QuantNet: Transferring Learning Across Systematic Trading Strategies

Adriano Koshiyama, Stefano B. Blumberg, Nick Firoozye and Philip Treleaven
University College London
{adriano.koshiyama.15, stefano.blumberg.17, n.firoozye, p.treleaven@ucl.ac.uk}

Sebastian Flennerhag
University of Manchester
sebastian.flennerhag@postgrad.manchester.ac.uk

Abstract

In this work we introduce QuantNet: an architecture that is capable of transferring knowledge over systematic trading strategies in several financial markets. By having a system that is able to leverage and share knowledge across them, our aim is two-fold: to circumvent the so-called Backtest Overfitting problem; and to generate higher risk-adjusted returns and fewer drawdowns. To do that, QuantNet exploits a form of modelling called Transfer Learning, where two layers are market-specific and another one is market-agnostic. This ensures that the transfer occurs across trading strategies, with the market-agnostic layer acting as a vehicle to share knowledge, cross-influence each strategy parameters, and ultimately the trading signal produced. In order to evaluate QuantNet, we compared its performance in relation to the option of not performing transfer learning, that is, using market-specific old-fashioned machine learning. In summary, our findings suggest that QuantNet performs better than non transfer-based trading strategies, improving Sharpe ratio in 15% and Calmar ratio in 41% across 3103 assets in 58 equity markets across the world. Code coming soon.

Keywords: Transfer Learning, Finance, Trading Strategies, Deep Learning, Parameter-transfer, Sequential Transfer Learning.
1 Introduction

Systematic trading strategies are model-based asset-allocation procedures aiming to maximize return over risk, provide insurance against market shocks, and so on. In order to obtain any of these desired behaviours, quantitative trading strategists have to deal with questions such as which assets to hold, trading periods, which model to use and how to fine-tune parameters. To this end, quantitative strategies usually employ a scheme where many variations of a strategy are tried on the same historical data, usually referred to in the literature as Backtesting [10, 4].

Nonetheless, if this search is performed exhaustively and without the proper tools the result is that trading strategies looking good on paper often perform poorly when presented with new data. This problem is often referred to in the literature as Backtest Overfitting [10, 24]. Many procedures have been proposed to deal with the problem, particularly by the Econometrics and Quantitative Finance communities: Data Snooping [53], Overestimated Performance [23, 24], Cross-Validation Evaluation [5], and Covariance-Penalty Corrections [29]. Also recently, Generative Adversarial Networks [31], a technique branching from the Machine Learning community, have also been used to improve trading strategies calibration.

This lack of generalization to new data is not a phenomena exclusive to finance: this is faced by any data-driven procedure, and has been widely studied by the Statistics and Machine Learning communities [12, 3, 43]. In its core, this issue can be attributed to spurious relationships, emerging between the input features (e.g. lagged returns) and the outcome variable (e.g. returns), potentially emerging or magnified by the limited amount of data. More recently, a form of modelling called Transfer Learning [38, 48, 22, 11] has been employed to circumvent this data scarcity problem. The basic idea is to pre-train a generic model across tasks that are similar to our target task; the knowledge obtained by the pre-trained model is then transferred by encouraging the target task model to yield similar parameters. Below we highlight a few benefits of this learning paradigm:

- Better target task performance: traditional data-driven modelling works in isolation, meaning that a bespoke model is built for each new task. In transfer learning each assignment is perceived as an opportunity to accumulate knowledge, and by transferring this to a new model it usually makes the combination better than the isolated baseline [11, 33].

- Improved total performance: since in transfer learning every new task can be used to enhance the pre-trained model, the previous tasks may also benefit from this boost in performance. Hence, by having this shared structure the average performance across tasks tend to be improved [8, 56].

- Model-development time: utilizing the sourced knowledge from the pre-trained architecture tends to make the learning process faster compared to learning from scratch [16, 46]. Also, tapping into a pre-trained model can reduce the necessity of extensive model selection, quickening the deployment process of target task model.

More specifically to fitting trading strategies, it is hard to glean general market dynamics from a single market due to spurious correlations, but by integrating idiosyncratic noise out, it may be possible to learn general market dynamics. Transfer learning is a framework for that. Using this learning paradigm, we introduce QuantNet: an architecture that is capable of learning market-specific and market-agnostic dynamics. QuantNet is trained over different markets, building trading strategies that can pick up the "signal" instead of the "noise" in the financial time-series. In summary, our findings suggest that QuantNet performs better than non transfer-based strategies, improving Sharpe ratio in 15% and Calmar ratio in 41% across 3103 assets in 58 equity markets across the world.

Beyond this introductory section, we organized this paper as follows: the next section provides a literature review on transfer learning, its different forms and a few models and applications that we have found of it in Finance. The third section focuses on the methodology employed in this work: first delving into QuantNet, highlighting its architecture and other relevant details; secondly, detailing the datasets, experiments, assumptions and metrics used to evaluate QuantNet. After this section, we present results and discussions, with the last section exhibiting our concluding remarks and future works.

2
2 Literature Review

In this section we aim to provide a general view of the different subareas inside transfer learning (rather than a thorough review about the whole area). With this information, our goal is to frame the current contributions in finance over these subareas, situate our paper contribution, as well as highlight outstanding gaps. Nonetheless, the reader interested in a thorough presentation about transfer learning should refer to these key references [38, 22, 58].

2.1 Transfer Learning: definition

We start by providing a definition of transfer learning, mirroring notation and discussions in [38, 44, 58]. A typical transfer learning problem presume the existence of a domain and a task. Mathematically, a domain $D$ comprises a feature space $X \in \mathcal{X}$ and a probability measure $P$ over $X$, where $x_i = \{x_1, \ldots, x_J\}$ is a realization of $X$. As an example for trading strategies, $\mathcal{X}$ can be the space of all technical indicators, $x_i$ a specific indicator (e.g. book-to-market ratio), and $x_i$ a random sample of indicators taken from $X$. Given a domain $D = \{\mathcal{X}, P(\mathcal{X})\}$ and a supervised learning setting, a task $T$ consists of a label space $Y \in \mathcal{Y}$, and a conditional probability distribution $P(Y|X)$ typically in trading strategies, $\mathcal{Y}$ can represent the next quarter earnings, and $P(Y|X)$ is learned from the training data $(x_i, y_i)$.

![Figure 1: Taxonomy of transfer learning sub-paradigms.](image)

The domain $D$ and task $T$ are further split in two subgroups: source domains $D_S$ and corresponding tasks $T_S$, as well as target domain $D_T$ and target task $T_T$. Therefore, the objective of transfer learning is to learn the target conditional probability distribution $P_T(Y_T|X_T)$ in $D_T$ with information gained from $D_S$ and $T_S$. Usually, either a limited number of labelled target examples or a large number of unlabelled target examples are assumed to be available. The way this learning is performed across

---

3 A more generic definition, that works for unsupervised and reinforcement learning, demands that along with every task $T_i$ we have an objective function $f_i$. 

---
the tasks, the amount of labelled information as well as inequalities between \( D_S \) and \( D_T \), and \( T_S \) and \( T_T \) give rise to different forms of transfer learning. Figure 1 presents these different scenarios.

In what follows we analyse each sub-paradigm of Figure 1.

### 2.2 Transfer Learning: sub-paradigms

**Inductive Transfer Learning**: it refers to the cases where labelled data is available in the target domain; in another sense, we have the typical Supervised learning scenario across the different domains and tasks. In inductive transfer methods, the target-task inductive bias is chosen or adjusted based on the source-task knowledge. The way this is done varies depending on which inductive learning algorithm is used to learn the source and target tasks [48]. The main variations occur on how this learning is performed: simultaneously across source and target tasks (Multi-Task); sequentially by sampling source tasks, and updating the target task model (Sequential Transfer); and with the constraints of using only few labelled examples (Few-shot). We outline each variation:

- **Multi-task Learning** [8, 56]: is an approach to inductive transfer that improves generalization by learning tasks in parallel while using a shared representation; hence, \( P_T(Y_T|X_T) \) and \( P_S(Y_S|X_S) \) are intertwined, with the update in the target task affecting the behaviour of the domain tasks, and vice-versa. In practice, the learned model architecture and parameters are fully-shared across domain and target tasks – inputs, weights or coefficients, transfer functions, and objective function. In finance, this mode of learning has been first used for stock selection [20]; lately, it has been applied for day trading [7] and yield curves [37].

- **Sequential Transfer Learning** [44]: is an approach to inductive transfer that improves generalization by learning tasks in sequence while using a shared representation to a certain extent; therefore, \( P_T(Y_T|X_T) \) and \( P_S(Y_S|X_S) \) are not completely intertwined, but the update in the target task impacts the behaviour of the domain tasks, and vice-versa. In practice, the learned model architecture and parameters are partially-shared across domain and target tasks – often weights, transfer functions, and sometimes the objective function. By not having to share the same inputs and other parts of the architecture, this mode of learning can be applied across different domains and make the learned model easier to reused in future tasks. In the context of financial applications, it has been mainly applied for sentiment analysis: One of such applications is FinBERT [2], a variation of BERT [11] specialized to financial sentiment analysis; it has obtained state-of-the-art results on FiQA sentiment scoring and Financial PhraseBank benchmarks. In [25] provide a similar application but feeding the sentiment analysis index generated by BERT in a LSTM-based trading strategy to predict stock returns.

- **Few-shot Learning** [16, 22, 52]: it is an extreme form of inductive learning, with very few examples (sometimes only one) being used to learn the target task model. This works to the extent that the factors of variation corresponding to these invariances have been cleanly separated from the other factors, in the learned representation space, and that we have somehow learned which factors do and do not matter when discriminating objects of certain categories. During the transfer learning stage, only a few labeled examples are needed to infer the label of many possible test examples that all cluster around the same point in representation space. So far we were unable to find any application in finance that covers this paradigm. However, we believe that such a mode of learning can be applied for fraud detection, stock price forecasting that have recently undergone initial public offering, or any other situation where limited amount of data is present about the target task.

**Transductive Transfer Learning**: it refers to the cases where labelled data is only available in the source domain, although our objective is still to solve the target task; hence, we have a situation that is somewhat similar to what is known as Semi-supervised learning. What makes the transductive transfer methods feasible is the fact that the source and target tasks are the same, although the domains can be different. For example, consider the task of sentiment analysis, which consists of determining whether a comment expresses positive or negative sentiment. Comments posted on the web come from many categories. A transductive sentiment predictor trained on customer reviews of media

---

3We should note that there are other possibilities, but they fall into Unsupervised or Reinforcement transfer learning. These other paradigms fall outside the scope of this work, which is mostly interested in (Semi-)Supervised transfer learning.
content, such as books, videos and music, can be later used to analyze comments about consumer electronics, such as televisions or smartphones. There are three main forms of transductive transfer learning: Domain Adaptation, Concept Drift and Zero-shot learning. Each form is presented below:

- **Domain Adaptation** [32]: in this case the tasks remain the same between each setting, but the domains as well as the input distribution are usually slightly different; therefore \( \mathcal{X}_S \approx \mathcal{X}_T \) or \( \mathbb{P}_T(X_T) \approx \mathbb{P}_S(X_S) \). The previous example of the sentiment predictor is a typical case, where the domains and the input distribution is somewhat different (books, videos and music reviews transferring to consumer electronics). We can presume that there is an underlying mapping that matches a certain statement to positive, neutral or negative sentiment, and what makes the problem harder to solve is that the vocabulary and context vary between domains. Surprisingly simple unsupervised pretraining has been found to be very successful for sentiment analysis with domain adaptation [21]. Similarly to Few-shot learning, this particular subarea of transfer learning has received less attention from the finance community, since most of the sentiment analysis and similar applications are handled using labelled data.

- **Concept Drift** [59, 14]: in this case the tasks and domains remain the same across settings, but the input distribution can gradually or abruptly change between them; therefore \( \mathbb{P}_T(X_T) \neq \mathbb{P}_S(X_S) \). Often concept drift modelling and detection focus on continuous data streams, such as time series, text messages, videos, that is, data with a temporal dimension or indexation. Using the previous example, we would be concerned with changing views about a specific film: reviews that were otherwise extensively positive, gradually become negative due to changes in audience’s view about how certain characters were portrayed, how the topic was approached, etc. This particular subarea has received substantial attention from the finance community: it has been used to discover relations between portfolio selection factors and stock returns [27]; price forecasting [36]; and fraud detection [47].

- **Zero-shot Learning** [46, 51]: is a form of transductive transfer learning, where the domains and input distributions are different, and yet learning can be achieved by finding a suitable representation; hence \( \mathcal{X}_S \neq \mathcal{X}_T \) and \( \mathbb{P}_T(X_T) \neq \mathbb{P}_S(X_S) \). Following the previous example, if we have a database with thorough reviews about road bicycles, such as describing their frame, suspension, drivetrain, etc. it would be possible to learn in principle what constitutes a good or bad bicycle. Zero-shot learning would attempt to tap into this knowledge, and transfer it to a new bicycle that we do not have reviews but use its design, 3d images, other descriptions, etc. to come up with an expected score, just based on users’ opinions about the product. In this case, the task is the same (deciding the expected review of bicycle), but the domains are radically different (textual description versus an image). Similar to Few-shot learning, we were unable to identify any piece of research from the finance community.

Also, there are four different approaches where the transference of knowledge from a task to another can be realized: instance, feature, parameters, and relational-knowledge. Table I presents a brief description, applications of each to the financial domain, and other key references. Undoubtedly, for financial applications parameter-transfer is the preferred option, followed by instance-transfer and feature-transfer. Such approaches are mainly used for sentiment analysis, fraud detection, and forecasting, areas that have been widely researched using more traditional techniques. Conversely, we were unable to find research for relational-knowledge. Despite that, we believe that researchers working on financial networks, peer-to-peer lending, etc. can benefit from methods in the relational-knowledge transfer approach.

Using this taxonomy, QuantNet can be classified as part of Sequential Transfer Learning, using a Parameter-transfer approach. In this sense, we aim to learn the target task model by sharing and updating the architecture’s weights and activation functions across the tasks. Since each task has different number of inputs/outputs, this component is task-specific. All of these details are better outlined in the next section.
Table 1: Approaches and applications of transfer learning across Finance and general domains.

| Approach          | Brief Description                                                                 | Financial Applications                                      | Other References |
|-------------------|------------------------------------------------------------------------------------|-------------------------------------------------------------|------------------|
| Instance          | Re-weighting labelled data in the source domain for use in the target domain       | News-rich to news-poor stocks [33]; mitigating class imbalance in credit scoring [33, 49] | [28, 40]         |
| Feature           | Find a suitable feature mapping to approximate the source domain to the target domain | Sentiment feature space [34]; Portfolio selection factors [27] | [52, 54]         |
| Parameter         | Learn shareable parameters or priors between the source and target tasks models     | BERT specialized to financial sentiment analysis [2, 25]; Stock selection, forecasting [20, 7]; yield curve forecasting [37] | [11, 9]          |
| Relational-knowledge | Learn a logical relationship or rules in the source domain and transfer it to the target domain |                                                             | [39, 50]         |

3 Methodology

In this section we outline QuantNet, an architecture to transfer knowledge across systematic trading strategies, and the datasets and experiments to empirically evaluate it. The first part focuses on describing QuantNet: (i) the general idea and how the sequential parameter-transfer is performed; (ii) pseudo-code describing the steps to perform its training; and (iii) the loss function and other details about it. The second part deals with the empirical evaluation of QuantNet: (i) the markets used and the period analysed; (ii) the hyperparameter optimization and model validation pursued; and (iii) assumptions, metrics, and the architecture implemented.

3.1 QuantNet

Figure 2 portrays QuantNet workflow: from market data, encoding, transferring of knowledge, to decoding/signal generation.
Every market \((M_1, M_2, \ldots, M_k)\) is composed of a dataset of assets excess returns \(\{r_1, r_2, \ldots, r_t, \ldots\}\) and a model composed of an encoder and decoder. For example in Figure 2 we outlined the following markets: S&P 500 (SPX), FTSE 100 (UKX), Saudi Arabia Tadawul All Shares (SASEIDX). A \(p \times J\) matrix of returns per market, with \(J\) as the number of assets and \(p\) as the sequence length, are then mapped using a market-level encoder to a new \(p \times N\) matrix. These \(N\) values per row are a projection to a shared latent space across markets. This is necessary so that the transfer layer, shared across markets, can sequentially map each market \(N\) inputs to another \(N\) output values. After this, a final mapping from the \(N\)-dimensional latent space of the transfer model to \(J\) signals are made by the decoder model. Algorithm 1 expresses step-by-step the process of training QuantNet.

**Algorithm 1 QuantNet training**

1: for number of training steps do
2:     for \(m\) in shuffle\((M_1, M_2, \ldots, M_k)\) do
3:         Sample a sequential minibatch of \(L\) examples from market \(m\):
4:             \(\{(r_t; r_{t-1}, \ldots, r_{t-p})^{(1)}, \ldots, (r_t; r_{t-1}, \ldots, r_{t-p})^{(L)}\}\) (1)
5:         Compute market-level encoder map \(E_m\) for all examples:
6:             \(e_t, \ldots, e_{t-p-1} = E_m(r_{t-1}, \ldots, r_{t-p})\) (2)
7:         Compute global transfer map \(Z\) for all examples:
8:             \(z_t, \ldots, z_{t-p-1} = Z(e_t, \ldots, e_{t-p-1})\) (3)
9:         Compute market-level decoder \(D_m\) trading signal for all examples:
10:            \(s_t, \ldots, s_{t-p-1} = D_m(z_t, \ldots, z_{t-p-1})\) (4)
11: Update the market-level decoder by ascending its stochastic gradient:
12:            \(\nabla \theta_{D_m} \frac{1}{L} \sum_{l=1}^{L} [SR(s_t, \ldots, s_{t-p-1}; r_t, \ldots, r_{t-p-1})]\) (5)
13: Update the global transfer map by ascending its stochastic gradient:
14:            \(\nabla \theta_Z \frac{1}{L} \sum_{l=1}^{L} [SR(s_t, \ldots, s_{t-p-1}; r_t, \ldots, r_{t-p-1})]\) (6)
15: Update the market-level encoder by ascending its stochastic gradient:
16:            \(\nabla \theta_{E_m} \frac{1}{L} \sum_{l=1}^{L} [SR(s_t, \ldots, s_{t-p-1}; r_t, \ldots, r_{t-p-1})]\) (7)
17:     end for
18: return \((E_{M_1}, D_{M_1}), \ldots, (E_{M_k}, D_{M_k})\) and \(Z\)
19: end for

For a number of training steps, and for all markets \(m\) randomly picked from a list of all markets \(M_1, M_2, \ldots, M_k\), repeat: (i) Sample a sequential minibatch of \(L\) examples from market \(m\); (ii) compute market-level encoder map \(E_m\); (iii) project the values mapped by \(E_m\) to another latent space using the global transfer layer \(Z\); (iv) transform these values in signals using market-specific decoder \(D_m\); (v) using the sequence of signals and assets returns, ascend the stochastic gradient from \(D_m\), \(Z\) and \(E_m\) using the average Sharpe ratio (\(SR\)) as the loss function:

\[SR(s_t, \ldots, s_{t-p-1}; r_t, \ldots, r_{t-p-1}) = \frac{1}{J_m} \sum_{j=1}^{J_m} SR_j(s_t, \ldots, s_{t-p-1}; r_t, \ldots, r_{t-p-1})\] (8)

with \(SR_j(s_t, \ldots, s_{t-p-1}; r_t, \ldots, r_{t-p-1}) = \frac{\mu^{(j)}_{s,r}}{\sigma^{(j)}_{s,r} \times \sqrt{252}}\) (9)
where $\mu_{j}$ is QuantNet’s $j$-th asset average return, and $\sigma_{j}$ its standard deviation (the $\sqrt{252}$ component is used to compute the annualized volatility). There are theoretical and empirical reasons for choosing Sharpe ratio instead of another more traditional metric like Mean Squared Error. In summary: (i) choosing a metric that is linked to the end problem improves the chance of selecting an architecture that can yield reasonable results; and (ii) Mean Squared Error minimization is a necessary, but not sufficient condition to maximize profitability of trading strategies. The interested reader can refer to [1, 30] for proofs and empirical results to both assertions.

We compare QuantNet with the alternative of not building a transfer learning-based trading strategy. We refer to it as No Transfer, and most of its components and description is identical to QuantNet. In fact it can be seen as a reduced version of QuantNet where its Encoder and Transfer map have been removed. Other design details and the empirical evaluation are described in the next topic.

### 3.2 Datasets and Experiments

Table 2 presents the datasets/markets used to empirically evaluate QuantNet. All the data was obtained via Bloomberg, with the description of each market/index and its constituents at [https://www.bloomberg.com](https://www.bloomberg.com) for instance, SPX can be found by searching using the following link [https://www.bloomberg.com/quote/SPX:IND](https://www.bloomberg.com/quote/SPX:IND). We tried to find a compromise between number of assets and sample size, hence for most markets we were unable to use the full list of constituents. We aimed to collect daily price data ranging from 03/01/2000 to 15/03/2019, but for most markets it starts roughly around 2010. Finally, due to restrictions from our Bloomberg license, we were unable to access data for some important equity markets, such as Italy and Russia.

**Table 2:** Markets used during our experiment. MEA - Middle East and Africa.

| Region       | Index/Market | Country     | # Samples | # Assets |
|--------------|--------------|-------------|-----------|----------|
| Americas     | IBOV         | Brazil      | 3250      | 29       |
| Americas     | Merval       | Argentina   | 3055      | 11       |
| Americas     | MEIX         | Mexico      | 3002      | 19       |
| Americas     | RTX          | US          | 2356      | 554      |
| Americas     | Spxx         | Canada      | 3173      | 129      |
| Americas     | SPX          | US          | 3291      | 376      |
| Asia and Pacific | A551      | Australia   | 2363      | 91       |
| Asia and Pacific | Fbmkklc1  | Malaysia    | 3131      | 23       |
| Asia and Pacific | Hsi        | China       | 2599      | 37       |
| Asia and Pacific | Jci        | Indonesia   | 2007      | 44       |
| Asia and Pacific | Kospi      | South Korea | 3041      | 297      |
| Asia and Pacific | Kse100     | Pakistan    | 2036      | 41       |
| Asia and Pacific | Nifty      | India       | 3066      | 38       |
| Asia and Pacific | Nkx        | Japan       | 3504      | 186      |
| Asia and Pacific | Nze50FPI   | New Zealand | 3258      | 21       |
| Asia and Pacific | Pcomp      | Philippines | 3013      | 16       |
| Asia and Pacific | Shs300     | China       | 2881      | 18       |
| Asia and Pacific | SGS        | Singapore   | 2707      | 27       |
| Asia and Pacific | Twse       | Taiwan      | 3910      | 227      |
| Europe       | Aex          | Netherlands | 4083      | 17       |
| Europe       | Aesh         | Greece      | 2944      | 51       |
| Europe       | Atx          | Austria     | 3511      | 13       |
| Europe       | Bell      | Belgium     | 3870      | 14       |
| Europe       | Bux          | Hungary     | 3753      | 8        |
| Europe       | Bvlx         | Portugal    | 3269      | 17       |
| Europe       | Cac          | France      | 3591      | 36       |
| Europe       | Cxy          | Cyprus      | 2056      | 42       |
| Europe       | Dax          | Germany     | 3616      | 27       |

Table 3 outlines the settings for QuantNet and No Transfer strategies. Since running an exhaustive search is computationally prohibitive, we opted to use random search as our hyperparameter optimization strategy. We randomly sampled a total of 200 values in between those ranges, giving larger bounds for configurations with less hyperparameters (No Transfer linear and QuantNet Linear-Linear). After selecting the best hyperparameters, we applied them in a holdout-set consisting of the last 752 observations of each time series (around 3 years). The metrics and statistics in this set are reported in our results section.

**Table 3:** Hyperparameters used by different strategies. *Region: Americas, Europe, Asia and Pacific, Middle East and Africa. |

**Note:** We refer to it as No Transfer, and most of its components and description is identical to QuantNet. In fact it can be seen as a reduced version of QuantNet where its Encoder and Transfer map have been removed. Other design details and the empirical evaluation are described in the next topic.

We have used 3 Month London Interbank Offered Rate in US Dollar as the reference rate to compute the annualized volatility. The interested reader can refer to [1, 30] for proofs and empirical results to both assertions.

We aimed to collect daily price data ranging from 03/01/2000 to 15/03/2019, but for most markets it starts roughly around 2010. Finally, due to restrictions from our Bloomberg license, we were unable to access data for some important equity markets, such as Italy and Russia.

**Table 2:** Markets used during our experiment. MEA - Middle East and Africa.

| Region       | Index/Market | Country     | # Samples | # Assets |
|--------------|--------------|-------------|-----------|----------|
| Americas     | IBOV         | Brazil      | 3250      | 29       |
| Americas     | Merval       | Argentina   | 3055      | 11       |
| Americas     | Meix         | Mexico      | 3002      | 19       |
| Americas     | RTX          | US          | 2356      | 554      |
| Americas     | Spxx         | Canada      | 3173      | 129      |
| Americas     | SPX          | US          | 3291      | 376      |
| Asia and Pacific | A551      | Australia   | 2363      | 91       |
| Asia and Pacific | FBMKKL1  | Malaysia    | 3131      | 23       |
| Asia and Pacific | HSI        | China       | 2599      | 37       |
| Asia and Pacific | JCI        | Indonesia   | 2007      | 44       |
| Asia and Pacific | KOSPI      | South Korea | 3041      | 297      |
| Asia and Pacific | KSE100     | Pakistan    | 2036      | 41       |
| Asia and Pacific | NIFTY      | India       | 3066      | 38       |
| Asia and Pacific | NKX        | Japan       | 3504      | 186      |
| Asia and Pacific | NZX50FPI   | New Zealand | 3258      | 21       |
| Asia and Pacific | PCOMP       | Philippines | 3013      | 16       |
| Asia and Pacific | SHS300     | China       | 2881      | 18       |
| Asia and Pacific | SGS        | Singapore   | 2707      | 27       |
| Asia and Pacific | TWSE       | Taiwan      | 3910      | 227      |
| Europe       | AEX          | Netherlands | 4083      | 17       |
| Europe       | AESH         | Greece      | 2944      | 51       |
| Europe       | ATX          | Austria     | 3511      | 13       |
| Europe       | BEL20        | Belgium     | 3870      | 14       |
| Europe       | BUX          | Hungary     | 3753      | 8        |
| Europe       | BVLX         | Portugal    | 3269      | 17       |
| Europe       | CAC          | France      | 3591      | 36       |
| Europe       | CYSMAPA      | Cyprus      | 2056      | 42       |
| Europe       | DAX          | Germany     | 3616      | 27       |

The reader can refer to [1, 30] for proofs and empirical results to both assertions.

We have used 3 Month London Interbank Offered Rate in US Dollar as the reference rate to compute the annualized volatility. The metrics and statistics in this set are reported in our results section. After a few warm-up runs, we opted to use 2000 training steps as a good balance between computational time and convergence. We trained the different models using the stochastic gradient descent optimizer AMSgrad [41], a variant of the now ubiquitously used Adam algorithm.
The first part of our results section focuses on QuantNet using LSTM encoders and decoders with a Linear transfer layer (dimension = 10) versus No Transfer linear (dimension = 10). The reasons why we opted for this configuration can be found in the second part, Ablation Studies and Sensitivity Analysis, where we provide evidence that these were the most competitive settings for transfer and no-transfer based strategies. Figure 3 shows QuantNet’s architecture throughout the results section.
where $\sigma$ and $\tau$ represent Sigmoid and Tanh activation functions respectively, and $u_s^{t \in \{i,f,o,g\}}$ and $v_s^{t \in \{i,f,o,g\}}$ linear transformations. The remaining components are the encoder cell $c_{E_m}^t$ and hidden state $e_{E_m}^t$ (eq. 10); Linear transfer layer mapping $z_{E_m}^t$ (eq. 11); decoder cell $c_{D_m}^t$ and hidden state $d_{D_m}^t$ (eq. 12), and final long-short trading signal $s_{E_m}^t \in [-1, 1]$ (eq. 13). In QuantNet, we interleave market specific and market agnostic parameters in the model. Each market is therefore associated with specific parameters $W_{E_m}^{s(x)}, W_{D_m}^{s(x)}, V_{E_m}^{s(x)}, V_{D_m}^{s(x)}, b_{E_m}^{s(x)}, b_{D_m}^{s(x)}, c_m, a_m$, while all markets share parameters $Z$ (eq. 11). These parameters are trained jointly through multi-task learning. We propose to use the Sharpe-Ratio (eq. 9) to train these parameters.

4 Results and Discussions

In this section we empirically assess QuantNet performance compared to a market-specific trading strategy – from now on called No Transfer strategy. Compared with QuantNet, No Transfer roughly consists of only the Encoder component, but with the output dimensionality similar to the Decoder architecture (number of assets). The network architecture consists of a linear layer, with the hyperparameters being selected according to the subsection Datasets and Experiments. This choice for comparison as well as other alternatives are grounded during the Ablation Studies and Sensitivity Analysis subsection. Nonetheless, before performing this cross comparison of modelling alternatives, the next subsection presents the main comparison between QuantNet and No Transfer. It is not enough to stress that all reported results are using the 3 years holdout set as described in the Datasets and Experiments subsection.

4.1 QuantNet vs No Transfer

4.1.1 Global analysis

Table 4 presents the aggregate statistics of QuantNet and No Transfer strategies performance on 3103 stocks across all markets analysed. Looking at Sharpe ratios (SR), we can perceive an improvement of about 15% on both average and median terms by using QuantNet. This swing increases the number of assets yielding SRs above 1.0 from 432 (No Transfer) to 583 (QuantNet). This improvement is also perceived in Calmar ratio (CR) terms (12% on average, and 41% on median), smaller Downside Risk (DownRisk), higher Skew and Sortino ratios (SortR). Statistically, QuantNet significantly outperform No Transfer both in Sharpe ($W = 2215630$, p-value < 0.001) and Calmar ($W = 2141782$, p-value < 0.001) ratios.

Table 4: Financial metrics of QuantNet and No Transfer strategies on 3103 stocks across all markets analysed.

| Metric       | No Transfer Mean (SD) | QuantNet Mean (SD) | No Transfer Median (MAD) | QuantNet Median (MAD) |
|--------------|-----------------------|--------------------|--------------------------|-----------------------|
| Ann Ret      | 0.038781 (0.151684)   | 0.008352 (0.049631) | 0.001537 (0.086348)      | 0.005377 (0.028968)   |
| Ann Vol      | 0.114349 (0.165882)   | 0.035833 (0.061821) | 0.00768 (0.141058)       | 0.025665 (0.0445)    |
| CR           | 0.431922 (2.110088)   | 0.481823 (1.039415) | 0.169345 (0.571706)      | 0.241255 (0.599684)  |
| DownRisk     | 0.077398 (0.115929)   | 0.036953 (0.046164) | 0.00124 (0.09553)        | 0.017534 (0.032915) |
| Kurt         | 33.40567 (59.98242)   | 30.29485 (48.50278)| 15.73864 (31.03957)      | 16.1996 (24.73363)   |
| MDD          | -0.14663 (-0.112596)  | -0.03455 (-0.07288) | -0.01286 (-0.07288)      | -0.03847 (-0.07288)  |
| SR           | 0.324257 (0.6541)     | 0.370918 (0.715636) | 0.360572 (0.5118)        | 0.354776 (0.572184)  |
| Skew         | 0.313173 (0.215676)   | 0.448467 (0.112596) | 0.171629 (0.1782)        | 0.297182 (0.072881)  |
| SortR        | 0.620225 (3.236364)   | 0.749848 (2.85022)  | 0.454035 (1.748046)      | 0.52190 (1.66854)    |

Before looking at market-level results, we contrast QuantNet and No Transfer SR distributions (Figure 4a) and relationships (Figure 4b) across assets. The histogram exhibits a small shift/positive skew in QuantNet distribution compared to No Transfer strategy. This discrepancy manifests itself
in statistical terms, with the Kolmogorov-Smirnov statistic indicating that these distributions are meaningfully different ($KS = 0.05385$, p-value < 0.001).

Figure 4: (a) Histogram of Sharpe ratio across 3103 assets for QuantNet and No Transfer. (b) Scatterplot of QuantNet and No Transfer Sharpe ratios overlaid by a linear regression curve.

Another way to outline the positive transfer that QuantNet is generating is by performing a linear regression between the SRs of No Transfer versus QuantNet. Figure 4b presents the linear regression curve, with intercept of 0.2879 (p-value < 0.0001), and slope of 0.2556 (p-value < 0.0001). These numbers translate as following: if No Transfer strategy obtains SR equal to 0.0 in a specific asset, we would on average expect that QuantNet would fare a SR of 0.2879. Having a slope less than 1.0 indicates that QuantNet will also provide less surprisingly positive and negative SRs – if No Transfer obtain SR = -0.5, QuantNet will at least return a SR near to zero. The next topic looks at aggregate and analyses both strategies at market-level.

4.1.2 Market-level Analysis

Figures 5a and 5b outline the average SR and CR across the 58 markets, ordered by No Transfer strategy performance. In SR terms, QuantNet outperformed No Transfer in its top 5 markets, with the opposite being true in CR values. Also, QuantNet dominates the bottom 10 markets that No Transfer has returned unprofitable results, both in SR and CR terms. Finally, in 7 of the top 10 largest ones (RTY, SPX, KOSPI, etc., see Table 2), QuantNet has also outperformed No Transfer.

Figure 6 maps every market to a country, and displays the relative outperformance (%) of QuantNet in relation to No Transfer in SR values. In the Americas, apart from Mexico and Argentina, Brazil, US (on average) and Canada, QuantNet has produced better results than No Transfer. Similarly, the core of Europe (Germany, United Kingdom and France), and India and China, QuantNet has produced superior SRs than No Transfer, with markets like Japan, Australia, New Zealand, and South Africa representing the reverse.

In a similar fashion to the global analysis, Figures 7a and 7b display the relationship between SRs and CRs of No Transfer with QuantNet for each market, with overlaid regression curves. The SR and CR models have the following parameters: SR intercept of 0.1506 (p-value = 0.036), and SR slope of 0.7381 (p-value < 0.0001); and CR intercept of 0.1851 (p-value = 0.015), and CR slope of 0.7379 (p-value < 0.0001). Both cases indicate that in a market where No Transfer fared a SR or CR equal to zero, we would expect No Transfer to obtain on average 0.15 and 0.18 of SR and CR, respectively. Since both models have slope < 1.0, it indicates that across markets QuantNet will tend to provide less surprisingly positive and negative SRs and CRs.

Table 5 presents a better break down of the statistics in a few big regional markets, such as United States S&P 500 components (SPX Index), United Kingdom FTSE 100 (UKX Index), Korea Composite Index (KOSPI Index) and Saudi Arabia Tadawul All Shares (SASEIDX Index). Each one of them show 2-10 times order of magnitude improvement in SRs and CRs by QuantNet, with similar benefits in Sortino ratios, Downside risks and Skewness.

These results by QuantNet also translate in superior cumulative returns (Figure 8), histograms with empirical distributions that stochastically dominate the No Transfer strategy, and finally positive
Figure 5: Average Sharpe (a) and Calmar (b) ratios of QuantNet and No Transfer across 58 equity markets.

Figure 6: World map of average relative (%) Sharpe ratio difference between QuantNet versus No Transfer. For visualisation purposes we have averaged the metric for US, China and Israel/Palestine.

In summary, markets that were otherwise not as profit-generating using only lagged information, become profitable due to the addition of a transfer layer of information across world markets.
Figure 7: Scatterplot of QuantNet and No Transfer average Sharpe (a) and Calmar (b) ratios of each market overlaid by a linear regression curve.

Table 5: Financial metrics of QuantNet and No Transfer strategies in SPX Index, UKX Index, KOSPI Index and SASEIDX Index.

| Metric        | Americna_SPX | Asia and Pacific_KOSPI | Europe_UKX | MEA_SASEIDX |
|---------------|--------------|------------------------|------------|-------------|
| **Mean (SD)** |              |                        |            |             |
| Ann Ret       | 0.00033 (0.001259) | 0.07337 (0.144194) | 0.000406 (0.00111) | 0.006642 (0.003219) |
| Ann Vol       | 0.002436 (0.00064) | 0.053136 (0.025008) | 0.002177 (0.004583) | 0.003598 (0.004739) |
| CR            | 0.133073 (0.377186) | 0.756976 (0.616175) | 0.210127 (0.445449) | 0.267246 (0.743929) |
| DownRisk      | 0.001717 (0.000522) | 0.035575 (0.009576) | 0.001661 (0.00433) | 0.002236 (0.00513) |
| Kurt          | 33.29913 (45.57039) | 19.51515 (19.28247) | 88.42658 (135.1903) | 34.1796 (87.54653) |
| MDD           | -0.00467 (-0.000296) | -0.06681 (-0.02664) | -0.00422 (-0.001905) | -0.00414 (-0.00191) |
| SR            | 0.061702 (0.512651) | 0.783197 (0.49204) | 0.108635 (0.529708) | 0.12883 (0.579236) |
| Skew          | -0.21186 (-2.351112) | 0.28355 (1.685894) | 0.347892 (6.586847) | 0.334534 (4.079455) |
| SortR         | 0.144905 (0.760463) | 1.245084 (0.847215) | 0.347892 (6.586847) | 0.334534 (4.079455) |

| Median (MAD) |              |                        |            |             |
| Ann Ret       | 0.000197 (0.000982) | 0.000326 (0.000982) | 0.000032 (0.000108) | 0.000032 (0.000108) |
| Ann Vol       | 0.002399 (0.000497) | 0.001732 (0.001269) | 0.002177 (0.004583) | 0.002177 (0.004583) |
| CR            | 0.045842 (0.271252) | 0.620101 (0.479759) | 0.00157 (0.00333) | 0.00157 (0.00333) |
| Kurt          | 33.29913 (23.64829) | 19.51515 (10.23454) | 88.42658 (96.22144) | 34.1796 (87.54653) |
| MDD           | -0.00419 (-0.000247) | -0.06681 (-0.02664) | -0.00422 (-0.001905) | -0.00414 (-0.00191) |
| SR            | 0.044563 (0.406313) | 0.407357 (0.400688) | 0.108635 (0.529708) | 0.12883 (0.579236) |
| Skew          | 0.144905 (0.760463) | 1.245084 (0.847215) | 0.347892 (6.586847) | 0.334534 (4.079455) |
| SortR         | 0.144905 (0.760463) | 1.245084 (0.847215) | 0.347892 (6.586847) | 0.334534 (4.079455) |
Figure 8: Average cumulative returns (%) of SPX Index, UKX Index, KOSPI Index and SASEIDX Index contrasting QuantNet and No Transfer strategies. Before aggregation, each underlying asset was volatility-weighted to 10%.

Figure 9: Histogram of Sharpe ratio of SPX Index, UKX Index, KOSPI Index and SASEIDX Index contrasting QuantNet and No Transfer strategies.

Figure 10: Scatterplot of Sharpe ratio of SPX Index, UKX Index, KOSPI Index and SASEIDX Index contrasting QuantNet and No Transfer strategies.

We close this section by fitting a traditional Fama-French 5 factor model, with the addition of Momentum factor [18, 15] using these four markets daily returns as dependent variables. Table 6 present the models coefficients, t-stats and whether they were or not significant (using a 5%
Regardless of the market, QuantNet provided significant alpha (abnormal risk-adjusted return) across markets, with very low correlation to other general market factors.

### Table 6: Models coefficients and t-stats for the different markets and factors.

| Market type                        | SPX  | UKX  | SASEIDX | KOSPI |
|------------------------------------|------|------|---------|-------|
| Alpha                              | 0.0003* | 0.0002* | 0.0005* | 0.0003* |
| t-stat                             | 2.554 | 2.258 | 3.856   | 4.034 |
| Market minus Risk-free rate        | -0.0004* | -0.0002 | -0.0006* | -0.0004* |
| t-stat                             | -2.367 | -1.558 | -2.804  | -0.213 |
| Small minus Big                    | 0.0003 | 1.158 | 1.075   | 0.0006 |
| t-stat                             | 0.0006 | 0.0001 | 1.856   | 0.182 |
| High minus Low                     | -0.0005 | -1.778 | -2.813  | -0.0002 |
| t-stat                             | 1.158 | 0.08  | -0.781  | -0.538 |

< p-value < 0.05

Next topic discusses certain features of QuantNet, going beyond the simply contrast with No Transfer strategy. We provide some insight on what market characteristics QuantNet is providing superior performance, as well as look at how each market is being represented inside its architecture.

#### 4.1.3 QuantNet Features

One of the key features of transfer learning is its ability to provide meaningful solutions in resource constrained scenarios – sample size, features, training budget, etc. With QuantNet this pattern persist; Figure 11a presents the average SR across different assets grouped by sample size used during training. We have subtracted QuantNet SR from No Transfer SR to reduce cross-asset variance and baseline effect. Apart from a downfall in the bracket 2200-2576 samples (10 years of data), overall we can see a downward trend from 1444-1823 (6-7 years) to 3706-4083 samples (15-16 years). This points out that assets with small sample size are benefiting more than ones with large samples.

![Figure 11a: Average Sharpe ratio difference between QuantNet versus No Transfer, aggregated by sample size (a)].

Another feature is number of assets in a specific market – Figure 11b outlines the results of QuantNet in terms of average SR. We have subtracted QuantNet SR from No Transfer SR to reduce cross-asset variance and baseline effect. In this case, it demonstrates that the bigger the market, the better QuantNet will perform. As we pointed out previously, apart from a few markets like Japan and US Small Caps, overall QuantNet have generated superior results than the baseline (like UK, US S&P 500, Germany’s DAX, etc.).

![Figure 11b: Average Sharpe ratio difference between QuantNet versus No Transfer, aggregated by number of assets per market (b)].

An additional analysis is how each market is being mapped inside QuantNet architecture, particularly in the Encoder layer. The key question is how they are being represented in this hidden latent space, and how close each market is to the other there. Figure 12 presents a dendrogram of hierarchical clustering done using the scores from encoder layer for all markets.
By setting an unique threshold across the hierarchical clustering we can form 6 distinct groups. Some clusters are easier to analyse, such as C5 that consist mainly of small European equity markets (Spain, Netherlands, Belgium and France) – all neighbours; C6 comprising mainly of developed markets in Europe and Americas, such as United Kingdom, Germany, US, and their respective neighbours Austria, Poland, Switzerland, Sweden, Denmark, Canada and Mexico. Some clusters require a more refined observation, such as C2 containing most developed markets in Asia like Japan, Hong Kong, Korea and Singapore, with C3 representing Asia and Pacific emerging markets: China, India, Australia, and some respective neighbours (New Zealand, Pakistan, Philippines, Taiwan). Figure 13 outlines all these groups in a map. Overall, it seems that the encoder of QuantNet is mapping and structuring the markets according to their development stage and geographical proximity. Apart from cluster C4 and to a certain extent C1, the remaining ones tend to confirm this hypothesis.

4.2 Ablation Study and Sensitivity Analysis

This subsection attempts to addresses the question: (i) could we get better results for the No Transfer strategy; and (ii) what are the impact in QuantNet architecture by increasing its dimensionality, and performing some ablation in its architecture. Table 7 presents the Sharpe ratio (SR) statistics for question (i) and (ii), by contrasting QuantNet and No Transfer strategies.
Table 7: Average Sharpe ratio per different dimensions and configurations of QuantNet and No Transfer strategies.

| Sharpe ratio | Dimension | No Transfer | QuantNet (Encoder/Decoder-Transfer Layer) |
|--------------|-----------|-------------|------------------------------------------|
| Mean (SD)    | 10        | 0.324257    | 0.356500                                 |
|              |           | 0.311424    | 0.361986                                 |
|              | 25        | 0.324257    | 0.333565                                 |
|              |           | 0.311424    | 0.324842                                 |
|              | 50        | 0.324257    | 0.326090                                 |
|              |           | 0.311424    | 0.353448                                 |
|              | 100       | 0.324257    | 0.326090                                 |
|              |           | 0.311424    | 0.353448                                 |
| Median (MAD) | 10        | 0.306572    | 0.338981                                 |
|              |           | 0.304244    | 0.345072                                 |
|              | 25        | 0.306572    | 0.314084                                 |
|              |           | 0.304244    | 0.301769                                 |
|              | 50        | 0.306572    | 0.302167                                 |
|              |           | 0.304244    | 0.303684                                 |
|              | 100       | 0.306572    | 0.307922                                 |
|              |           | 0.304244    | 0.330039                                 |

In relation to No Transfer, we can perceive that there is no benefit from moving to a LSTM architecture – in fact, we produced worst outcomes in general. Maybe the lack of data per market has impacted the overall performance of this architecture. Similarly with QuantNet, a full LSTM model generated worst outcomes regardless of the dimensionality used. Linear components in QuantNet have produced better outcomes, with Linear encoders/decoders and LSTM transfer layers providing the best average results across dimensions. However, small layer sizes are linked with better SRs, and particularly for size equal to 10, the QuantNet architecture using LSTM encoders/decoders and Linear transfer layer generated the best average SRs. In terms of computational time, No Transfer Linear takes 1364.46s every 1000 training steps, compared to QuantNet LSTM-Linear 1805.81s per 1000 training steps.

5 Conclusions

In this work we introduced QuantNet: an architecture that is capable of transferring knowledge across systematic trading strategies in several financial markets. QuantNet is a Transfer learning-based approach, where every market-specific trading strategies share a common layer that acts as a vehicle to share knowledge, cross-influence each strategy parameters, and ultimately the trading signal produced. As pointed out in the methodology section, and grounded during the ablation and sensitivity analysis, QuantNet architecture consist of a LSTM-based encoder and decoder, with a Linear layer responsible to perform the transfer of knowledge across markets.

In order to evaluate QuantNet, we compared its performance in relation to the option of not performing transfer learning, that is, using market-specific old-fashioned machine learning. In summary, our findings suggest that QuantNet performs better than non transfer-based trading strategies, improving Sharpe ratio in 15% and Calmar ratio in 41% across 3103 assets in 58 equity markets across the world. In a few big regional markets, such as S&P 500, FTSE 100, KOSPI and Saudi Arabia Tadawul All Shares, QuantNet showed 2-10 times order of magnitude improvement in Sharpe ratios and Calmar ratios, with similar benefits in Sortino ratios, Downside risks and Skewness. QuantNet also generated positive and statistically significant alpha according to Fama-French 5 factors model. By analysing QuantNet encoders, it appeared that they are mapping and structuring the markets according to their development stage and geographical proximity.

In future works we aim to investigate different architectures, such as Transformer layers, as it seems that they are providing significant outperformance in other tasks with sequence data (mainly text). Expanding the empirical evaluation to include other asset classes beyond equities, such as foreign exchange, interest rate swaps, or commodities can potentially improve the overall results since it can provide additional knowledge to trade some equities, and vice-versa.

Acknowledgments

Adriano Koshiyama would like to acknowledge the National Research Council of Brazil for his PhD scholarship. We would also like to thank Gerald Rushton for the idea on computing the Fama-French factor loadings, and Emre Kazim for proofreading and reviewing our work.
References

[1] Emmanuel Acar and Stephen Satchell. *Advanced trading rules*. Butterworth-Heinemann, 2002.

[2] Dogu Araci. Finbert: Financial sentiment analysis with pre-trained language models. *arXiv preprint arXiv:1908.10063*, 2019.

[3] Sylvain Arlot, Alain Celisse, et al. A survey of cross-validation procedures for model selection. *Statistics surveys*, 4:40–79, 2010.

[4] David H Bailey, Jonathan M Borwein, Marcos López de Prado, and Qiji Jim Zhu. Pseudo-mathematics and financial charlatanism: The effects of backtest over fitting on out-of-sample performance. *Notices of the AMS*, 61(5):458–471, 2014.

[5] David H Bailey, Jonathan M Borwein, Marcos Lopez de Prado, and Qiji Jim Zhu. The probability of backtest overfitting. *Journal of Computational Finance (Risk Journals)*, 2015.

[6] James Bergstra and Yoshua Bengio. Random search for hyper-parameter optimization. *Journal of Machine Learning Research*, 13(Feb):281–305, 2012.

[7] Zsolt Bitvai and Trevor Cohn. Day trading profit maximization with multi-task learning and technical analysis. *Machine Learning*, 101(1-3):187–209, 2015.

[8] Rich Caruana. Multitask learning. *Machine learning*, 28(1):41–75, 1997.

[9] Sihong Chen, Kai Ma, and Yefeng Zheng. Med3d: Transfer learning for 3d medical image analysis. *arXiv preprint arXiv:1904.00625*, 2019.

[10] Marcos Lopez De Prado. *Advances in financial machine learning*. John Wiley & Sons, 2018.

[11] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

[12] Cynthia Dwork, Vitaly Feldman, Moritz Hardt, Toni Pitassi, Omer Reingold, and Aaron Roth. Generalization in adaptive data analysis and holdout reuse. In *Advances in Neural Information Processing Systems*, pages 2350–2358, 2015.

[13] Martin Eling and Frank Schuhmacher. Does the choice of performance measure influence the evaluation of hedge funds? *Journal of Banking & Finance*, 31(9):2632–2647, 2007.

[14] Tatiana Escovedo, Adriano Koshiyama, Andre Abs da Cruz, and Marley Vellasco. Detecta: abrupt concept drift detection in non-stationary environments. *Applied Soft Computing*, 62:119–133, 2018.

[15] Eugene F Fama and Kenneth R French. A five-factor asset pricing model. *Journal of financial economics*, 116(1):1–22, 2015.

[16] Li Fei-Fei, Rob Fergus, and Pietro Perona. One-shot learning of object categories. *IEEE transactions on pattern analysis and machine intelligence*, 28(4):594–611, 2006.

[17] Sebastian Flennerhag, Hujun Yin, John Keane, and Mark Elliot. Breaking the activation function bottleneck through adaptive parameterization. In *Advances in Neural Information Processing Systems*, pages 7739–7750, 2018.

[18] Kenneth R French. Kenneth r. french-data library. *Tuck-MBA program web server. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html* (accessed October 20, 2010), 2012.

[19] Felix A Gers, Jürgen Schmidhuber, and Fred Cummins. Learning to forget: Continual prediction with lstm. 1999.

[20] Joumana Ghosn and Yoshua Bengio. Multi-task learning for stock selection. In *Advances in Neural Information Processing Systems*, pages 946–952, 1997.

[21] Xavier Glorot, Antoine Bordes, and Yoshua Bengio. Domain adaptation for large-scale sentiment classification: A deep learning approach. In *Proceedings of the 28th international conference on machine learning (ICML-11)*, pages 513–520, 2011.

[22] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.

[23] Campbell R Harvey and Yan Liu. Evaluating trading strategies. *Available at SSRN 2474755*, 2014.
[24] Campbell R Harvey and Yan Liu. Backtesting. The Journal of Portfolio Management, pages 12–28, 2015.

[25] Joshua Zoen Git Hiew, Xin Huang, Hao Mou, Duan Li, Qi Wu, and Yabo Xu. Bert-based financial sentiment index and lstm-based stock return predictability. arXiv preprint arXiv:1906.09024, 2019.

[26] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[27] Yong Hu, Kang Liu, Xiangzhou Zhang, Kang Xie, Weiqi Chen, Yuran Zeng, and Mei Liu. Concept drift mining of portfolio selection factors in stock market. Electronic Commerce Research and Applications, 14(6):444–455, 2015.

[28] Shuhui Jiang, Haiyi Mao, Zhengming Ding, and Yun Fu. Deep decision tree transfer boosting. IEEE transactions on neural networks and learning systems, 2019.

[29] Adriano Koshiyama and Nick Firoozye. Avoiding backtesting overfitting by covariance-penalties: an empirical investigation of the ordinary and total least squares cases. The Journal of Financial Data Science, 1(4):63–83, 2019.

[30] Adriano Koshiyama and Nick Firoozye. Avoiding backtesting overfitting by covariance-penalties: an empirical investigation of the ordinary and total least squares cases. The Journal of Financial Data Science, 1(4):63–83, 2019.

[31] Adriano Koshiyama, Nick Firoozye, and Philip Treleaven. Generative adversarial networks for financial trading strategies fine-tuning and combination. arXiv preprint arXiv:1901.01751, 2019.

[32] Wouter Marco Kouw and Marco Loog. A review of domain adaptation without target labels. IEEE transactions on pattern analysis and machine intelligence, 2019.

[33] Wei Li, Shuai Ding, Yi Chen, and Shanlin Yang. A transfer learning approach for credit scoring. In International Conference on Applications and Techniques in Cyber Security and Intelligence, pages 64–73. Springer, 2018.

[34] Xiaodong Li, Haoran Xie, Raymond YK Lau, Tak-Lam Wong, and Fu-Lee Wang. Stock prediction via sentimental transfer learning. IEEE Access, 6:73110–73118, 2018.

[35] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692, 2019.

[36] Zongying Liu, Chu Kiong Loo, and Manjeevan Seera. Meta-cognitive recurrent recursive kernel os-elm for concept drift handling. Applied Soft Computing, 75:494–507, 2019.

[37] Manuel Nunes, Enrico Gerding, Frank McGroarty, and Mahesan Niranjan. A comparison of multitask and single task learning with artificial neural networks for yield curve forecasting. Expert Systems with Applications, 119:362–375, 2019.

[38] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10):1345–1359, 2009.

[39] Wonpyo Park, Dongju Kim, Yan Lu, and Minsu Cho. Relational knowledge distillation. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2019.

[40] Chen Qu, Feng Ji, Minghui Qiu, Liu Yang, Zhiyu Min, Haqing Chen, Jun Huang, and W Bruce Croft. Learning to selectively transfer: Reinforced transfer learning for deep text matching. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining, pages 699–707. ACM, 2019.

[41] Sashank J Reddi, Satyen Kale, and Sanjiv Kumar. On the convergence of adam and beyond. arXiv preprint arXiv:1904.09237, 2019.

[42] Tom Rollinger and Scott Hoffman. Sortino ratio: A better measure of risk. Futures Magazine, 1(02), 2013.

[43] Joseph P Romano and Michael Wolf. Efficient computation of adjusted p-values for resampling-based stepdown multiple testing. Statistics & Probability Letters, 113:38–40, 2016.

[44] Sebastian Ruder, Matthew E Peters, Swabha Swayamdipta, and Thomas Wolf. Transfer learning in natural language processing. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Tutorials, pages 15–18, 2019.
[45] William F Sharpe. The sharpe ratio. *Journal of portfolio management*, 21(1):49–58, 1994.

[46] Richard Socher, Milind Ganjoo, Christopher D Manning, and Andrew Ng. Zero-shot learning through cross-modal transfer. In *Advances in neural information processing systems*, pages 935–943, 2013.

[47] Akila Somasundaram and Srinivasulu Reddy. Parallel and incremental credit card fraud detection model to handle concept drift and data imbalance. *Neural Computing and Applications*, 31(1):3–14, 2019.

[48] Lisa Torrey and Jude Shavlik. Transfer learning. In *Handbook of research on machine learning applications and trends: algorithms, methods, and techniques*, pages 242–264. IGI Global, 2010.

[49] Andrew Voumard and Ghassan Beydoun. Transfer learning in credit risk. In *ECML PKDD*, pages 1–16, 2019.

[50] Donghui Wang, Yanan Li, Yuetan Lin, and Yueting Zhuang. Relational knowledge transfer for zero-shot learning. In *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence*, AAAI’16, pages 2145–2151. AAAI Press, 2016.

[51] Wei Wang, Vincent W Zheng, Han Yu, and Chunyan Miao. A survey of zero-shot learning: Settings, methods, and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(2):13, 2019.

[52] Yaqing Wang, Quanming Yao, James Kwok, and Lionel M. Ni. Generalizing from a few examples: A survey on few-shot learning, 2019.

[53] Halbert White. A reality check for data snooping. *Econometrica*, 68(5):1097–1126, 2000.

[54] Zhilin Yang, Jake Zhao, Bhuwan Dhingra, Kaiming He, William W Cohen, Ruslan R Salakhutdinov, and Yann LeCun. Glomo: unsupervised learning of transferable relational graphs. In *Advances in Neural Information Processing Systems*, pages 8950–8961, 2018.

[55] Terry W Young. Calmar ratio: A smoother tool. *Futures*, 20(1):40, 1991.

[56] Yu Zhang and Qiang Yang. A survey on multi-task learning. *arXiv preprint arXiv:1707.08114*, 2017.

[57] Fuzhen Zhuang, Xiaohu Cheng, Ping Luo, Sinno Jialin Pan, and Qing He. Supervised representation learning: Transfer learning with deep autoencoders. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*, 2015.

[58] Fuzhen Zhuang, Zhiyuan Qi, Keyu Duan, Dongbo Xi, Yongchun Zhu, Hengshu Zhu, Hui Xiong, and Qing He. A comprehensive survey on transfer learning. *arXiv preprint arXiv:1911.02685*, 2019.

[59] Indrė Žliobaitė, Mykola Pechenizkiy, and Joao Gama. An overview of concept drift applications. In *Big data analysis: new algorithms for a new society*, pages 91–114. Springer, 2016.