Forecasting Hedge Fund Index Returns by Level and Classification: A Comparative Analysis of Neural Network Topologies

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Abstract

Over the recent past, stylized facts have not yielded a synthesis regarding the predictability of returns for alternative investment assets such as hedge funds. Recent studies on alternative asset return predictability have added to the ambiguity. These studies suggest that classification prediction methods may dominate more traditional return-level prediction methodology. This paper examines the predictive accuracy of three alternate radial basis function neural networks when applied to the returns of thirteen Credit Swiss First Boston/Tremont (CSFB) hedge fund indices. We provide evidence that the Kajiji-4 RBF neural network dominates within the RBF topology in the prediction of hedge fund returns by both level and classification. The results also show that the Kajiji-4 method is capable of near perfect directional prediction.

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I. Introduction

Whether the investor's objective is to trade direction or maximize trading returns in a particular market, an optimal trading rule is necessary if the investor is to form an expectation of the future return. Recent comparisons of alternative return prediction methodologies offer a mixed view as to the comparative accuracy of classification methods versus return-level prediction approaches. Unlike return-level forecasts that attempt to predict a future return level, classification-based methods focus on the direction of the expected movement. However, the value of future return predictions depends solely upon the efficacy of the forecasting method. The determination of which prediction methodology is a preferred has been subjected to a meaningful debate. So far, this debate has yielded support for methods that predict return levels of associated capital market instruments.

In a recent study on the predictability of three international capital market indices, Leung, et. al. (2000) present findings that challenge the contemporary view supporting the dominance of return-level prediction over classification prediction methods. Leung reported that classification-based prediction dominates return-level methods in the number of times a predicted observation was consistent with its actual outcome. Additionally, a threshold trading rule simulation found greater wealth creation from trading activity to be associated with a classification based approach. The probabilistic classification methods examined by Leung included linear discriminant analysis, logit- and probit-modeling along with a probabilistic neural network (PNN). The return-level forecasting methods were exponential smoothing, multivariate transfer function (ARIMA), vector autoregression with Kalman filter, and multilayered feedforward neural network (MLFN). In a comparison of predictive strength, Leung concludes that the artificial neural network architecture (MLFN) achieved superior within class performance.

If, as these findings report, that classification methods dominate traditional return-level forecasting strategies this would certainly provide an interesting challenge to some of the earliest and most influential findings on predicting asset class returns as observed in the U.S. and international markets (see, for example, Keim and Stambaugh (1986), Campbell and Shiller (1989), Fama and French (1989), Ferson and Harvey (1991), Barberis (2000), Harasty and Roulet (2000), and Lynch (2000)). We note, however, that the Leung analysis is based upon a software product (ThinkPro computer package) for which there is no active Internet site nor any other published academic evaluations. The absence of a comparative reference does not permit a certification of the modeling software nor does it help to position the efficiency of the ThinkPro computer package against more recognized ANN applications.[1]

The purpose of this study is twofold. First, it is to reexamine and reconcile the findings on alternative hedge fund returns prediction provided by Leung on the one hand and Amenc, et. al. (2002) on the other. Second, it is to extend the modeling of hedge fund indexes by applying the Kajiji-4 RBF ANN to the Credit Swiss First Boston/Tremont (CSFB/T) family of hedge fund index returns. The nonparametric Kajiji-4 RBF ANN algorithm has proven to be an efficient and dominant algorithmic tool when compared against the GARCH framework and a broad range of alternative ANN topologies. For example, in a direct comparison to both the generalized regression and backpropagation ANN algorithmic structures, Dash et. al. (2003) demonstrate the method's dominance when modeling high frequency volatility. Elsewhere, Dash and Kajiji (2002) provide additional evidence of algorithmic dominance in a comparison of the Kajiji-4 method against well-known RBF ANNs in an application of 1-hour FX volatility.

The paper proceeds as follows. Section 2 of the paper presents a discussion of the multivariate statistical method used to uncover and update existing findings regarding the predictability of hedge fund returns. Section 3 of the paper identifies the comparative RBF topologies that are tested for efficient prediction of the hedge fund returns. Results of the prediction experiment are presented in section 5. The paper concludes with a summary and conclusion in section 6.

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[1] See Balci (2001) for an analytical framework for certifying modeling and simulation software applications. Also, for contemporary issues related to software compactness see Debray, et al (2000), Fraser and Wendt (1986), Hanson (1983), Lindvall, et.al (2003), Dyba (2000), Sheldon and Greiner (1999), and Mayrand, et.al (2000).

2. The Structure of Hedge Fund Returns

Exposition guidelines lead us to center the analysis on two of the thirteen hedge funds within the CSFB/T group. Throughout the paper we refer to the Dedicated Short Bias fund and the Equity Market Neutral fund as the focus indices. They are chosen for this role based on the level of their relative volatility (coefficient of variation). For the time period of this study, the Dedicated short bias is the most volatile of the indexes and the Equity Market Neutral index is the least volatile within the group.

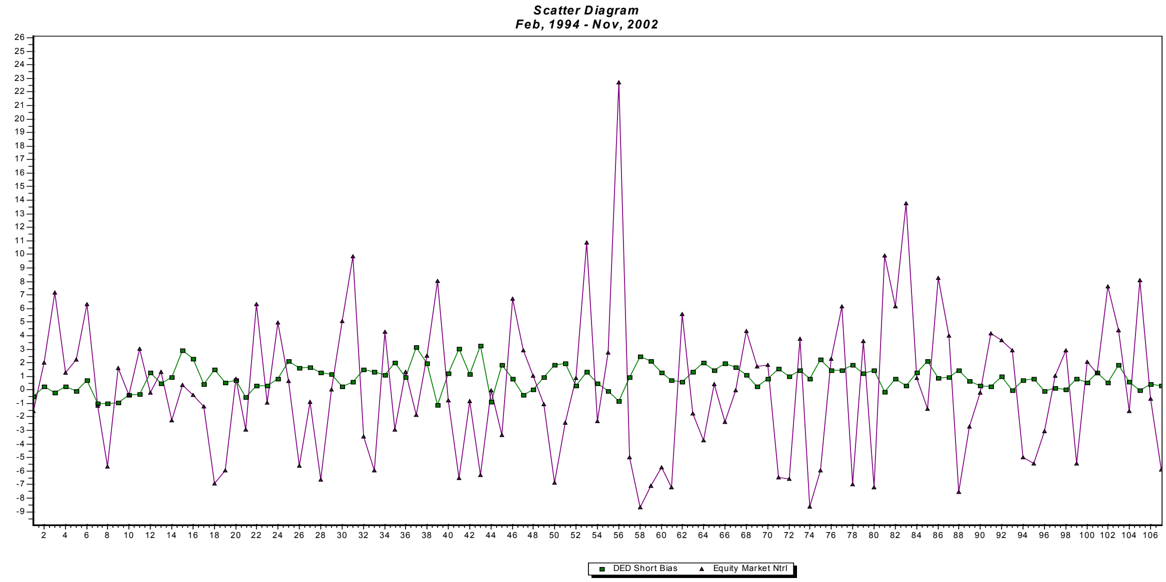
2.1 Data

The data for this analysis consists of 108 monthly return observations from January 1994 to December 2002 on the group of hedge fund indexes published by CSFB/T. The 13 CSFB/T hedge fund indices range from a high volatility style (Dedicated Short Bias) to a much lower volatility style (Equity Market Neutral). Detailed descriptive characteristics of the fund indexes are reported in Amenc (2002). Performance characteristics on the CSFB/T indexes are provided by Lhabitant (July 2002). Because one of our objectives here is to model returns by tactical style for the purpose of obtaining accurate predictions, we augment the previously presented statistical findings on returns symmetry. The added information is necessary to fully achieve our objective, which is to compare performance differences among the alternative RBF topologies on a small monthly returns database.

2.2 Hedge Fund Returns

Figure 1 displays a scatter diagram of the returns for the two focus hedge funds. This display is complemented by the descriptive statistics as presented in table 1. This table is designed to assist in the assessment or returns symmetry. To that end, both a skewness and kurtosis measure are presented. Additionally, the table presents the results of applying the small sample Shapiro-Wilk test for normality.

Figure 1: Scatter Diagram of DED Short Bias v/s Equity Market Neutral Fund



In a manner that is consistent with prior findings we a test the Gaussian properties of the index returns (see, Fung and Hsieh (1999) and Kat and Lu (2002) for detailed reviews on hedge fund Gaussanity). The reported *p*-values extracted from the application of the Shapiro-Wilk test support the conventional wisdom that hedge fund returns are not characteristic of a normal distribution. Additionally, we find strong and significant evidence that the CSFB/T returns are leptokurtic (fat-tailed). Specifically, we find only one fund (Equity Market Neutral) with a kurtosis measure that is close to zero (-0,006). Interestingly, the skewness measure for this one index is also very small and positive (we expected a negative value). However, this finding cannot be generalized to seven of the thirteen indexes. Within this subgroup of seven indexes, the kurtosis measure is measurably different from zero and, in some cases, quite high. At the low end in this group is the Emerging Markets index with a kurtosis value of 2.999. The Event Driven index tops this subgroup with a measure of 20.153. The returns distributions for this group all display negative skewness coefficients. This leads us to conclude that the distributions within this subgroup are asymmetrical. Asymmetries are further evidenced within the subgroup by the negative skewness coefficients. The implication for the risk-averse investor is not a promising one. That is, these findings suggest the potential for extreme negative returns; a finding that negates the application of traditional mean-variance diversification. As we look ahead to the forecasting simulation, it will be interesting to focus on the ability of the various algorithmic methods to treat the observable asymmetries.

Table 1. Descriptive Statistics

	Mean	Standard Deviation	Variance	CV	Skewness	Kurtosis	W:Normal*
CSFB/T Hedge Fund Index	0.879	2.569	6.599	2.924	0.110	1.238	0.889
Convertible Arbitrage	0.825	1.405	1.973	1.704	-1.602	3.877	0.826
Dedicated Short Bias	0.203	5.310	28.201	26.177	0.825	1.819	0.802
Emerging Markets	0.547	5.361	28.739	9.795	-0.477	2.999	0.895
Equity Market Neutral	0.882	0.922	0.849	1.045	0.126	-0.006	0.919
Event Driven	0.851	1.813	3.288	2.132	-3.272	20.153	0.773
Distressed	0.983	2.092	4.375	2.127	-2.609	14.281	0.821
E.D. Multi Strategy	0.783	1.919	3.684	2.452	-2.499	14.522	0.807
Risk Arbitrage	0.680	1.326	1.758	1.949	-1.345	5.775	0.874
Fixed Income Arbitrage	0.547	1.184	1.402	2.165	-3.155	14.930	0.734
Global Macro	1.172	3.668	13.453	3.129	-0.018	1.459	0.907
Long / Short	0.973	3.325	11.055	3.417	0.236	2.717	0.859
Managed Futures	0.571	3.463	11.993	6.062	0.042	0.743	0.913

2.3 Hedge Fund Predictors

To parsimoniously capture the covariance structure of the hedge fund returns with recognizable predictor variables, we follow the APT encompassing approach of Han (2002). In the absence of daily (or greater) observations over a sufficiently long horizon we are not able to invoke a dynamic factor multivariate stochastic volatility test. Our reliance on monthly data also rules out the ability to invoke the Bollerslev (1986) multivariate GARCH model or the multivariate stochastic volatility of Chib, et. al. (2001). Therefore, we proceed by first identifying the commonly used predictor variables in forecasting and modeling returns by ANN methods. Next, we employ factor analytic methods to reduce the collinear structure of these subjectively chosen predictor variables.

2.3.1 Predictor Variables

The selection of predictor variables for ANN models remains an elusive science. Since an objective of this paper is to re-examine earlier prediction efforts, we adapt the choice of predictor variables from Leung, et. al. (2000) and Amenc (2002). The variable(s) used to proxy each dimension is listed below the dimension identifier in table 2. It is well known that many of the predictor proxies listed below exhibit collinear structure. Unless specifically adapted, ANN algorithms require predictor variables to maintain statistical independence. Some ANN methods, like the Kajiji-4 algorithm, resolve collinearity. Nevertheless, where possible statistical independence is desired. As an alternative to exhaustive testing of alternative model specifications, we employ multivariate principal component analysis (PCA) with Varimax rotation to reduce dimensionality and to uncover the latent uncorrelated factor structure among the economic proxies.

2.3.2 Varimax Rotation

The results of applying the Varimax rotational technique to the predictor variables are presented in table 3. The factor analysis results produced six factors with eigenvalues of at least 1.0. These factors explain slightly more than 76 percent of the total variation in the predictor variables.

Table 2. Contemporary Predictor Variables

Economic Dimension	Pneumonic(s)	Proxy-a	Proxy-b
Short Term Interest Rates	3TBYld; 1D3TBYld	Yield on the 3-month T-bill rate for the US	First difference of yield on 3-month US T-bill rate
Long Term Interest Rates	1D20TB	First difference of the 20 year government bond rate for the US	
Consumer Price Index (CPI)	1DCPI	First difference US CPI	
Industrial Production Level	1DIP	First difference of US industrial production index	
Dividend Yield	S&PdivYld	Dividend yield on the S&P stocks	
Default Spread	MBaaMAAA	Difference between the yield on Moody's long term Baa bonds and the yield on Moody's long term AAA bonds	
Term Spread	10TB-3TB	Difference between the yield on 10-year T-bond and 3-month T-bill	
Implicit Volatility	ΔVIX	Change in the average intra-month values of the VIX	
Market Volume	ΔNYSE	Change in the market value on the NYSE	
Events	MLHBF; MLHBFCC	Merrill Lynch High Yield Bond Fund	Log-differenced returns on the Merrill Lynch High Yield Bond Fund
Oil Price	WTXOIL; WTXOILlag	Average price of west Texas intermediate crude	Lag price of west Texas intermediate crude
US Equity Factor	S&PlagCC; S&PCC	One period lag of the log-differenced returns of the S&P500 Index.	Log-differenced returns of the S&P500 Index
World Equity Factor	MSCIlagCC	Log-differenced returns on the MSCI World Index excluding US	
Currency Factor	1DCRB; USDTW	First difference in the Bridge Commodity Research Bureau Currencies Index	Trade-weighted Exchange Value of USD
Futures Index	CRBF; 1DCRBF	CRB Futures Index	First difference CRB Futures Index

Table 3: Varimax Rotated Factor Loading

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Row %
MLHBF	-0.946	.	.	.	.	.	.	.	0.949
S&PdivYld	0.928	.	.	.	.	.	.	.	0.967
USDTW	-0.834	.	.	.	.	.	.	.	0.902
CRBF	0.805	.	.	.	.	.	.	.	0.800
MBaaMAAA	-0.466	0.744	.	.	.	.	.	.	0.821
1D3TBYld	.	.	.	.	.	-0.660	.	.	0.630
3TBYld	.	-0.907	.	.	.	.	.	.	0.931
10TB-3TB	.	0.886	.	.	.	.	.	.	0.887
WTXOILlag	.	.	.	-0.915	.	.	.	.	0.927
WTXOIL	.	.	.	-0.940	.	.	.	.	0.955
1DCRBF	.	.	.	.	.	.	.	0.495	0.637
1DCRB	.	.	.	.	.	0.522	.	.	0.545
MLHBFCC	.	.	.	.	0.864	.	.	.	0.827
S&PCC	.	.	0.936	.	.	.	.	.	0.923
ΔVIX	.	.	-0.558	.	-0.595	.	.	.	0.800
MSCIlagCC	.	.	0.951	.	.	.	.	.	0.944
1DCPI	.	.	.	.	.	.	0.804	.	0.822
1D20TB	.	.	.	.	.	-0.773	.	.	0.663
S&PlagCC	.	.	.	.	0.833	.	.	.	0.789
ΔNYSE	.	.	.	.	.	.	0.745	.	0.773
1DIP	.	.	.	.	.	.	.	0.837	0.755
Eigenvalue	3.716	2.600	2.407	2.345	2.047	1.501	1.378	1.251	
Cum%VarExp	0.177	0.301	0.415	0.527	0.625	0.696	0.762	0.821	

2.3.3 Latent Factor Descriptions

The latent factor dimensions are subjectively classified and presented in table 4.

Table 4: Latent Factor Classification

Factor	Domain Characteristic
F1	Yields on Equity and Risky Bonds with Currency and Futures Effects
F2	Default and Term Spread with Inverse 3-Tbill Effect
F3	Continuously compounded returns on domestic and world Equity markets with inverse effects of VIX
F4	Oil
F5	Continuously compounded returns on high yield bonds with lagged equity returns and inverse VIX
F6	First Differenced 20-year Tbond and 3-Tbill with inverse on differenced currency effect
F7	Effect of CPI and change in domestic market volume
F8	Change in industrial production

2.3.4 Factor Scores

Based on the extracted factors, we compute factor scores of each subject as a means of reducing the predictor variables down to six latent variables that correspond to the rotated domains. We follow the method of Thomson (1951). If f_r is the score of the r^{th} factor corresponding to a response of **x**, then we estimate f_r by a linear combination of the x_i:

$\hat{f}_r = a_r x$. We choose $\boldsymbol{a}_r$ such that $E\left[\left(\hat{f}_r - f_r\right)^2\right]$ is minimized. In vector notation

$f' = \left(f_1, \ldots, f_k\right)$, and the solution is estimated by:

$$\hat{F} = \hat{\Lambda}' \hat{\sum} x, \qquad (1)$$

where Λ is the factor loading matrix, $\sum$ the covariance matrix, and $\boldsymbol{x}$ the original data matrix. From each set of responses $\boldsymbol{x}$ we obtain the vector of factor scores $\boldsymbol{f}$.

3. The Kajiji-4 Benchmark Radial Basis Function

In this section we present the methodology supporting the use of the Kajiji-4 RBF as the control neural network against which the alternate neural network topologies are tested. Within the radial basis function class of neural networks we explicitly consider the RBF algorithms produced by StatSoft (2001) and SPSS (2001).[2]

The optimal weighting values used within the RBF network are generally extracted by applying a supervised least-squares method to a subset of the data series (the training set). The supervised learning function is stated as,

$$y = f(x) \tag{2}$$

where, y the output vector is a function of x the input vector with n number of inputs. Alternatively, the supervised learning function can be restated as the following linear model,

$$f(x_i) = \sum_{j=1}^{m} w_j h_j(x) \tag{3}$$

where, *m* is the number of basis functions (centers), *h* is the hidden units, *w* is the weight vectors, and *i = 1..k* output vectors (target variables). The flexibility of *f(x)* and its ability to model many different functions is inherited from the freedom to choose different values for the weights. Then applying the least-squares principle is similar to minimizing the sum of squared errors as represented by:

$$SSE = \sum_{i=1}^{p} \left(\hat{y}_i - f(x_i)\right)^2 \tag{4}$$

Kajiji (2001) presents the RBF mapping function as a modified Tikhonov regularization equation (1977). Tikhonov regularization adds a weight decay parameter to the error function to

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[2] Dash and Kajiji (2002) report seriously inconsistent performance characteristics for the Matlab RBF ANN. In addition to excessively long computation times vis-à-vis alternative RBF implementations, the Matlab RBF method was also prone to numerical under- and over-flow conditions that failed the program. These reasons forces us to defer including Matlab in this test of numerical efficiency.

penalize mappings that are not smooth. If a weight penalty term is added to the SSE, the SSE can be restated as the following cost function

$$C = \sum_{i=1}^{p} \left(\hat{y}_i - f(x_i) \right)^2 + \sum_{j=1}^{m} k_j w_j^2 \qquad (5)$$

where k_j are regularization parameters or weight decay parameters. Under this specification the function to minimize is:

$$\frac{\text{argmin}}{k} \left(\varsigma \sum_{i=1}^{p} (y_i - f(x_i \mid \bar{k}))^2 + \sum_{j=1}^{m} k_j w_j^2 \right) \qquad (6)$$

Iterative techniques are commonly employed to compute the weight decay parameter, *k*, or a vector of parameters $\bar{k}$. But, since the introduction of weight decay methods by Hoerl and Kennard (1970) and Hemmerle (1975) it is generally understood that iterative techniques are computationally burdensome and lack specificity [see, Orr (1996; 1997)]. Further, computational experience has established that iteration often leads to local minima or, in the case where the weight decay approaches infinity, inflated residual sums of squares. By contrast, the Kajiji RBF algorithm is a Bayesian regularization algorithm that derives a globally optimized regularization parameter based on a cross-population of recent extensions in optimal ridge regression parameter estimation by Crouse (1995). The Kajiji algorithm directly attacks the twin evils that deter efficient ANN modeling: the "*curse*" of dimensionality (over-parameterization) and inflated residual sum of squares (inefficient weight decay).

4. The Modeling Process

Let $r_t = (r_{it},\ldots,r_{pt})$ represent a vector of *p* returns observed at time *t*, $t = 1,\ldots,n$. Let $F_t = (F_{1t},\ldots, F_{kt})$ specify *k* latent factors with which there are corresponding maximum validity factor scores denoted by S_t for *k* latent factors. The following economic model is formulated for each of the *m* CSFB/T indexes, where $m = 1,\ldots,M$ for the 13 published indexes.

$$HFI_m = f(S_1,\ldots,S_k). \qquad (7)$$

HFI_m is the individual hedge fund that is subjected to the model comprised of the S_k factor scores.

4.1. Measurement Errors in Return Level Prediction

Comparative evaluation relies upon the computed residuals for the training, out-of-sample validation, and fitness (entire sample) data subsets. Specifically, model errors are computed as,

$$MSE_{training} = \sum_{i=1}^{t} \left(y_i - \hat{y}_i \right)^2 \Big/ t \tag{8}$$

$$MSE_{validation} = \sum_{i=1}^{v} \left(y_i - \hat{y}_i \right)^2 \Big/ v \tag{9}$$

$$MSE_{fitness} = \sum_{i=1}^{T} \left(y_i - \hat{y}_i \right)^2 \Big/ T \tag{10}$$

where $MSE_{training}$ is local to the training sub-set (T_t) and the $MSE_{validation}$ measure captures the out-of-sample error component ($T_{t+1}..T_v$). The $MSE_{fitness}$ measure is computed over all (T) observations. For purposes of this paper, all algorithmic comparisons rely solely on the direct evaluation of the computed $MSE_{fitness}$.

4.2. Measurement Errors - Classification Prediction

Neural network classification topology generally relies upon an output function of probabilities to assign group membership. Leung preferred this approach. However, for return classification it is possible to use a direction measure to test the number of times a prediction neural network predicts the direction of the predicted return movement correctly. In this study in order to minimize the chance of introducing new specification errors by from the use of alternative neural network architecture we implement measurement errors that take into account the simultaneous behavior of trend and magnitude within the trend.

4.2.1. Direction Measure

Direction is defined as the number of times the prediction followed the up and down movement of the underlying index. The initial calculations were presented by Harvey, et. al. (2002) and later modified Castiglione (2001) as shown below.

$$\zeta = \frac{1}{|T|} \sum_{i+1 \in T} HS\left(P_{i+1} G_{i+1}\right) + 1 - HS\left(\left|P_{i+1}\right| + \left|G_{i+1}\right|\right) \qquad (11)$$

where:

P_{i+1}	=	$Index_{i+1} / Index_i$ is the percentage return on the index at time step $i+1 \in T$
G_{i+1}	=	the forecast percentage return on the index at time step $i+1 \in T$
T	=	the number of days in the validation period
HS	=	a modified Heavyside function where HS(x)=1 for x>0, and 0 otherwise.

4.2.2. Modified Direction Measure

A more robust method of direction was presented by Merton (1981) and named modified direction:

Modified Direction = *((# of correct up predictions / # of times index up) +*
(# of correct down predictions / # times index down)) – 1 *(12)*

4.2.3. Time Dependent Directional Profit

The two direction measures each provide a summary of how well the predicted time-series and the actual time-series move together at any given point in time. We introduce the Yao (Access Year: 2003) time dependent directional profit measurement error (TDDP) as a means by which to capture the simultaneous effects of time and profit in the forecast simulation. Under this method incorrectly predicted directional moves are penalized more heavily than are correct predictions. The weights are then adjusted based on the amount of change from one forecast point to the next. In essence, a large adjustment to the weights is made given a wrong directional forecast, which is accompanied by a large change in the underlying values. Conversely, a small adjustment to the weights is signaled by a correct directional forecast for a correspondingly large change in the underlying. The TDDP error measure is defined as,

$$E_{TDP} = \frac{1}{2N}\sum_{p=1}^{N} f_{TDP}(p)(t_p - o_p)^2 \qquad (13)$$

where $f_{TDP} = f_{DP}(p) * w(p)$, and the vectors *t* and *o* capture the target-prediction and observed values over the *p* prediction periods. Changes in the underlying and direction as described above are determined by $f_{DP} = F(|t_p - t_{p-1}|, sign(\Delta t_p, \Delta o_p))$. At prediction point *p*, the directional profit adjustment factor is determined according to

$$f_{DP}(p) = \begin{cases} a_1 & if\, \Delta t_p * \Delta o_p > 0 and\, |\Delta t_p| \le \sigma \\ a_2 & if\, \Delta t_p * \Delta o_p > 0 and\, |\Delta t_p| > \sigma \\ a_3 & if\, \Delta t_p * \Delta o_p < 0 and\, |\Delta t_p| \le \sigma \\ a_4 & if\, \Delta t_p * \Delta o_p < 0 and\, |\Delta t_p| > \sigma \end{cases} \qquad (14)$$

where σ is the standard deviation of the target variable over all *N* observations (training and validations observations). Simulation results for the monthly time scale lead us to the following parameter values: $a_1 = 0.5$; $a_2 = 0.8$; $a_3 = 1.2$; and, $a_4 = 1.5$. We caution, however, that there is insufficient evidence to recommend the extrapolation of these settings to other time scales such as daily or higher frequencies.

5. Modeling Results

In this section we present the results of applying the sample data to each one of the three test algorithms. The hardware configuration for this experiment consisted of a 2ghz Pentium-4 CPU with 512 MB of random access memory. All program executions were made under the Microsoft XP Professional operating system. Algorithmic differences in solution execution times were measurable but small. Solutions times ranged from about 4 seconds (Kajiji-4) to just under 10 seconds (SPSS). While this difference is negligible for the relatively small monthly dataset used in this study, it is an issue that may require renewed attention under tests involving large-scale datasets consisting of thousands of high frequency observations. Despite the similar model solving times, other similarities and substantial differences arise when comparing the relative modeling efficiency of the three RBF ANNs. Specific modeling results for the Kajiji-4 method are presented next. This is followed by the presentation of results for the solutions generated by SPSS and StatSoft algorithms, respectively.

5.1 Kajiji-4

The analysis of algorithmic efficiency begins with a review of the MSE validation measures are presented in table 5. The validation error is just over 1 percent for the Dedicated Short Bias index and is even smaller (just under 0.04 percent) for the Equity Neutral hedge fund index. We note that the Global Macro index fund achieved a comparable low fitness error measure (0.04 percent). As we extend the analysis to uncover overall algorithmic efficiency, we observe that the two low MSE models also have correspondingly low skewness and kurtosis measures. This finding suggests that model efficiency improves as the effects of skewness and kurtosis diminish. When the third- and fourth-moment characteristics are considered the algorithmic results reported for the Equity Market Neutral index appear interestingly efficient. At the other end of the modeling spectrum is the model applied to the Event Driven index. This model produced a fitness MSE (6.7 percent) that was almost 150 times larger than that reported for the two low error models. This result yields an interesting insight into the algorithmic performance when applied to monthly hedge fund returns. We note that the Event Driven index has the highest absolute skewness coefficient (-3.272) and the highest kurtosis measure (20.153). These results add to our earlier observations about the importance of understanding the role of distributional symmetry in hedge fund returns. In the former case, low values for skewness and kurtosis were associated with low fitness MSE results. In this latter case, relatively high skewness and kurtosis measures are associated with deterioration in modeling accuracy as measured by the fitness MSE. The reported modeling efficiency is buttressed by the cross-plot of the observed and target observations. Figures 2 and 3 provide a visual validation that the error deviation within the validation set is small for the two indices of interest.

Next, we assess the ability of the Kajiji-4 algorithm to correctly predict the directional change of hedge fund returns. Both the direction and modified direction measures report identical results across all model applications. The direction measure solves at 0.988 and the modified direction measure is constant at its maximum value of 1.0. The modified direction measurement of 1.0 does not necessarily imply that the prediction is perfect. A more conservative interpretation of the result allows us to conclude that the target variable correctly attempts to model the peaks and troughs found in the observed dataset. Take together, these two measures provide strong evidence that the Kajiji-4 algorithm when applied to monthly return data for alternative assets can achieve near perfect results in forecasting directional changes in the returns data.

The strong performance of the directional measures does not address the profit incentive held by investors. The profit-enhanced TDDP measure presents a very clear picture of modeling efficiency.

Table 5: Kajiji-4 Model Results

	SFB / Tremont Hedge Fund	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	E.D. Multi-Strategy	Risk Arbitrage	Fixed Income Arbitrage	Global Macro	Long / Short	Managed Funds
Lambda	1.051	1.129	1.165	1.912	46.713	0.238	0.195	0.469	0.792	0.154	9.764	1.530	1.982
Return-level Error Measures													
Training Error	1.271	1.107	1.019	1.248	1.189	1.136	1.079	1.186	1.040	1.165	1.295	1.212	0.853
Validation Error	0.143	0.531	0.757	0.227	0.400	0.191	0.219	0.207	0.508	0.132	0.111	0.309	1.095
Fitness Error	0.022	0.021	0.401	0.046	0.000	0.221	0.425	0.111	0.065	0.098	0.000	0.035	0.233
Classification Error Measure													
Direction	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988
M. Direction	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
TDDP	0.0054	0.0052	0.1418	0.0114	0.0001	0.0718	0.1374	0.0361	0.0229	0.0308	0.0001	0.0087	0.0802

Figure 2: Actual and Predicted Using Kajiji-4 RBF on Dedicated Short Bias Fund

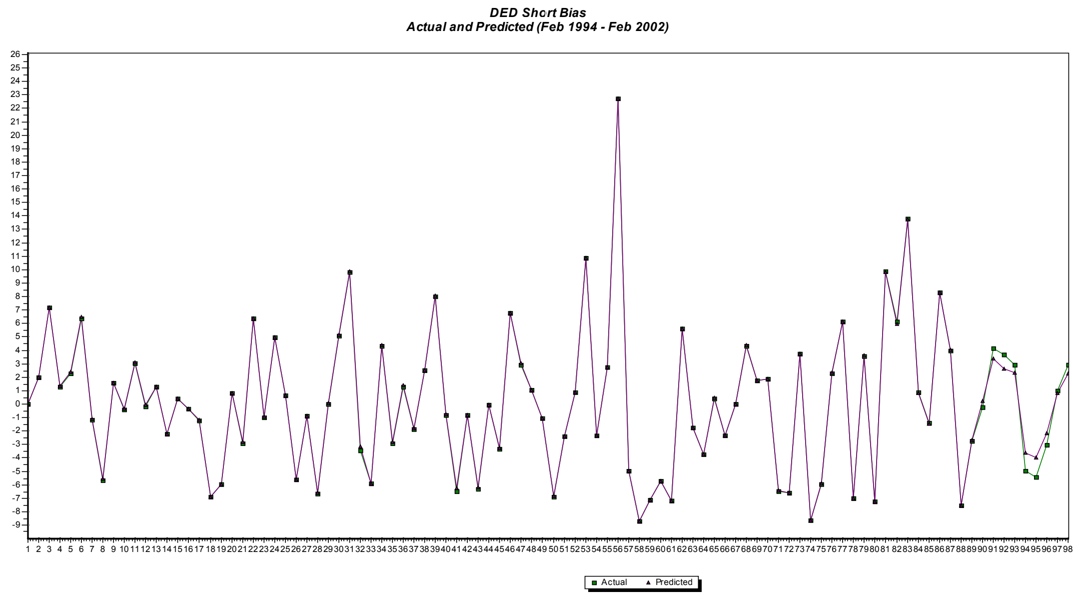
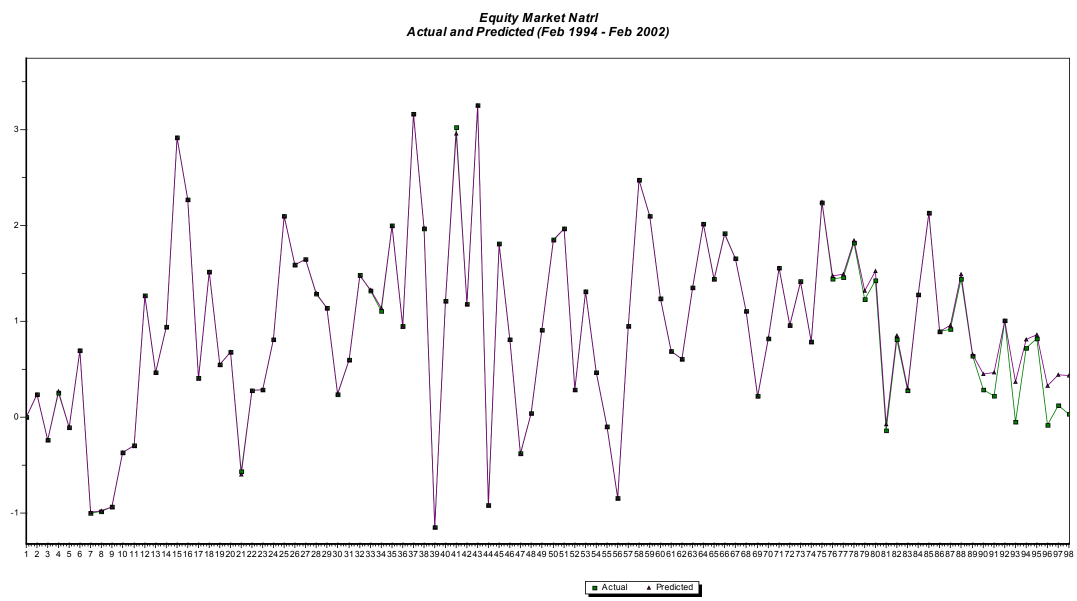


Figure 3: Actual and Predicted Using Kajiji-4 RBF on Equity Market Neutral Fund



5.2 SPSS's Neural Connection

The SPSS RBF results, presented in table 6, differ markedly from those produced by the Kajiji-4 algorithm. Based on a comparison of within algorithmic MSE results, the SPSS RBF modeling experiment achieves the lowest error value when modeling the Equity Market Neutral index. This is one of the two focus indices. But, the SPSS reported error measure for this index is more than 3,425 times larger than that produced by the Kajiji-4 simulation. For the other focus index, Dedicated Short Bias, the SPSS fitness MSE is more than 1,975 times higher than that produced by the Kajiji-4 counterpart. This is also the largest MSE reported by the application of the SPSS procedure. Returning to our examination of how RBF algorithms perform under conditions of distributional asymmetry we note that except for one case (the Fixed Income Arbitrage index), the SPSS algorithm generates a consistent performance ratio for hedge fund indices with absolute skewness levels above 3.00 and kurtosis measures greater than 14.0. Within the subgroup defined by the Event Driven, Distressed, and E.D. Multi-Strategy indices, the reported fitness MSE measures ranged from 3.172028 to 3.642675. By comparison, the Kajiji-4 algorithm also performed consistently across this same subgroup; but the reported MSE measures were decidedly lower under Kajiji-4 achieving levels that ranged from 0.030 to 0.037. In summary, the SPSS RBF algorithm demonstrated the ability to produce consistent performance across monthly return indices with high absolute skewness and high kurtosis measures. Unfortunately, asymmetry issues aside, the performance of the algorithm dissipate as the level of relative variation (CV) increases. A graphical display of the two focus indexes is provided in figures 4 and 5, respectively.

Table 6. SPSS Model Results

	SFB / Tremont Hedge Fund	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	E.D. Multi-Strategy	Risk Arbitrage	Fixed Income Arbitrage	Global Macro	Long / Short	Managed Funds
Return-level Error Measures													
Training Error	1.074746	0.998806	1.018551	1.073490	0.948484	0.98785	0.464553	0.91175	0.860569	0.522714	0.70402	1.01266	0.939322
Validation Error	0.279682	0.827859	0.868138	0.503276	0.544275	0.75957	0.899311	0.63094	0.671334	0.788974	0.22464	0.33472	1.210085
Fitness Error	6.999264	2.468697	27.655226	28.473214	1.370447	3.64267	3.127028	3.49122	1.698769	0.767644	10.93985	10.94859	12.059491
Classification Error Measure													
Direction	0.5046	0.6697	0.4404	0.5138	0.5780	0.5596	0.5688	0.5963	0.6055	0.6514	0.6789	0.5229	0.5413
M. Direction	0.3425	0.3080	0.1521	0.2103	0.3271	0.2917	0.5255	0.3644	0.2735	0.4862	0.4496	0.3112	-0.0137
TDDP	1.6879	0.8222	7.8533	5.3780	0.2697	0.8478	0.6223	1.0244	0.4540	0.1597	1.7682	3.4983	3.5241

Figure 4. Actual and Predicted Using SPSS RBF on the Dedicated Short Bias Fund

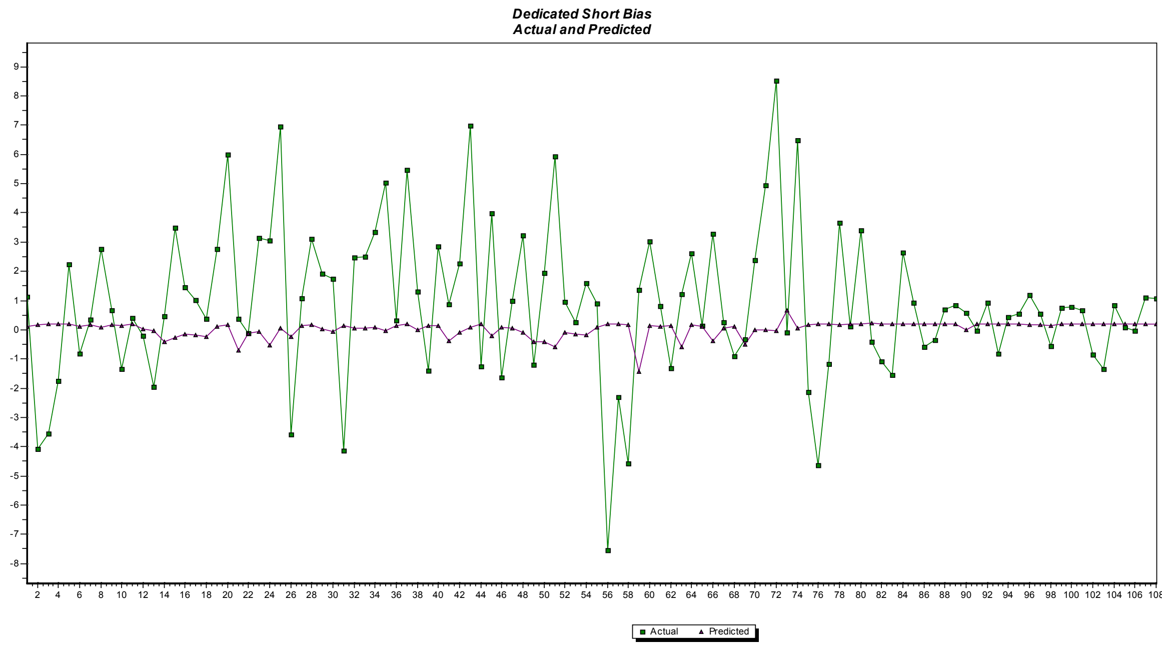
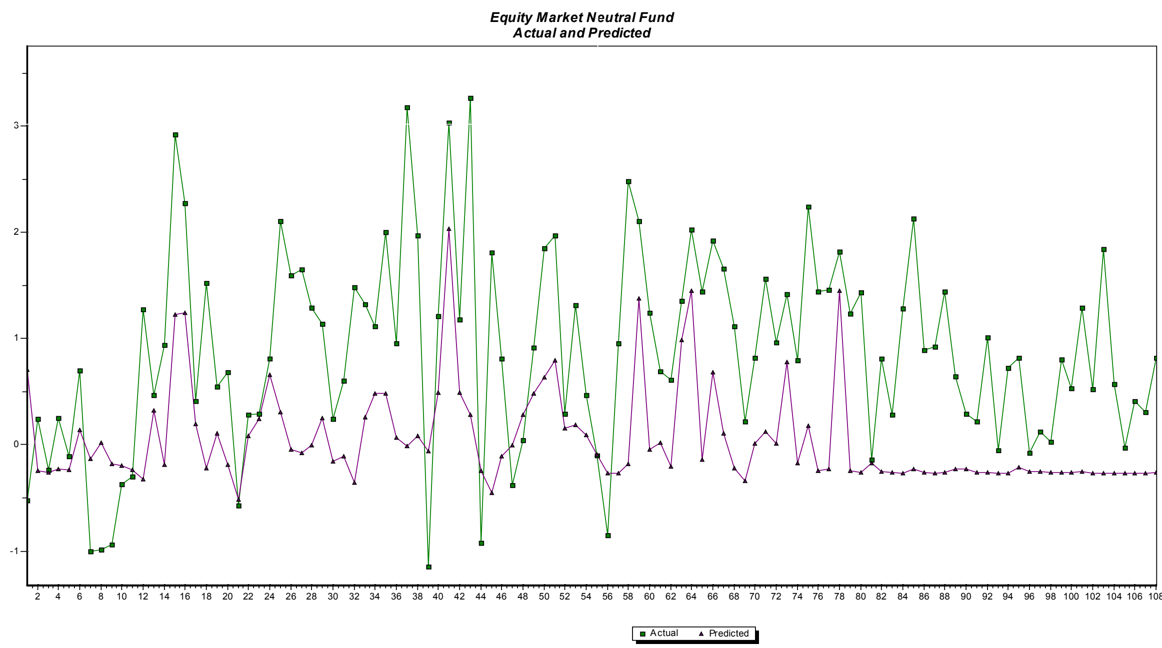


Figure 5. Actual and Predicted Using SPSS on Equity Market Neutral Fund



5.3 StatSoft's Statistica

On average, the results produced upon the application of the StatSoft RBF algorithm to the modeling problem fall in between those produced by the other two RBF algorithmic methods. Before presenting the details as provided in table 7, we wish to note that the user interface of the StatSoft algorithm differs considerably from that presented by either the Kajiji-4 or SPSS methods. For the StatSoft-based experiment, where possible, optional parameter settings were set to levels specified as default levels under the Kajiji-4 method. We then undertook a manual optimization process with the goal of identifying parameter settings that would produce best (if not optimal) solution results for the sample data. Stated differently, while we were able to apply default settings without modification under the Kajiji-4 and SPSS experiments, that was not possible in this case.

Like the Kajiji-4 algorithm, the StatSoft method reported the lowest fitness MSE for the Equity Market Neutral index model. The MSE reported by the StatSoft method is approximately 1.4 times larger than that achieved by application of the Kajiji-4 network. For the other focus index, Dedicated Short Bias, at 23.051 the fitness MSE is the highest recorded across all test models. This result is more than 1,600 times that achieved for the same index under the Kajiji-4 method. Figure 6 and 7 provide a graphical view of the algorithm's predictive ability for the Dedicated Short Bias and Equity Neutral fund returns. It is clear from this view that the target variable achieves reasonable directional performance but falls short in its ability to replicate the magnitude of the changes. We observe that the StatSoft method performs best when modeling monthly hedge fund returns with relatively low coefficients of variation. The algorithm's predictive ability dissipates noticeably as relative variation (CV) increases. How, if at all, this deterioration is impacted by distributional asymmetry is not immediately clear from the results generated by this experiment.

Table 7. Staistica-4 Model Results

	SFB / Tremont Hedge Fund	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Dis-tressed	E.D. Multi-Strategy	Risk Arbitrage	Fixed Income Arbitrage	Global Macro	Long / Short	Managed Funds
Return-level Error Measures													
Training Error	0.3647	0.5030	0.1663	0.1280	0.9018	0.4456	0.3509	0.4142	0.6886	0.6328	0.1994	0.2182	0.2826
Validation Error	0.4937	0.5097	0.1747	0.1227	0.5999	0.5693	0.4590	0.4475	0.6107	0.6829	0.2747	0.1314	0.4146
Fitness Error	5.0695	1.0008	23.0509	16.0618	0.7297	3.2304	3.2736	3.4262	1.4754	1.1334	15.0169	7.1130	10.8056
Classification Error Measure													
Direction	0.6330	0.8532	0.6055	0.6422	0.7523	0.7431	0.6422	0.6055	0.7248	0.6881	0.5963	0.5596	0.5229
M. Direction	0.1901	0.5861	0.3245	0.5216	0.0556	0.5211	0.4792	0.2315	0.2890	0.0415	0.0659	0.4142	0.2421
TDDP	1.0963	0.3143	6.4969	3.0278	0.1067	1.1203	0.8245	1.1080	0.4369	0.3822	4.3435	2.1328	3.0088

Figure 6. Actual and Predicted Using the StatSoft ANN on Dedicated Short Bias Fund

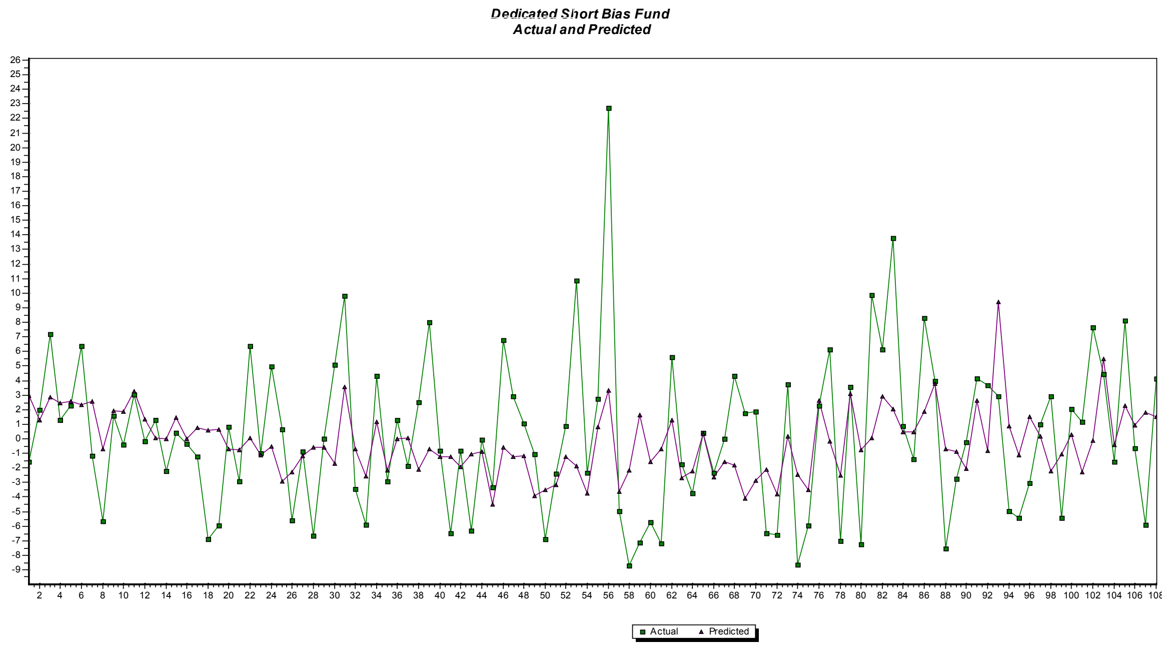
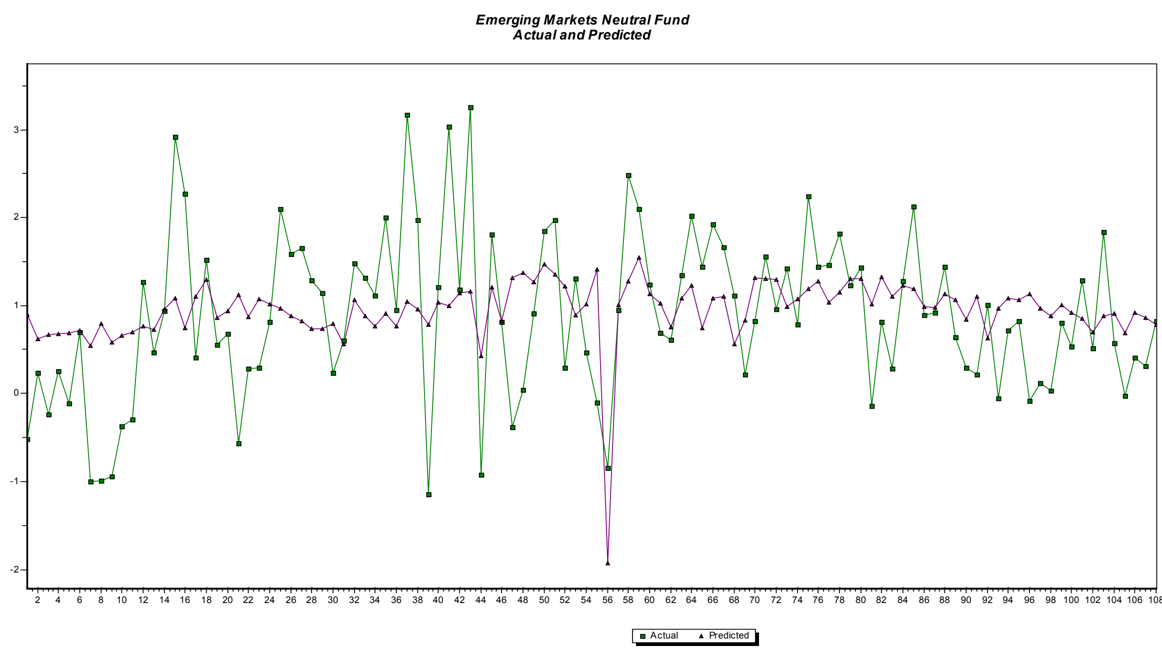


Figure 7. Actual and Predicted Using the StatSoft ANN on Equity Market Neutral Fund



5.4 Efficient Model Selection

A comparative analysis of the three RBF algorithms points to the role of CV and distributional symmetry (skewness and kurtosis) as factors that can measurably impact modeling accuracy. Table 8 provides a concentrated view of these three statistical properties by algorithm. If we look at how these three factors influence the models with the lowest fitness MSE, it becomes apparent that the SPSS and StatSoft models choose the indices with the thirteenth ranked CV and kurtosis (also the lowest). These indices are the tenth ranked by the skewness measure. That is, these two algorithms perform well when asymmetry issues are smallest. On the other hand, the Kajiji-4 algorithm performed at its best when relative dispersion was at or near it's highest. Although the Kajiji-4 algorithm was able to model observed variables with moderate levels of skewness and kurtosis, it too performed best when asymmetry are decreasing.

As noted above, the highest MSE produced by the Kajiji-4 method was significantly smaller than the highest produced by either of the other two algorithms. Hence, it is interesting to observe that under the Kajiji-4 algorithm the highest MSE occurred for an index that had the highest skewness and kurtosis measures. Under SPSS and StatSoft the highest MSE was associated with an index that had significantly less distributional asymmetry.

Table 8. Relative Dispersion Comparison

	Kajiji-4	SPSS	StatSoft
Lowest Validation MSE	Dedicated Short Bias [1,7,9]; and Global Macro [5,13,10]	Equity Market Neutral [13,10,13]	Equity Market Neutral [13,10,13]
Highest Validation MSE	Event Driven [9,1,1]	Dedicated Short Bias [1,7,9]	Dedicated Short Bias [1,7,9]

Rankings for CV, Skewness, Kurtosis are in parentheses

5.5 Directional Efficiency

Table 9 provides a comparison of directional forecasting accuracy. Results are reported by algorithmic method in order to show which forecast produced the minimum and maximum for each directional error measure. We note that the results generated by application of the Kajiji-4 method are at the theoretical maximum of 0.988 and constant across all tested models. Only the value changes for the Kajiji-4 results under the modified direction measure (all 1.0). Tables 10 and 11 present an augmented comparative analysis of the results achieved by the application of the SPSS and StatSoft algorithms. These tables rank the performance based on the direction measure. What is most obvious is the lack of a ranking consistency. Except for a weak argument to the benefit of the Managed Funds index, there is no overlap in the rankings achieved across the remaining two algorithms. Despite this lack of consistency, it does appear that the StatSoft algorithm maintains an efficiency edge over the SPSS algorithm in directional accuracy.

Table 9. Summary of Direction and Modified Direction

	Kajiji-4	SPSS	StatSoft
Min Direction	ALL (0.988)	Dedicated Short Bias (0.440367)	Managed Funds (0.522936)
Max Direction	ALL (0.988)	Global Macro (0.678899)	Convertible Arbitrage (0.853211)
Min Modified Direction	ALL (1.000000)	Managed Funds (-0.013723)	Fixed Income Arbitrage (0.041528)
Max Modified Direction	ALL (1.000000)	Distressed (0.525463)	Convertible Arbitrage (0.586124)

Computed values in parentheses

Table 10. Rankings of the SPSS Direction / Modified Direction

	Direction	M Direction	Rank Direction	Rank M Direction
Global Macro	0.678899	0.449631	1	3
Convertible Arbitrage	0.669725	0.308014	2	6
Fixed Income Arbitrage	0.651376	0.486157	3	2
Risk Arbitrage	0.605505	0.273533	4	10
E.D. Multi-Strategy	0.59633	0.364352	5	4
Equity Market Neutral	0.577982	0.327091	6	7
Dis-tressed	0.568807	0.525463	7	1
Event Driven	0.559633	0.291165	8	9
Managed Funds	0.541284	-0.013723	9	13
Long / Short	0.522936	0.311213	10	8
Emerging Markets	0.513761	0.210284	11	11
SFB / Tremont Hedge Fund	0.504587	0.34246	12	5
Dedicated Short Bias	0.440367	0.152098	13	12

Table 11. Rankings of the StatSoft Direction / Modified Direction

	Direction	Modified Direction	Rank Direction	Rank M. Direction
Convertible Arbitrage	0.85321	0.58612	1	1
Equity Market Neutral	0.75229	0.05556	2	12
Event Driven	0.74312	0.52108	3	3
Risk Arbitrage	0.72477	0.28904	4	7
Fixed Income Arbitrage	0.68807	0.04153	5	13
Distressed	0.6422	0.47917	6	4
Emerging Markets	0.6422	0.52163	7	2
CSFB / Tremont Hedge Fund	0.63303	0.19008	8	10
Dedicated Short Bias	0.60551	0.32448	9	6
E.D. Multi-Strategy	0.60551	0.23148	10	9
Global Macro	0.59633	0.06593	11	11
Long / Short	0.55963	0.41419	12	5
Managed Funds	0.52294	0.24208	13	8

5.6 Directional Profit Efficiency

The TDDP measure is a correction weight that is designed to compensate for incorrect directional forecasts by overall magnitude of the movement. The weight is applied to future forecasts generated by the forecasting model. The smaller the weight, the more accurate the training phase of the model. By definition, large weights are indicative of a missed direction, an incorrect magnitude adjustment, or some combination of the two. Table 12 presents the TDDP measures for the three RBF ANN under study here.

The TDDP also provides a new layer of support for the efficiency of the Kajiji-4 algorithm. In profit induced scenarios where it is important to predict the correct turning point of a time series as well as the magnitude by which the time series is expected to move, the Kajiji-4 algorithm requires the least weighted adjustment. An improvement ratio is presented in the last two columns of table 12. This is simply the TDDP of the selected method divided by the TDDP produced by solution of the Kajiji-4 method. Of the seven funds that exhibited asymmetrical return distributions, only one (Emerging Markets) had an improvement ratio over 60. This observation confirms that the while the Kajiji-4 method is more efficient when predicting returns associated with asymmetrical and leptokurtic distributions, the gains are not as great when the distributions exhibit fat-tails and skewness.

Table 12. TDDP Measures with Asymmetrical Identification

	Kajiji-4	SPSS	StatSoft	SPSS/Kajiji-4	StatSoft/Kajiji-4	Asymmetrical
Convertible Arbitrage	0.0052	0.8222	0.3143	158.1	60.4	A
Equity Market Neutral	0.0001	0.2697	0.1067	2697	1067	
Event Driven	0.0718	0.8478	1.1203	11.8	15.6	A
Risk Arbitrage	0.0229	0.4540	0.4369	19.9	19.1	A
Fixed Income Arbitrage	0.0308	0.1597	0.3822	5.2	12.4	A
Distressed	0.1374	0.6223	0.8245	4.5	6.0	A
Emerging Markets	0.0114	5.3780	3.0278	471.8	265.6	A
CSFB / Tremont Hedge Fund	0.0054	1.6879	1.0963	312.6	203.0	
Dedicated Short Bias	0.1418	7.8533	6.4969	55.4	45.8	
E.D. Multi-Strategy	0.0361	1.0244	1.1080	28.4	30.7	A
Global Macro	0.0001	1.7682	4.3435	17682	43425	
Long / Short	0.0087	3.4983	2.1328	402.1	245.1	
Managed Futures	0.0802	3.5241	3.0088	43.9	37.5	

5.7 Post Model Return Residuals

In this section we apply a PCA with Varimax rotation to the post model residual returns. The appointed task of the PCA analysis is to uncover latent common variation. In the absence of any measurable levels of common variation the PCA analysis will return one significant factor (a factor with an eigenvalue of at least 1.0). Specifically, we subject E to the PCA procedure, where $E = \{HFI - f(S_1 \ldots S_k)\}$.

The results of this application are presented in table 13. As with the earlier factor analytic presentation, we replace factor loadings below the absolute value of 0.40 with a period. Additionally, only those factors with eigenvalues of 1.0 or higher are retained for display purposes. Two factors are reported in the table. Factor 2 is differentiated from factor 1 by the asymmetry characteristics of the hedge fund indices. For the skewness dimension, only the Emerging Markets index has a negative skewness above -3.0. Similarly, for the kurtosis dimension (with the same exception for the Emerging Markets index) each index that loads on factor 2 has a kurtosis measure that exceeds 14.0. The factor analytic results provide additional support for the MSE directional analysis that produced observed differences in model efficiency based on the existence of asymmetry in the observed hedge fund returns.

Table 13. Varimax Solution of After Model Residuals

Fund Name	Factor 1	Factor 2	Row %
Global Macro	0.9625	.	96.73%
Managed Funds	0.9509	.	94.38%
SFT/Tremont Hedge Fund	0.9197	.	88.71%
Distressed	0.8138	.	67.95%
Dedicated Short Bias	0.8037	.	67.97%
Equity Market Neutral	-0.7893	.	63.69%
Long/Short	-0.7252	.	53.55%
Risk Arbitrage	-0.6540	.	45.39%
Fixed Income Arbitrage	-0.5113	-0.5972	61.81%
Emerging Markets	.	0.7347	68.48%
Event Driven	.	-0.9171	93.40%
E.D. Multi-Strategy	.	0.8562	78.47%
Convertible Arbitrage	.	0.6195	38.70%
Eigenvalue	6.1157	3.0765	
Percent of Variance Explained	47.04%	70.71%	

6. Summary and Conclusions

The results reported by the comparative model experiment presented in this paper lend support to earlier findings that it is possible to model accurately hedge fund returns. However, the research findings contradict the conclusions offered by Leung that classification methods are more accurate than return-level methods under ANN examination. Instead, the Kajiji-4 RBF algorithm surfaced as the dominant ANN when tested against well-known competing RBF designs. This paper also established a role for developing efficient predictor variables under the monthly time-scale. The factor score method proved it was capable of producing a new reduced set of predictors that effectively examined all variability except that associated with skewness and kurtosis. Controlling for these two dimensions is an obvious extension for future research.

The Kajij-4 method has proven robust in modeling and prediction of hourly and daily high-frequency financial time-series involving hundreds to thousands of observations. This research has documented the effectiveness of the method on low frequency, but volatile, monthly data. In a manner that is consistent with emerging stylized facts regarding effective modeling for return-level prediction, the Kajiji-4 algorithm is a weighty contender for consideration.

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