$\text{head}_i = \text{Att}(QW^Q_i, KW^K_i, VW^V_i)$$

(7)

here, each head (out of $h$ heads) refers to the $i$th attention mechanism of Equation 5, and learned parameter matrices:

$$W^Q_i \in \mathbb{R}^{d_{\text{model}} \times d_q}, \quad W^K_i \in \mathbb{R}^{d_{\text{model}} \times d_k}, \quad W^V_i \in \mathbb{R}^{d_k \times d_{\text{model}}}$$

where typically $d_q = d_k = d_v = d_{\text{model}}/h$ is used.

4.2.2 Feed-Forward Network/Multilayer Perceptron (MLP). This component introduces non-linearity via its activation and facilitates interactions across different parts of the inputs.

4.2.3 Stacking Encoder Layers. A single encoder block $\xi(\cdot)$ can be expressed as:

$$\xi(x) = \Gamma(z + \delta(\phi(z)))$$

(8)

$$z = \Gamma(x + \delta(\text{MHA}(x)))$$

(9)

where $\Gamma(\cdot)$ and $\delta(\cdot)$ are respectively the layer normalisation and dropout functions. Additionally, $\phi(\cdot)$ represents a projection onto a fully-connected layer, and MHA(·) is the multi-head attention module. Stacking multiple encoder layers iteratively feeds an encoder’s output into the next, and this grows the model’s ability to learn more complex representations:

$$\xi(x) = \xi_1(\ldots(\xi_N(x)))$$

(10)

where $\xi(x)$ in Equation 10 above denotes a stacked encoder involving a series of $N$ encoder layers.

4.3 Model Architecture

Identical to [34], our Re-ranking model closely resembles the Transformer’s encoder component. Presented with a list of top-ranked currencies provisioned by an initial ranker, we pass each input through a fully connected layer of size $d_{fc}$. Next, we feed this through $N$ stacked encoders before sending the results to another fully-connected layer that is used to compute scores. This entire pipeline can be compactly expressed as:

$$f(x) = \phi_{\text{output}}(\xi(\phi_{\text{input}}(x)))$$

(11)

and is graphically represented on the right of Figure 2.

5 PERFORMANCE EVALUATION

5.1 Dataset Overview

Using daily data obtained from the Bank for International Settlements (BIS) [4], we construct our daily portfolios using the same set of 31 currencies used in [5]. Our study spans 2000 to 2020 with the USD set as the quote currency (i.e. how much USD is required to buy 1 unit of foreign currency).

5.2 Backtest and Predictor Description

Both LTR models and the MLP are tuned in blocks of 5-year intervals, with the calibrated weights and hyperparameters fixed and then used for portfolio rebalancing in the following out-of-sample 5-year window. Following [5], we rebalance daily and form equally weighted long/short portfolios with six currencies (i.e. using the 3 most extreme pairs on each side).

For predictors, we use a simple combination of returns-based features:

(1) 1-month raw returns – Based on the best model in [27], which involves scoring instruments based on returns calculated over the previous one month.

(2) Normalised returns – Returns over the past 1, 3, 5, 10 and 21-day periods standardised by daily volatility and then scaled to the appropriate time scale.

(3) MACD-based indicators – Final momentum trading indicator along with its constituent raw signals as defined in [5] and [35].

5.3 Models and Comparison Metrics

The LTR and benchmark algorithms (with their corresponding shorthand in parentheses) used in this paper are:

(1) Random (Rand) - Buys/sells at random. Included to give some absolute baseline sense of performance.

(2) Volatility Normalised MACD (Baz) - Heuristics-based ranker with a sophisticated trend estimator proposed by [5].
5.4 Results and Discussion

Cumulative returns for all strategies are plotted in Figure 3, and various measures of financial performance are listed in Table 1. To facilitate comparing strategies, we introduce an additional layer of volatility scaling at the portfolio level—aligning returns with our 15% volatility target. All returns are computed in the absence of transaction costs to focus on the models’ raw predictive ability. From both the returns plot and performance figures, we see that re-ranked algorithms, i.e. those that undergo ranking refinement, outperform various comparator models on the majority of performance measures.

Across figures in Table 1, we discern a broad trend of LTR-based models outperforming the benchmarks—with re-ranked LTR models further surpassing their original LTR counterparts. Looking first at profitability, the best re-ranked model (LM.R) return is approximately double the best benchmark (1MR). On a risk-basis, while all models exhibit similar levels of returns volatility and downside deviation, the benchmarks generally fared worse in terms of MDD with Random suffering nearly a 70% loss on portfolio equity at its lowest point. Finally, it is evident that re-ranked models outperform the baselines on financial performance.

Across benchmarks, we see that MLP is inferior to both 1MR and Baz despite its relatively sophisticated construction involving a neural network architecture. We suspect that this might be due to a combination of factors—over-fitting arising from working with limited and noisy data, as well as the sub-optimality of MLP’s regress-then-rank approach [35]. Furthermore, the MLP is essentially forecasting daily returns and this has been regarded as a difficult problem [14] that is exacerbated by the fact that all models studied in this work are confined to only using price-based data. Finally among re-ranked and LTR models, we note that the ‘poorer’ re-ranked model (LLR) is unable to surpass the best LTR benchmark (LM) —suggesting that the extent to which performance can be improved via re-ranking is limited.

6 CONCLUSION

In the context of the currency CSM strategy, LTR algorithms outperform contemporary methods and produce accurate rankings on average. Given their construction, however, they fail to account for the possibility that extreme assets—which are ultimately used to construct the trading portfolios—might be distributed differently in the feature space. We demonstrate in this work how Transformers can be adapted to encode the features of these extreme instruments, with the results subsequently used to re-rank an initial ranking produced by ListNet and LambdaMART, both of which are well-known and performant LTR algorithms. Backtesting on a slate of 31 currencies, our proposed methodology significantly boosts Sharpe ratios—by about 20% over the original LTR models and double versus traditional baselines.

New directions for future work includes conducting a comprehensive performance study of re-ranked LTR models across a wider set loss functions, innovating on the underlying Transformer-based architecture and validating this re-ranking technique on different data sets (e.g. higher frequency LOB data).

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Figure 3: Log Cumulative Returns of all Algorithms - Rescaled to Target Volatility.
Table 1: Performance Metrics – Rescaled to Target Volatility.

| Benchmarks | LTR | Ranking Ref. |
|------------|-----|---------------|
| Rand       | Baz  | 1MR | MLP | LI | LM | LLR | LM.R |
| E[returns] | -0.049 | 0.077 | 0.100 | 0.050 | 0.124 | 0.172 | 0.148 | *0.198 |
| Volatility | 0.157 | 0.158 | 0.158 | *0.156 | 0.160 | 0.158 | 0.156 | 0.157 |
| Sharpe     | -0.315 | 0.491 | 0.635 | 0.317 | 0.772 | 1.086 | 0.945 | *1.261 |
| Downside Dev. | 0.114 | 0.106 | 0.107 | 0.109 | 0.107 | 0.105 | 0.107 | *0.103 |
| MDD        | 0.671 | 0.403 | 0.355 | 0.360 | 0.283 | 0.356 | *0.240 | 0.331 |
| Sortino    | -0.432 | 0.728 | 0.939 | 0.453 | 1.159 | 1.640 | 1.379 | *1.911 |
| Calmar     | 0.074 | 0.192 | 0.283 | 0.138 | 0.437 | 0.483 | *0.616 | 0.596 |
| % +ve Returns | 0.496 | 0.519 | 0.520 | 0.516 | 0.517 | 0.529 | 0.527 | *0.531 |
| Avg. P / Avg. L | 0.962 | 1.008 | 1.027 | 0.989 | 1.068 | 1.071 | 1.052 | *1.095 |

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A CURRENCY DATASET DETAILS

Following [5], we work with 31 currencies with the USD expressed as the quote currency (i.e. the amount of USD per one unit of foreign currency) over the period 2-May-2000 to 31-Dec-2020. The full currency list is as follows:

- G10: AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, USD
- EM Asia: HKD, INR, IDR, KRW, MYR, PHP, SGD, TWD, THB
- EM Latam: BRL, CLP, COP, PEN, MXN
- CEE/EMEA: CZK, HUF, ILS, PLN, RUB, TRY
- Africa: ZAR

In order to reduce the impact of outliers, we winsorise the data by capping and flooring it to be within 3 times its exponentially weighted moving (EWM) standard deviation from its EWM average that is calculated using a 252-day span.

B ADDITIONAL TRAINING DETAILS

Python Libraries: LambdaMART uses XGBoost [12], while both ListNet and MLP are developed using TensorFlow [1].

Hyperparameter Optimisation: Hyperparameters assume discrete values and are tuned using HyperOpt [6]. For LambdaMART, we refer to the hyperparameters as they are named in the XGBoost library.

Multi-layer Perceptron (MLP):
- Dropout Rate – [0.2, 0.4, 0.6, 0.8]
- Hidden Width – [128, 256, 512, 1024]
- Learning Rate – [10⁻¹, 10⁻², 10⁻³, 10⁻⁴]
- Minibatch Size – [60, 120, 240, 480]

LambdaMART:
- ‘objective’ – ‘rank:pairs:wise’
- ‘eval_metric’ – ‘ndcg’
- ‘eta’ – [10⁻⁶, 10⁻⁵, 10⁻⁴, 10⁻³, 10⁻², 10⁻¹, 1]
- ‘num_boost_round’ – [5, 10, 20, 40, 80, 160, 320]
- ‘max_depth’ – [2, 4, 8, 16, 32]
- ‘reg_alpha’ – [10⁻⁵, 10⁻⁴, 10⁻³, 10⁻², 10⁻¹]
- ‘reg_lambda’ – [10⁻⁵, 10⁻⁴, 10⁻³, 10⁻², 10⁻¹]
- ‘tree_method’ – ‘gpu_hist’

ListNet:
- Dropout Rate – [0.2, 0.4, 0.6, 0.8]
- Hidden Width – [128, 256, 512, 1024]
- Learning Rate – [10⁻⁴, 10⁻³, 10⁻², 10⁻¹]
- Minibatch Size – [2, 4, 8, 16]

Adapted Transformer for Re-ranking (Longs):
- \( d_{fc} \) – [2, 4, 8, 16]
- \( d_{model} \) – [2, 4, 8, 16]
- Dropout Rate – [0.2, 0.4, 0.6, 0.8]
- Learning Rate – [10⁻⁴, 10⁻³, 10⁻², 10⁻¹]
- Minibatch Size – [2, 4, 8, 16]
- No. of Encoder Layers – [1, 2, 3]
- No. of Attention Heads – 1

Adapted Transformer for Re-ranking (Shorts):
- \( d_{fc} \) – [128, 256, 512, 1024]
- \( d_{model} \) – [128, 256, 512, 1024]
- Dropout Rate – [0.2, 0.4, 0.6, 0.8]
- Learning Rate – [10⁻⁴, 10⁻³, 10⁻², 10⁻¹]
- Minibatch Size – [2, 4, 8, 16]
- No. of Encoder Layers – [1, 2, 3]
- No. of Attention Heads – 1