

Residual Switching Network for Portfolio Optimization

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Abstract—This paper studies deep learning methodologies for portfolio optimization in the US equities market. We present a novel residual switching network that can automatically sense changes in market regimes and switch between momentum and reversal predictors accordingly. The residual switching network architecture combines two separate residual networks (ResNets), namely a switching module that learns stock market conditions, and the main module that learns momentum and reversal predictors. We demonstrate that over-fitting noisy financial data can be controlled with stacked residual blocks and further incorporating the attention mechanism can enhance powerful predictive properties. Over the period 2008 to H12017, the residual switching network (Switching-ResNet) strategy verified superior out-of-sample performance with an average annual Sharpe ratio of 2.22, compared with an average annual Sharpe ratio of 0.81 for the ANN-based strategy and 0.69 for the linear model.

INTRODUCTION

Deep learning has been extensively applied to large financial datasets in recent years. Researchers have extended the application of ANN as a non-parametric approach to optimize portfolios and built algorithmic trading strategies that are orthogonal to conventional statistical arbitrage strategies [2, 3]. It began with shallower machine learning models such as one-layer artificial neural networks (ANN) [7] and support vector machines [4], which demonstrated powerful predictive properties on financial time series [6, 8, 12]. As time progressed, the research community ventured into deeper non-linear topological structures for financial signal representation [11, 13] and observed significant improvement over the performance of traditional machine learning methods [15, 16].

The application of deep learning in finance can be broadly categorized by three approaches: stacked auto-encoders (SAE) [5, 13], recurrent neural networks (RNN) [11, 13, 19], and feedforward neural networks (FNN) [18]. Bao et al. used stacked auto-encoders to hierarchically extract deep financial features in an unsupervised manner, the features are then passed through the LSTM, a type of RNN with feedback links attached to certain layers of the network, to predict future trends in the stock market. Many researchers have extensively studied the use of feed-forward network for financial asset predictions [19, 20], and Deng et al. successfully applied RNN to make high frequency trading decisions whilst minimizing transaction cost and slippage.

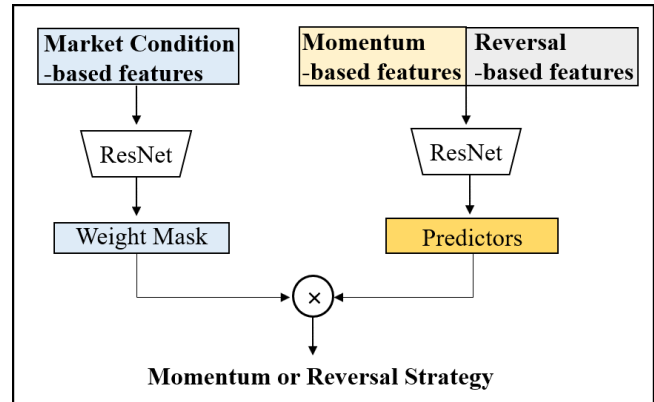


Fig. 1. Switching-ResNet combines the regime-switching module (left) with the main module (right). The conditional weight mask combines with predictors by element-wise product, \otimes . As market conditions change over time, our network can switch between momentum-based and reversal-based strategies accordingly.

It is challenging to fit “substantially deep” networks on noisy non-stationary financial data. Even though non-linear relationships exist in financial markets, forcefully fitting an extremely non-linear model such as a 22-layer plain ANN, often results in the tendency to over-fit, causing out-of-sample accuracy/performance to deteriorate. When fitting “substantially deep” plain networks on stock price data, regularization methods such as dropout and weight penalization are difficult to control.

In this paper, we first address the over-fitting problem by applying Attention ResNet to noisy financial data to predict US equities’ monthly returns. We evaluate and compare the in-sample and out-of-sample performance of the deep Attention ResNet with a regularized deep plain ANN, as well as the linear model. We demonstrate that stacked attention enhanced residual blocks can strike a balance between over-fitting (deep plain ANN) and under-fitting (linear model), and optimize the degree of non-linearity when modeling stock price fluctuations. Our proposed architecture also consists of attention masks that interface with hidden layers to generate attention enhanced financial feature representations.

We then present the residual switching network that automatically senses a change in financial market conditions and switch between prominent market anomalies accordingly.

There are various stylized predictors in portfolio management, the two most prominent market anomalies are momentum and reversal [26]. We develop a robust switching module that weighs the relative importance of momentum and reversal anomalies conditional on SP500 realized volatility, squared VIX and SP500 variance risk premium, see Fig 1 and 2. Our method is based on the notion that market anomalies are directly associated with market regimes, where a bullish market regime is often associated with lower market volatility, and the bearish market regime is associated with higher market volatility [27]. As an intermediate result, we demonstrate that the standalone switching module can accurately model and predict SP500 realized volatility. We then combine the switching module with a residual network to complete the Switching ResNet. The switching module computes a conditional weight mask, which is applied to the last hidden layer of the main ResNet to identify relative important stylized predictors (momentum or reversal hidden units) as market regime changes over time. Finally, the switching module is combined with the main ResNet to select long/short portfolio (delta neutral) to reap higher rewards in portfolio management. The main contributions of our proposed method are listed as follows:

- We introduce a novel supervised learning approach for portfolio management in the US equities market. The Attention-ResNet significantly increases network depth for applying deep learning methods to noisy financial data, whilst finding an optimal balance between over-fitting and under-fitting.
- We leverage the attention module to guide abstract financial feature learning to improve predictive accuracy as well as model flexibility.
- We introduce a novel Switching-ResNet that can learn financial market conditions to guide our proposed model to switch between momentum and reversal predictors as market regime changes, which significantly differentiates the Switching-ResNet from previous learning-based approaches for portfolio management.

RELATED WORKS

Recent advancements in residual learning allow researchers to exploit much deeper network architectures than its predecessors [9]. Residual learning has been extensively applied in computer vision and has proven to be a successful supervised learning approach. Residual network (ResNet) is constructed by stacking residual blocks, which are modified from plain ANNs using short circuits so that it is easier for ResNets to learn the identity mapping rather than an un-referenced mapping [9]. When modeling noisy financial data, the ResNet can increase network depth whilst control for over-fitting.

Attention module enhances feature representations at selected focal points [21,22]. Previous works have shown that attention module can be easily applied to the feed-forward network architecture, and the incorporation of stacked attention modules can capture both low and high-level refined features that lead to consistent performance improvement for image classification and machine translation tasks [34]. By contrast, our proposed method demonstrates that the concept behind residual learning and attention module is cross-fertilizing and hopeful for model-driven portfolio optimization.

Hamilton (1989) first introduced the Markov regime-switching model. This auto-regressive regime-switching process involves multiple equations to characterize multiple regimes, where the switching module is regulated by past values of an unobserved state variable [31]. The Markov switching model and its many variants have been extensively applied to economic and financial time series. Kim and Nelsons regime-switching model examines business cycle duration dependency to see whether a regime change depends on how long an economy was in a boom or recession [33]. Researchers also experimented with variants of the Markov switching model in the foreign exchange market and found supporting evidence for its superior predictive power on the direction of change for exchange rates [32]. Inspired by Markov regime-switching model and recent advances in attention mechanism for deep learning, we are the first to incorporate a regime-switching module on the deep residual network. Our proposed deep learning framework enhances portfolio management by allowing the switching module to switch between prominent stock market anomalies when market condition changes over time.

OUR APPROACH

In this section, we introduce the Attention-ResNet and the Switching-ResNet. We first present the self-attention concept to establish the self-attention enhanced residual block and constructs the 22-layer deep Attention-ResNet in section 3.1. Section 3.2 discusses the details of the switching module and analyze the guided-attention concept behind the switching module. We then construct the deep residual switching network. The model configurations and training procedures are described in section 3.3.

3.1 Attention Enhanced ResNet (Self-Attention)

The self-attention mechanism can be naturally combined with residual block to guide financial feature learning [10]. The self-attention mask estimate a set of weights learned from the input to residual block using a fully connected layer followed by SoftMax function to normalize weights to a range from 0 to 1. Shown in figure 3, the attention mask weights are applied to the output units of the residual block via element-wise product (i.e. after the σ activation function). Formally, the self-attention enhanced residual block is formulated as follows:

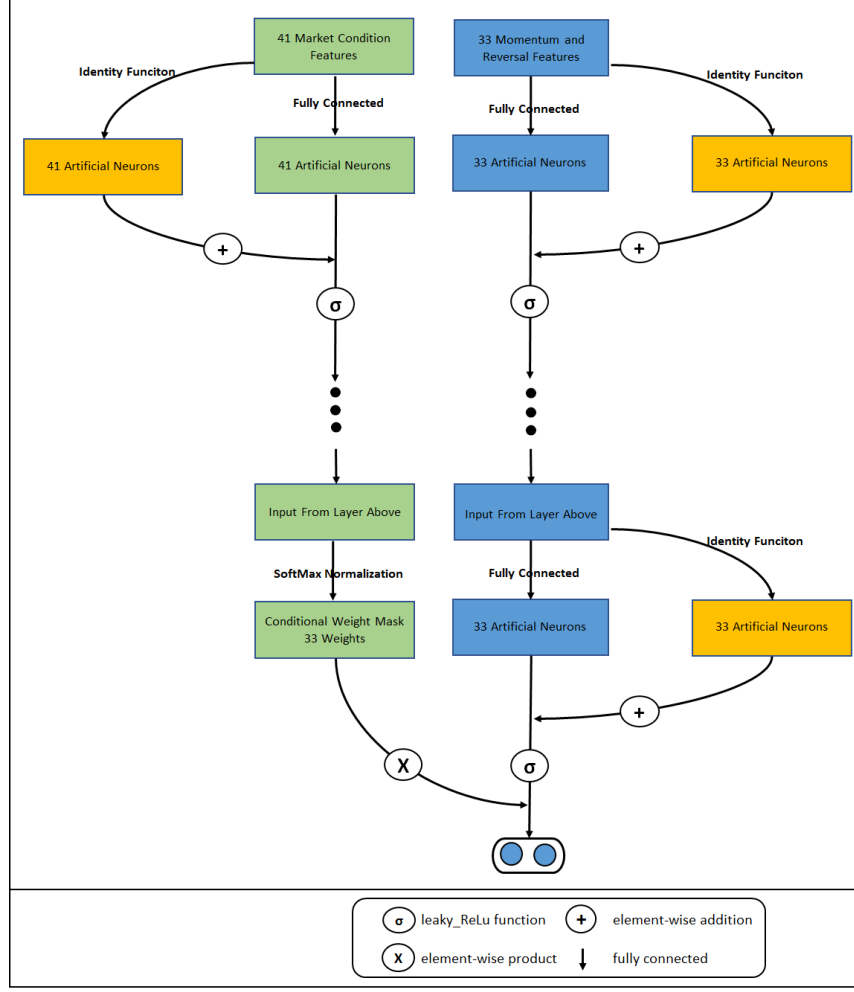


Fig. 2. Switching-ResNet combines the main module (ResNet in blue) with the switching module (ResNet in green). The main module learns momentum and reversal predictors of 2000 individual stocks. The switching module learns market conditions of SP500 realized volatility, squared VIX and SP500 variance risk premium. The switching module outputs a conditional weight mask, which is combined with the last parameter layer of the main ResNet (via element-wise product) to select long and short portfolios.

Given $n \in \{1, 2, \dots, N\}$, $i, j \in \{1, 2, 3, \dots, D\}$, $f^{(0)}(X) = X$ is the input vector. In (1) and (2), the attention module learns a hidden layer on $f^{(n-1)}(X)$ the input vector to the block. Equations (3) and (4) computes the mask weights $f^{a,(n+1)}(X)$, which normalizes $z^{a,(n+1)}(X)$ via SoftMax function, Φ . In (5), we apply attention mask weights $f^{a,(n+1)}(X)$ to the output of residual block, $f^{(n+1)}(X)$, via element-wise product.

Self-Attention Module,

$$z^{a,(n)}(X) = W^{a,(n)} \cdot f^{(n-1)}(X) + b^{a,(n)} \quad (1)$$

$$f^{a,(n)}(X) = \sigma(z^{a,(n)}(X)) \quad (2)$$

$$z^{a,(n+1)}(X) = W^{a,(n+1)} \cdot f^{a,(n)}(X) + b^{a,(n+1)} \quad (3)$$

$$f^{a,(n+1)}(X) = \Phi(z^{a,(n+1)}(X)) \quad (4)$$

Residual Block,

$$z^{(n)}(X) = W^{(n)} \cdot f^{(n-1)}(X) + b^{(n)} \quad (5)$$

$$f^{(n)}(X) = \sigma(z^{(n)}(X)) \quad (6)$$

$$z^{(n+1)}(X) = W^{(n+1)} \cdot f^{(n)}(X) + b^{(n+1)} \quad (7)$$

$$z^{(n+1)}(X) + f^{(n-1)}(X) \quad (8)$$

$$f^{(n+1)}(X) = \sigma(z^{(n+1)}(X) + f^{(n-1)}(X)) \quad (9)$$

Combine Self-Attention Module with Residual Block,

$$f^{(n+1)}(X) \otimes f^{a,(n+1)}(X) \quad (10)$$

To construct the Attention-ResNet, we stack attention enhanced residual blocks. Assuming the underlying mapping for the plain ANN is $F(\mathbf{X}, \Theta)$, the residual network asymptotically approximates equation (6), where $R(\mathbf{X}, \Theta)$ represents the learned residual mapping. In equation (7), attention mask $M(\mathbf{X}, \Theta)$ is applied via element-wise product to enhance predictive power and model flexibility [9, 10].

$$\mathbf{Y} = R(\mathbf{X}, \Theta) + \mathbf{X} \quad (11)$$

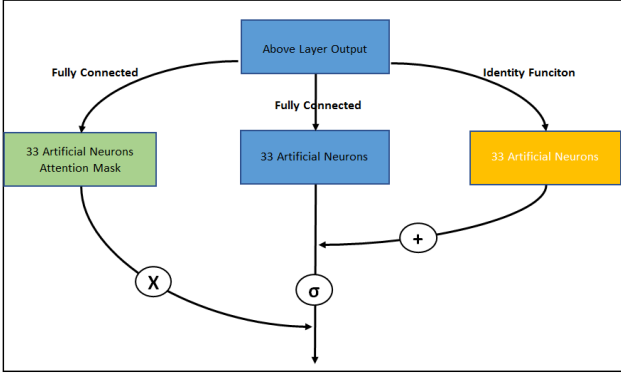


Fig. 3. Attention Enhanced Residual Block, \oplus denotes element-wise addition, σ denotes Leaky-ReLU activation function, and \otimes denotes element-wise product. The short circuit in yellow occurs before σ activation, and attention mask in green is applied after σ activation.

$$\mathbf{Y} = (R(\mathbf{X}, \Theta) + \mathbf{X}) \cdot M(\mathbf{X}, \Theta) \quad (12)$$

Since our target variable is binary (see section 4.1), we minimize the error between the estimated conditional probability and the correct target label formulated as the following cross-entropy loss with weight regularization:

$$\begin{aligned} \Theta^{Optimal} = \operatorname{argmin}_{\Theta} \{ & \frac{-1}{M} \sum_m y^{(m)} \cdot \log \mathbf{F}(x^{(m)}; \Theta) \\ & + (1 - y^{(m)}) \cdot \log(1 - \mathbf{F}(x^{(m)}; \Theta)) \\ & + \lambda \sum_n \|\Theta\|_F^2 \} \end{aligned} \quad (13)$$

Cross-entropy loss function speeds up convergence when trained with gradient descent algorithm, also imposes a heavy penalty if $p(y = 1|X) = 0$ when the true target label is 1, and vice versa.

3.2 Residual Switching Network (Guided-Attention)

The switching module is a guided-attention mechanism conditional on SP500 realized volatility, squared VIX, and SP500 variance risk premium. As the market regime shifts from bullish to bearish, the switching module can guide the ResNet to switch from momentum to reversal predictors, and vice versa. Shown in Figure 2, the switching module (in green, guided by market conditions) computes a conditional weight mask that is then combined with the main module ResNet (in blue) right before the output. More formally:

$f^{(s,0)}(X^s) = X^s$ are market condition feature inputs for the switching module. At layer N , $n = N$, $f^{s,(N)}(X^s)$ computes the conditional mask weights, which normalizes $z^{s,(N)}(X^s)$ using SoftMax function, Φ . The conditional weights are normalized to strictly positive and sums to 1.

$$f^{s,(N)}(X^s) = \Phi(z^{s,(N)}(X^s)) \quad (14)$$

$$\Phi(z^{s,(N)}(X^s)) = \left[\frac{\exp(z_1^{s,(N)}(X^s))}{\sum_c \exp(z_c^{s,(N)}(X^s))}, \dots, \frac{\exp(z_c^{s,(N)}(X^s))}{\sum_c \exp(z_c^{s,(N)}(X^s))} \right]^T$$

Now, we apply conditional weight mask, $f^{s,(N)}(X)$, to the N th parameter layer of the main module, i.e. blue ResNet in Figure 2.

$$f^{(N)}(X) \otimes f^{s,(N)}(X^s) \quad (15)$$

The main module in Figure 2 learns both momentum and reversal predictors for approximately 2000 stocks listed in the US. In a bullish regime, the conditional weight mask can place higher weights on momentum predictors and near-zero weights on reversal predictors. As the market enters a bearish regime, the conditional weight mask switches higher weights onto reversal predictors and near-zero weights onto momentum predictors.

$$\mathbf{Y} = (R(\mathbf{X}, \Theta) + \mathbf{X}) \cdot M(\mathbf{X}^s, \Theta^s) \quad (16)$$

3.3 Training Paradigm

For the self-attention ResNet, we use 22 ResNet layers for the main module and 12 fully connected layers for the self-attention module. Each parameter layer has dimension 33 to match the dimension of input tensors (momentum and reversal features). For the Switching ResNet, we use 6 ResNet layers for the main module, each parameter layer has dimension 33, and also 6 ResNet layers for the switching module, each parameter layer has dimension 41 to match the dimension of (market condition features). See figure 2. We use the leaky-ReLU activation function with batch size set to 512. We implement batch normalization [1] on every hidden layer except the output layer. We first add random Gaussian noise $N(0, 0.1)$ to the input tensor for noise resistance and robustness. We set λ to 50 with exponential decay of 0.999, and set dropout rate to 0.5 for every hidden layer. We use the ADAM optimizer with an initial learning rate of 1e-3 and 0.995 exponential decay. We train the proposed networks for approximately 5 epochs and validate our networks every 10k steps.

Figure 4 depicts the rolling dataset arrangement for the entire sample period. We employ five years of historical data to train and validate our model, 90 percent for training, and 10 percent for validation. We utilize the subsequent one-year's data to test the performance. The procedure continues from Jan 2008 to H12017 to obtain in-sample results from Jan 2008 to the end of 2012, and out-of-sample results from Jan 2013 to H12017.

EXPERIMENTS

In this section, we carry out experiments to demonstrate the effectiveness of our proposed networks and evaluate their

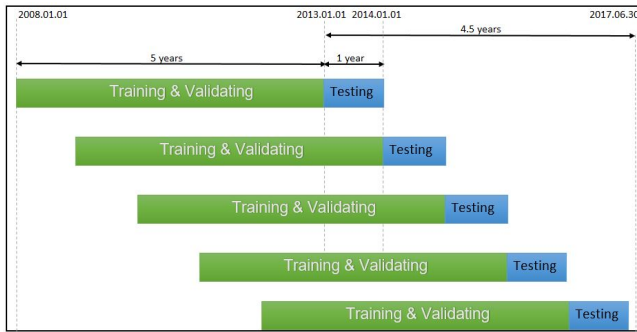


Fig. 4. Rolling dataset arrangement for training, validating, and testing from Jan 2008 to H12017.

performance. In section 4.1, we describe the dataset in our experiments. Section 4.2 validates the effectiveness of Attention-ResNet. We demonstrate the benefits of the switching module in section 4.3. We further illustrate the performance boost from Switching-ResNet in 4.4.

4.1 Dataset

The trading universe comprises of approx. 2000 stocks listed on NYSE, NASDAQ, and AMEX. Our sample period spans 9.5 years beginning in Jan 2008 and ending on June 2017. The dataset includes stocks’ adjusted daily closing price data and daily VIX index data from Bloomberg. To ensure liquidity, we sample stocks with price traded above 5 USD and market capital over one billion USD at the time of portfolio formation [24]. We implement the same model input features as in Takeuchi and Lee 2013. These are price momentum and reversal features, which include 12 normalized monthly returns for month $t - 2$ through to $t - 13$, 20 normalized past daily returns, and an indicator variable for the month of January to capture turn-of-the-year-patterns. Input features for switching module are 41 market condition features on the SP500, these include 12 normalized SP500 return variance for month $t - 2$ through to $t - 13$, 23 past daily squared VIX values, and 6 SP500 variance risk premiums for month $t - 1$ through $t - 6$. For target, we label stocks with monthly return above the median as class 1, and class 0 otherwise. The holding period spans 20 trading days [5].

4.2 Validation of Attention-ResNet

Experiment Setting: We back-test trading signals through empirical data. We construct delta-neutral long-short portfolio by ranking the estimated conditional probabilities for all stocks in the trading universe, then long and short stocks with estimated probabilities in the top and bottom decile, respectively. We also back-test the predictive accuracy in terms of cross-entropy error. We evaluate and compare the performance of the Attention ResNet with the plain ANN and the linear model (logistic regression).

Results and Discussion: The in-sample predictive accuracy (cross-entropy error) of the 22-layer ANN outperformed the 22-layer Attention-ResNet, and the Attention-ResNet

outperformed the logistic regression, see Table 1. Similarly, the in-sample historical PNL of the plain ANN outperformed the Attention-ResNet, and the Attention-ResNet outperformed and the linear model, see Fig 5. This validates our hypothesis that the 22-layer plain ANN over-fits the dataset and the linear model under-fits the dataset. The 22-layer Attention ResNet can strike an optimal balance between the two. The out-of-sample cross-entropy error of the 22-layer Attention-ResNet outperformed the other two models.

Year	Attention ResNet	ANN	Linear Model
In-Sample Mean	0.6783	0.6586	0.6918
Out-Sample Mean	0.6838	0.7014	0.6931

TABLE I
CROSS-ENTROPY ERROR. IN SAMPLE 2008 TO 2012, OUT-SAMPLE 2013 TO H12017.

The out-of-sample predictive accuracy (cross-entropy error) of the Attention ResNet outperformed the other two models, see Table 1. The out-of-sample historical PNL of the Attention ResNet also outperformed the other two models, see Fig 5. In terms of annualized return, the 22-layer Attention-ResNet averaged 8.86%, the other two models averaged just over 2%. Sharpe ratio for the 22-layer Attention-ResNet averaged 1.77, whereas the other two models averaged below 1. We further validate our results by a t-test with the null hypothesis stating no statistically significant difference between the models out-of-sample monthly returns. The t-test rejects the null at the 10 percent level and supports the superior out-of-sample performance of Attention-ResNet.

Year	Attention ResNet (Return)	ANN (Return)	Linear Model (Return)
2008	18.69%	30.74%	-5.67%
2009	43.79%	57.24%	36.12%
2010	37.37%	52.25%	40.93%
2011	20.54%	31.71%	13.41%
2012	24.16%	27.45%	9.30%
2013	16.93%	8.57%	7.74%
2014	14.91%	3.74%	8.07%
2015	10.27%	4.69%	9.97%
2016	-2.95%	-10.43%	-10.63%
H12017	5.16%	4.94%	-1.95%
Out-Sample Mean	8.86%	2.30%	2.64%

TABLE II
ANNUALIZED RETURN. IN SAMPLE 2008 TO 2012, OUT-SAMPLE 2013 TO H12017.

4.3 Validation of Switching Module

Experiment Setting: We first test the predictive power of the standalone switching module on S&P500 index’s realized volatility (RV). We illustrate that the switching module can accurately predict S&P500’s RV. Our sample period is approx. 13 years beginning in Jan 2005 and ending in Dec 2017. We employ ten years of historical data for training and validation, and the subsequent three years to test the out-of-sample R^2 . The target is next months S&P500’s RV,

Year	Attention ResNet (Sharpe)	ANN (Sharpe)	Linear Model (Sharpe)
2008	4.96	8.99	-0.69
2009	5.98	6.64	3.68
2010	4.57	5.27	3.22
2011	5.60	8.19	2.12
2012	7.70	7.36	1.43
2013	2.17	1.44	1.58
2014	2.15	0.72	1.41
2015	3.31	2.14	2.51
2016	-0.98	-3.09	-4.43
H12017	2.18	2.84	2.40
Out-Sample Mean	1.77	0.81	0.69

TABLE III

SHARPE RATIO. IN-SAMPLE 2008 TO 2012, OUT-SAMPLE 2013 TO H12017. SHARPE RATIO DEFINED AS $\mu-r/s$, WHERE μ , r , s ARE THE ANNUALIZED RETURN, RISK FREE RATE AND STANDARD DEVIATION OF THE PNL.

Network Architecture	In-Sample R^2	Out-of-Sample R^2
Simple Strategy	43%	57%
Linear Regression	65%	58%
1-layer ANN	71%	63%
2-layer ANN	78%	68%
3-layer ANN	85%	59%
2-layer ResNet	67%	56%
4-layer ResNet	69%	57%
6-layer ResNet	73%	71%

TABLE IV

R^2 SCORES FOR S&P500 REALIZED VOLATILITY PREDICTION.

$1/22 \sum_{t=1}^{22} \ln(SP_t/SP_{t-1})^2$. There are 41 input features (see section 4.1), the variance risk premium can be quantified as the difference of variance swap rate and ex-post RV in equations below [29], using statistical probability \mathbb{P} , $m_{t,T} = M_{t,T}/\mathbb{E}_t^{\mathbb{P}}[M_{t,T}]$ where $M_{t,T}$ is a pricing kernel. We use VIX as an approximator for 30-day variance swap rate on the S&P500, and formulate the variance risk premium for S&P500 returns as the difference between VIX and S&P500 index's one month realized variance [30].

Results and Discussion: We evaluate predictive accuracy performance in terms R^2 for different models: simple strategy, linear regression, 1-3 layer ANN, 2-6 layer ResNet. The simple risk model is often used as the benchmark for out-of-sample R^2 evaluation [28]. Shown in Table , the out-of-sample R^2 improves with 1-layer and 2-layer plain ANNs, but the 3-layer ANN over-fits the dataset with very high in-sample R^2 and deteriorated out-of-sample R^2 . The ResNet architecture exhibit better control for over-fitting. ResNet's in-sample R^2 steadily increases with gradual improvement in out-of-sample R^2 , and we conclude that the 6-layer ResNet demonstrates superior predictive power for S&P500 realized volatility.

$$SW_{t,T} = \frac{\mathbb{E}_t^{\mathbb{P}}[M_{t,T}RV_{t,T}]}{\mathbb{E}_t^{\mathbb{P}}[M_{t,T}]} = \mathbb{E}_t^{\mathbb{P}}[m_{t,T}RV_{t,T}] \quad (17)$$

$$SW_{t,T} = \mathbb{E}_t^{\mathbb{P}}[m_{t,T}RV_{t,T}] = \mathbb{E}_t^{\mathbb{P}}[RV_{t,T}] + \text{Cov}_t^{\mathbb{P}}(m_{t,T}, RV_{t,T})$$

Network Architecture	In-Sample R^2	Out-of-Sample R^2
Simple Strategy	43%	57%
Linear Regression	65%	58%
1-layer ANN	71%	63%
2-layer ANN	78%	68%
3-layer ANN	85%	59%
2-layer ResNet	67%	56%
4-layer ResNet	69%	57%
6-layer ResNet	73%	71%

TABLE V

R^2 SCORES FOR S&P500 REALIZED VOLATILITY PREDICTION.

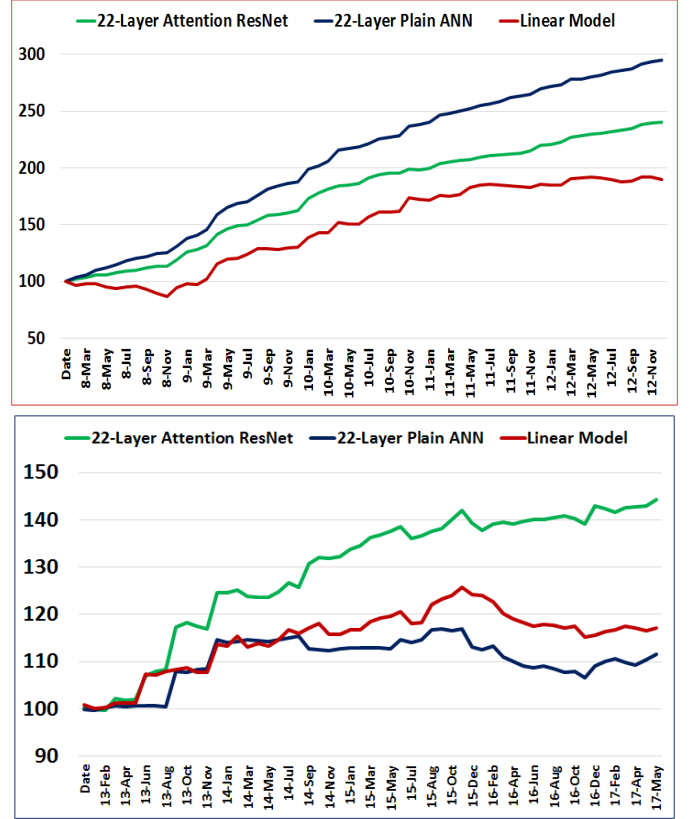


Fig. 5. Top: In-sample historical PNL comparison. Bottom: Out-of-sample historical PNL comparison.

4.4 Validation of Switching-ResNet

Experiment Setting: We combine the switching module (6-layer ResNet from section 4.2) with the main module to complete the Switching-ResNet, as described in section 3.2. We evaluate the ability of the switching module to switch between momentum and reversal predictors as market regimes changes (bullish or bearish). We analyze the dynamic behavior of the conditional weight mask. Finally, we evaluate the out-of-sample performance of the Switching-ResNet.

Results and Discussion: The dynamic behavior of the conditional weight mask demonstrates the effectiveness of the attention on momentum and reversal predictors as

Year	Attention ResNet (Self Attention)	Switching ResNet (Guided Attention)
	Annual Return	Annual Return
2013	16.93%	12.20%
2014	14.91%	13.41%
2015	10.27%	14.38%
2016	-2.95%	8.30%
H1 2017	5.16%	5.49%
Mean	8.86%	10.76%
	Sharpe Ratio	Sharpe Ratio
2013	2.17	2.08
2014	2.15	1.93
2015	3.31	2.43
2016	-0.98	2.52
H1 2017	2.18	2.15
Mean	1.77	2.22

TABLE VI
OUT-OF-SAMPLE RETURN AND SHARPE RATIO.

market conditions changes from bullish to bearish market regime, and vice versa. The switching module computes 33 weights in the range $[0,1]$ and the sum of the weights is 1. We observe two patterns on the weight mask. Weights assigned to reversal predictors are higher during periods of high market volatility and positively correlated with the VIX index. Weights assigned to momentum predictors are lower during periods of high market volatility and negatively correlated with the VIX index.

Figure 6 plots the co-movement of VIX index and conditional weights. When VIX spiked in Q3 2008, Q2 2010, Q3 2011 and H2 2015, weights on reversal predictors spiked to 0.8, and weights assigned to momentum predictors dipped. The correlation matrix below shows that the VIX index and reversal weights are correlated by 23%, whereas the VIX index and momentum weights are correlated by -19%. The conditional weights on reversal and momentum predictors are correlated by -59%. This result further supports our hypothesis that in a bullish regime with lower VIX, the conditional weight mask gives more attention to momentum predictors, and as the market changes to bearish regime with higher VIX, the switching model guides attention back on reversal predictors.

	VIX Index	Reversal Weight	Momentum Weight
VIX Index	100%	23%	-19%
Reversal Weight		100%	-59%
Momentum Weight			100%

The Switching-ResNet’s out-of-sample historical PNL outperformed the Attention-ResNet in 2016, and their performance for other years was relatively similar, see Table 5. When the S&P500 volatility and the VIX index spiked in late 2015 to mid-2016, the Attention-ResNet was not profitable during this period. The Switching-ResNet was able to correctly identify the change in market conditions, and guide attention from momentum predictors back onto reversal predictors to reap higher rewards in the US equities market.

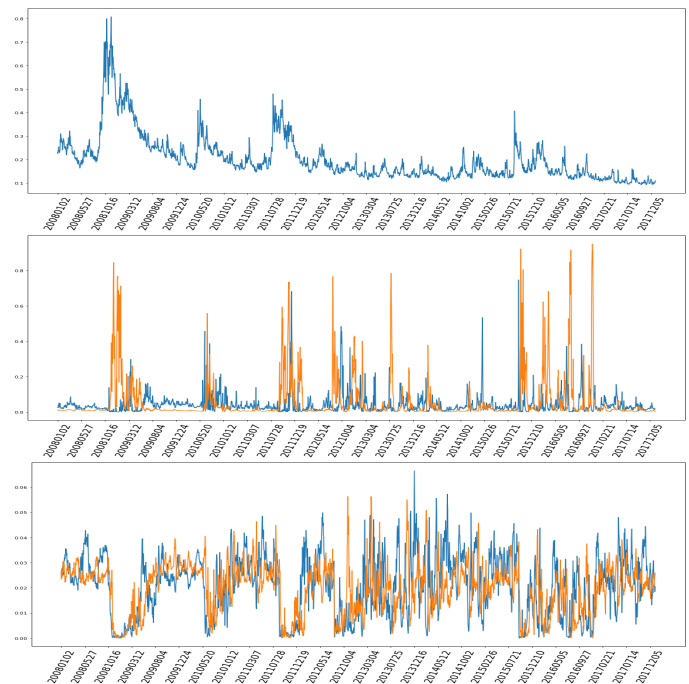


Fig. 6. Top: VIX index from Jan 2008 to Dec 2017. Middle: Weights assigned to reversal predictors. Bottom: Weights assigned to momentum predictors.

CONCLUSION

We propose the Residual Switching Network to combine a regime-switching module with the residual network. The advantages of our network are in two folds. The first advantage comes from leveraging the guided-attention mechanism to automatically sense dynamic changes in stock market conditions, and guide our network to place more attention on momentum and reversal predictors accordingly. Our experiment validates the effectiveness of the switching module and provides direct evidence for our network’s ability to generate superior out-of-sample Sharpe ratio as market conditions change over time. The second advantage lies with residual learning’s ability to train very deep networks while addressing the over-fitting problem when applying DL models to noisy financial data. Our experiments verify that our deep Attention-ResNet can strike a balance between linear and complex non-linear models for financial modeling. The scope of our work extends residual learning and attention mechanism to portfolio management, these concepts are hopeful for other financial fields.

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