Comparative Nonlinear Modeling of FX Futures Options Volatility in Heterogeneous Markets

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Abstract

This paper compares the modeling performance of three radial basis function (RBF) artificial neural networks (ANN) to the (G)ARCH framework when applied to the high frequency realized volatility patterns of futures options FX contracts. The comparative analytics presented in this research confirm the extant literature on RBF modeling efforts in general and offer new findings that document the ability of the Kajiji-4 Bayesian closed-form regularization RBF to produce a statistically smaller modeling error than alternative RBF ANNs when applied to high-frequency realized volatility. Moreover, we find that when subjected to Kajiji-4 examination, the volatility models of global hourly trading of futures options contracts on foreign exchange provide strong evidence to support the existence of heterogeneous traders in the global FX derivatives market.

I. Introduction

Over the past decade empirical examination of the conditional second moment form of volatility has been subjected to a number of different econometric methodologies. The earliest studies introduced the parametric ARCH framework of Engle (1982). This was followed by the GARCH model of Bollerslev (1986) and the IGARCH framework of Engle and Bollerslev (1986) and the Fractionally Integrated ARCH (FIGARCH) model of Baillie et. al. (1996). By contrast, some economic model builders have been attracted to the ‘black box’ computational intelligence of nonparametric methods, like artificial neural networks (ANN), to approximate complex nonlinear Borel measurable functions to any degree of accuracy (for example, see Hornik et. al. (1989)). Early evidence on the ability of ANNs to model complex option valuation characteristics was provided by Lo, et. al. (1994) and Hanke (1999). More recent evidence on the performance of alternative ANN topologies when applied to high-frequency time series has been explored by both Dash et. al. (2003) and Rech (2002)).

This paper applies a variant of the RBF topology, the Kajji-4 Bayesian closed-form regularization method (Kajji-4)\(^1\), to approximate the hourly realized volatility estimates produced by global FX futures options traders. The application specifically examines for evidence of heterogeneous global trading. Finally, following Lai and Wong (2001) we provide a comparative analysis within a well-defined architecture of the single-layer RBF network.

2. Intradaily Volatility Modeling

2.1 Data

The normative results reported in this research are based on hourly returns obtained from closing quotes on the dollar exchange with the German deutsche mark (DM), Japanese Yen (JY), and the Swiss Franc (SF) as traded on the upper trading floor of the Chicago Mercantile Exchange (CME). Tick observations on currency futures options are obtained from the Futures Industry Association (FIAFII) while closing tick-quotes for futures contracts are obtained from Tick Data, Inc.\(^2\) Evidence of news and announcement effects in the 5-minute returns of U.S. Treasury bonds (TB) is quite strong (see Bollerslev, et. al. (2000)). Additionally, the futures contract on the Federal Reserve Bank of Atlanta’s trade-weighted dollar index (DX) is included. Observations for the JY and SF contracts are from 04-January-99 to 31-December-99, inclusive. Data limitations restrict the DM sample period to August 06, 1999. Tick observations are aggregated into equally spaced intervals of one-hour beginning with the first tick closest to Monday 9:00 a.m. closing quote. Although tick data obtained from the FIAFII is consistent with the CME’s upper trading floor trading hours of 7:20 a.m. to 2:00 p.m., model parsimony requires return measurement to reflect the 8:30 a.m. (or later) daily start as reported by Tick Data, Inc. The last quote of the day is captured with the closest tick to the 1:59 p.m. stamp. This process is repeated for all available trading days of the business week within the sample period. This results in 750 observations for the DM and 1,248 observations for the other two contracts. Finally, because these are option contracts, the data set is augmented by the inclusion of returns on the U.S. Treasury Bill futures contract (RF).

\(^1\) The Kajji-4 RBF ANN is part of the WinORS\(_a\) software system. See www.nkd-group.com for details.

\(^2\) See http://www.fiafii.org and http://www.tickdata.com, respectively.
2.2 Modeling Futures Options

The extraction of a returns vector for each option series follows the methods of Muller et al. (1990) and Dacorogna et al. (1993) and (1998). Hourly prices are derived from a linearly interpolated logarithmic average of the bid ask quotes from the 9:00 a.m. tick to the closest tick to the 1:59 p.m. trade. Hourly returns are calculated based on the first difference of the logarithmic prices. Weekend effects and holiday peculiarities are not at issue for CME exchange traded data. In addition to the these returns an hourly estimate of the continuously compounded risk-free rate is computed from the Tick Data futures contract on the 90-day T-Bill. The realized volatility is obtained from the variability of these returns (see, Anderson, et. al. (2002))

Following Beckers (1981), implied standard deviation (ISD) estimates are extracted for every tick observation on each of the three currency contracts by inverting closest at-the-money calls. It is well known that for out-of-the money options if strike prices increase the implied volatility will increase. Conversely, it can be shown that in-the-money calls are less expensive than the Black-Scholes theory predicts. All estimates are derived hourly for call options with 60 or fewer days to expiration from the Black (1976) model for European options on futures:

$$C = e^{-rT}[FN(d_1) - EN(d_2)],$$  

Where: 

$$d_1 = \frac{\ln(F/E) + \left(\frac{\sigma^2}{2}\right)T}{\sigma \sqrt{T}},$$  

$$d_2 = d_1 - \sigma \sqrt{T},$$  

Jorion (1995), has shown that using a model based on European style options tends to overestimate the true volatility of the option by approximately 12%. In this study we follow conventional wisdom and compute the hourly ISD based on the geometric average of calls traded within the time frame that begins on the hour and terminates 59 minutes past the hour.

2.3 Modeling Conditional Volatility

The weak-form GARCH model of Bollerslev (1986) generalized the original autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982) so that a time series variable $x_t$, is expressed as:

$$x_t = \sigma_t z_t,$$

$$\sigma^2_t = \alpha_0 + \alpha_1 x_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where $z_t \sim NID(0,1)$, for $\alpha_0, \alpha_1 \geq 0$ and $t = 1..T$. The model implies that $x_t | \Omega_{t-1} \sim N(0, \sigma^2_t)$. The model is particularly useful in financial research as it permits $x_t$ to be leptokurtotic; a fact that infers the model’s ability to capture stylized seasonality (or volatility clustering). It is possible to use other non-normal conditional distributions, but that consideration is beyond the scope of this study.

2.4 Modeling Heterogeneous Markets

At any point in time, the heterogeneous (or homogeneous) composition of the financial market and the differentiated responses to new information acted upon by a large number of geographically dispersed and uniquely socialized agents is all summarized in one unique measurement – price. For the FX markets, Dacorogna, et. al. (1995; 2001) contradict the widely held assumption of rational homogeneous agent behavior given the instantaneous absorption of new valuation news. In addition to different time horizons and dealing frequencies, Dacorogna observed that memory in the volatility process is relatively weak at 0.5 to 1.5 business days when market participants are on opposite sides of the globe. Conversely, they provide evidence that memory is relatively strong at lags of 1.0 to 2.0 business days -- a time frame when identical groups of participants are participating in the FX market.

Heterogeneous market structure is examined analytically by Zumbach and Lynch (2001, 2003). They develop a statistical estimate derived from an underlying price process $p(t)$, that is capable of describing the latent trading behavior of market agents. The approach relies upon the computation of the volatility time derivative to statistically measure the correlation between the change of volatility and the realized volatility. After the implementation of a Monte Carlo simulation, a three-dimensional view of how a change in volatility at a given time scale triggers a response in volatility at all shorter time scales that is clustered to identifiable market participants is produced.

We directly examine the realized volatility of the price process to uncover the existence of heterogeneous markets in global trading of FX futures options. In the analytical scheme of this paper, one business day is represented by five one-hour observations. We employ the three RBF algorithms to test the validity of the heterogeneous markets hypothesis. Specifically, lagged input variables for a 2- and 7-hour period are specified to capture a business time-scale of 0.5 to 1.5 trading days. Similarly, the hypothesis of a 1 to 2 day lag is
tested by the inclusion of lagged inputs at 5- and 10-hour level, respectively.

3. RBF Networks with Prior Information and Regularization

It is well established that the RBF ANN is capable of efficient mapping against any complex function. Figure 1 presents a flow diagram of the basic RBF algorithmic process.

\[ y = f(x) \]  

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

\[ f(x_i) = \sum_{j=1}^{m} w_j h_j(x_i) \]

where for \( i = 1...q \) output vectors, \( m \) is the number of basis functions (centers), \( h_j \) is a function for the hidden units, and \( w_j \) is the regularization weight. The contemporary RBF algorithm proceeds by applying the least-squares principle (similar to minimizing the sum of squared errors):

\[ SSE = \sum_{i=1}^{p} (\hat{y}_i - f(x_i))^2. \]  

(7)

The Kajiji-4 enhances the method as it treats the RBF mapping function as a modified Tikhonov regularization equation (Tikhonov and Arsenin (1977)):

\[ C = \sum_{i=1}^{p} (\hat{y}_i - f(x_i))^2 + \sum_{j=1}^{m} k_j w_j^2 \]

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

\[ \arg\min_{k} \left( \sum_{i=1}^{p} (y_i - f(x_i | k))^2 + \sum_{j=1}^{m} k_j w_j^2 \right) \]

(9)

The Kajiji-4 enhancements produce an RBF algorithm that more efficiently attacks the twin evils of ANN modeling: the “curse” of dimensionality (over-parameterization) and inflated residual sum of squares (inefficient weight decay). Because the function mapping capabilities of ANNs is highly dependent upon a proprietary software design, we examine modeling efficiency by simultaneous and comparative execution of all models under RBF ANN methods produced by Matlab (2001) and SPSS (2001). We assume that all test algorithms have been optimized structurally; hence, any divergence in modeling accuracy is attributed directly to theoretical design differences.

4. Estimation and Comparative Analytics

4.1 Descriptive Statistics

In this section we present the results of computing descriptive statistics for the futures options contracts. All contracts follow the March-June-September-December cycle. Rolling over expiring contracts into the nearest-at-the-money contract in the next expiration month creates a continuous contract of hourly returns, implied- and realized-volatilities. The hourly returns for the three FX contracts follow a pattern that is well documented for high frequency data.

4.2 Autocorrelation and Heterogeneous Markets

Autocorrelation profiles of realized volatility for up to 50 lags were computed for each of the futures contracts. We add the 95 percent confidence bands for a Gaussian process about the sample mean for reference. We find that the hourly autocorrelation structure of futures options volatility mirrors reported results for 20-minute exchange rate returns. That is, for hourly futures options trading, there is reasonable evidence of a three continent world market model as initially identified by Dacorogna et al (2001) for FX returns. The DM futures options contract showed evidence of both daily and weekly seasonality. Given a truncated 5-hour day, we observe a peak structure that is significantly higher than the confidence intervals at each 5-hour (daily) interval. Both a weekly and a half-weekly effect are also visible. Additionally, there is a latent, but distinct, lag at approximately the one-half day (7 to 8 hour) mark that is evident at twice the frequency of the daily lag throughout the autocorrelation structure. While not as pronounced as the half-day lags found in 20-minute exchange rate data, there appears to be sufficient evidence to conclude that there is a three continent world trading effect for the DM futures option contract. The evidence for JY and SF was similar. One notable difference for the JY was a pronounced evidence of a unique weekly structure.

4.3 RBF Parameter Specification and Error Measurement

Comparative RBF analytics are derived based on the use of default parameter settings for each test
algorithm. Table 2 presents the setting used for each of the test algorithms investigated in this study.

\[ MSE_{\text{fitness}} = \frac{1}{T} \sum_{i=1}^{T} (y_i - \hat{y}_i)^2 \]  

(10)

where \( MSE_{\text{training}} \) is local to the training subset \((T_t)\) and the \( MSE_{\text{validation}} \) measure captures the out-of-sample error component \((T_{te1}, T_e)\). The \( MSE_{\text{fitness}} \) measure is computed over all \((T)\) observations. For purposes of this paper, all algorithmic comparisons rely solely on the direct evaluation of the computed \( MSE_{\text{fitness}} \).

4.4 RBF Comparative Performance

Table 3 presents the results of simulating the three RBF test procedures on hourly-realized volatility. The input variables reflect stylized facts as currently recognized in the finance and time-series literature. Specifically, three latent state dimensions are captured: volatility, macroeconomic news, and market heterogeneity. The volatility component is represented by the ISD and GARCH estimate. DX and TB represent the macroeconomic and news dimension. Except for the application of the SPSS algorithm to the DM time series, each algorithm iterated to a final solution. For every solution across all economic models the Kajiji-4 RBF algorithm produced the lowest reported fitness MSE. In the case of the more volatile JY contract the Kajiji-4 results were a magnitude better than the other two RBF algorithms. For the SF, the Matlab results were more consistent with those produced by the Kajiji-4 algorithm. Algorithmic results obtained for all applications against the DM and SF contracts produced pattern-matching results that were of a similar scale.

Several numerical accuracy anomalies appear in the reported results. The Matlab RBF algorithm showed a tendency to produce inflated MSE values for the validation and fitness data subsets. The SPSS algorithm did not produce inflated MSE values, but it did report validation and fitness MSE values that were markedly higher than those reported for the training set.

Figure 2 provides a visual representation of the computational findings for the DM contract. This figure displays the absolute value of the predicted volatility curve (target variable) for model III of the DM analysis. Two observations are immediately evident. First, the complex nature of the nonlinear target variable is clearly visible. Second, the figure provides a confirmation of the tabular reports of modeling accuracy. The Kajiji-4 model produces the most accurate mapping of the target variable. Over a range, the Kajiji-4 induced mapping appears to be near-perfect. The Matlab algorithm produced a result that appears to be a linear extrapolation of the target variable. Only at the very end of the time series is it possible to observe a reasonable representation of the complex nonlinear behavior of the target variable. Finally, the SPSS RBF mapping shows some ability to pattern-match. But the SPSS algorithm appears to suffer noticeably from under-specification. This, in turn, results in an overall loss of generality for the method when applied to the volatility-modeling problem.

Modeling accuracy aside, what about the identification of heterogeneous trading? The analysis begins with a focus on the DM. The best model (determined by smallest fitness MSE) produced by the application of both the Kajiji-4 and the SPSS algorithms failed to include any lagged information. By contrast, the best Matlab model included two lagged variables; the 5- and 10-hour lags. In fact, for the two contracts where the Matlab algorithm included lagged information (DM and SF), the model of choice was defined by the inclusion of the 5- and 10-hour lag. The solutions generated by the Kajiji-4 algorithm present an interesting contrast. This algorithm produced MSE fitness values below 0.0300 for three economic models. One is a model that is specified with no lags (0.0262). Another is a model that, like Matlab, includes the 2- and 7-hour lag (0.0276). The final model is one that includes the 5- and 10-hour lag variables (0.0291). These apparently conflicting results elicit the need to invoke the ‘preponderance of evidence’ rule as a plausible method by which to accurately collapse individual ANN solutions into a set of policy findings.

Under the umbrella of the preponderance of evidence rule, the Kajiji-4 results provide the most convincing confirmation of the heterogeneous market hypothesis. Owing to its greater volatility, the JY proved to be an especially challenging exercise for the three ANN algorithms. For each RBF application, the best solutions negated the use of any lagged state variable associated with the test of heterogeneous trading. But, the SPSS algorithm, which performed rather weakly in overall tests, did display a penance to include lagged state-variables for the JY contract with only slightly higher MSE values than the lowest value in this particular test set. However, under closer scrutiny it becomes clear that, based on MSE alone, the SPSS results show that algorithm performance is deterred by the classic
“curse of dimensionality” problem. For example, not only are the MSE values high, but the SPSS fitness MSE for JY Model VIII, a model that includes the 2-and 7-hour lagged information variables, is not very different from the fitness MSE reported for the best JY economic model (3.0046 versus 2.9903). Considering the issues as detailed, we treat the SPSS evidence as a spurious result.

In the case of the SF the best models for both the Kajiji-4 and SPSS algorithms include the 2- and 7-hour lag variables. The best Matlab solution also includes lagged information but its choice is the 5- and 10-hour lagged variables. In summary, of the three futures options contracts under study, we conclude that returns volatility of the JY seems least affected by heterogeneous global trading activity. On the other hand, both the DM and the SF contracts are noticeably impacted by transaction activity on opposite sides of the globe as well as one-day delayed activity in the same trading market.

5. Ex Post Multiple Comparison of Predicted Variables

The analysis turns to a nonparametric test introduced by Kruskal-Wallis (1952). The computed values for the \( H \) statistic are reported in Table 6 are greater than the critical value of \( 5.991 \). Therefore, we reject the null-hypothesis and conclude there is a significant difference in the prediction residuals at the training-, validation-, and fitness-set levels for each of the three ANN algorithms.

\[ (11) \]

\[
|R_u - R_v| \geq q(\alpha, k, \infty) \left[ \frac{k(n+1)^{1/2}}{12} \right]^{1/2}
\]

where the right-hand side of the equation is the defined as the critical constant and \( q(\alpha, k, \infty) \) is the upper \( \alpha \) percentile point of the range of \( k \) independent \( N(0,1) \) variables. The \( q \) values as reported in Hollander and Wolfe (1973) were initially calculated by Harter (1960). Other defined terms include,

\( \tau_u \) and \( \tau_v \) which are the two treatments (u and v) for comparison,

\( k \) which reports the number of treatments, \( n \) accounts for the sample size, and

\( R_u \) is the average of rank for treatment \( u \).

If the computed value (left hand-side) is greater than the right hand side of the equation we can conclude that the two-treatment comparison is significantly different.

The results of applying Kruskal-Wallis multiple comparison tests to the contract residuals produced by a given algorithmic method are presented in Table 7. The Kajiji-4 algorithm is significantly different for tests involving the DM and SF contracts. The JY moderates this strong finding. The validation subset for the JY contract does not report a significant difference between the Kajiji-4 and SPSS algorithm. With this one exception noted, the Kajiji-4 algorithm generally trains, validates, and has a fit in a significantly different manner than the other two RBF algorithms when applied to hourly-realized volatility patterns of FX futures options contracts.

6. Summary and Conclusions

The purpose of this paper was twofold. We explicitly employed the RBF ANN topology to test the heterogeneous trading hypothesis as it may pertain to the hourly trading of option contracts on futures written against currency exchange. The ‘preponderance of evidence’ rule for ANN policy inference yielded significant information about the role heterogeneous traders. We find significant evidence of global heterogeneous traders for both the DM and SF FX futures option contracts. We also find significant differences among the tested RBF networks to conclusively identify this effect. For example, the Matlab results offered a weak confirmation of 1- and 2-day lags in same market trading volatility for both the DM and SF. By way of contrast, application of the Kajiji-4 algorithm yielded strong evidence of trading on opposite sides of the globe with both a 0.5 and 1.5 day lag in contemporaneous volatility realization. In total, the results obtained from the application of the RBF topology to hourly FX futures option volatility confirm the Dacrogna hypothesis of global activity in markets that are one-half day to two-days removed.

Secondly, recognizing that alternative software implementations of aANN topology may yield different levels of results, we provided a comparative analysis of three RBF algorithms when applied to futures options microstructure. We report conclusive evidence of computational and pattern-matching dominance by the Kajiji-4 method over the RBF algorithms produced by Matlab and SPSS. Not only was the Kajiji-4 algorithm capable of producing smaller MSE values over the training, validation, and fitness data subsets, but by application of the nonparametric Kruskal-Wallis procedure it was shown that the Kajiji-4 modeling functions were
statistically different than those produced by the other two test algorithms.

We are also able to add the following subjective observations. For software ease of use our preferential rank order is Kajji-4, SPSS, and Matlab. We found the Matlab product somewhat taxing and difficult to use. For example, the software would benefit by the addition of a user-friendly data import and export facility as well as more traditional support for the Window’s clipboard. The Matlab product is best left to expert users of the product.

Graphical output is a required part of ANN evaluation. As an application supported within the WinORS product, the Kajji-4 algorithm has access to an excellent graphing and plotting environment. Matlab graphs are also well known for their professional display characteristics. Their performance was consistent with this reputation. We can also report that SPSS plotting was on par with the other products as reviewed.

While not examined as a part of this research, we note that parameter setting flexibility is a necessary part of any ANN software system. Based on our experience with each product it apparent that each product has markedly different approaches to help researchers identify near-optimal parameter levels for any particular application. This is a research topic that is worthy of future investigation.
References


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Figure 2: Comparative Predicted Functions

Table 2: Parameter Settings for Alternative RBF Algorithms

<table>
<thead>
<tr>
<th>Model</th>
<th>Kajiji-4</th>
<th>Neural Connection from SPSS</th>
<th>Neural Network Toolbox from Matlab</th>
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<tbody>
<tr>
<td># in Test Set</td>
<td>10</td>
<td>10</td>
<td>10</td>
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<tr>
<td># in Validation Set</td>
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<td>120</td>
<td>120</td>
</tr>
<tr>
<td># in Training Set</td>
<td>DM: 620; SF: 1118; JY: 1118</td>
<td>DM: 620; SF: 1118; JY: 1118</td>
<td>DM: 620; SF: 1118; JY: 1118</td>
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<td>Spread Constant</td>
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<tr>
<td>Number of Centers</td>
<td>Internally set to # in Training Set</td>
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<td>25.0</td>
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<tr>
<td>Maximum Centers</td>
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<td>50.0</td>
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<tr>
<td>Iteration Starting Value</td>
<td>Statistically computed</td>
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<td>based on initial value of computed SSE</td>
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<tr>
<td>Max Iterations</td>
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<td>50 Centers or 0.001% of Last Error</td>
<td>0.05 of Last Error</td>
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<td>Max Epoch</td>
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<tr>
<td>Average Time to Solution</td>
<td>&lt; 1 min</td>
<td>&lt; 1 min</td>
<td>15 min to 6 hours</td>
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<td>Error Distance</td>
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Table 6: Kruskal-Wallis H'Statistic

<table>
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<tr>
<th>Contracts</th>
<th>Training</th>
<th>Validation</th>
<th>Fitness</th>
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<tbody>
<tr>
<td>DM</td>
<td>345.196</td>
<td>96.039</td>
<td>1095.852</td>
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<td>SF</td>
<td>180.992</td>
<td>227.601</td>
<td>8612.867</td>
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<tr>
<td>JY</td>
<td>101.807</td>
<td>11.310</td>
<td>9485.024</td>
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Table 7: Multiple Comparisons

<table>
<thead>
<tr>
<th>Trials</th>
<th>Comparisons</th>
<th>Training</th>
<th>Validation</th>
<th>Fitness</th>
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<td>DM</td>
<td>Critical Constant</td>
<td>70.903</td>
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<td>77.028</td>
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<td>541.070</td>
<td>107.308</td>
<td>611.722</td>
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<td>Kajiji-4 v/s Matlab</td>
<td>393.818</td>
<td>116.542</td>
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<td>147.252</td>
<td>9.233*</td>
<td>105.822</td>
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<td>Critical Constant</td>
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<td>31.483</td>
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<td>Kajiji-4 v/s SPSS</td>
<td>511.143</td>
<td>131.825</td>
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<td>Critical Constant</td>
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<td>Kajiji-4 v/s SPSS</td>
<td>372.920</td>
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<td>52.575*</td>
<td>25.300*</td>
<td>1696.077</td>
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</table>

Founded in 1892, the University of Rhode Island is one of eight land, urban, and sea grant universities in the United States. The 1,200-acre rural campus is less than ten miles from Narragansett Bay and highlights its traditions of natural resource, marine and urban related research. There are over 14,000 undergraduate and graduate students enrolled in seven degree-granting colleges representing 48 states and the District of Columbia. More than 500 international students represent 59 different countries. Eighteen percent of the freshman class graduated in the top ten percent of their high school classes. The teaching and research faculty numbers over 600 and the University offers 101 undergraduate programs and 86 advanced degree programs. URI students have received Rhodes, Fulbright, Truman, Goldwater, and Udall scholarships. There are over 80,000 active alumnae.

The University of Rhode Island started to offer undergraduate business administration courses in 1923. In 1962, the MBA program was introduced and the PhD program began in the mid 1980s. The College of Business Administration is accredited by The AACSB International - The Association to Advance Collegiate Schools of Business in 1969. The College of Business enrolls over 1400 undergraduate students and more than 300 graduate students.

**Mission**

Our responsibility is to provide strong academic programs that instill excellence, confidence and strong leadership skills in our graduates. Our aim is to (1) promote critical and independent thinking, (2) foster personal responsibility and (3) develop students whose performance and commitment mark them as leaders contributing to the business community and society. The College will serve as a center for business scholarship, creative research and outreach activities to the citizens and institutions of the State of Rhode Island as well as the regional, national and international communities.

The creation of this working paper series has been funded by an endowment established by William A. Orme, URI College of Business Administration, Class of 1949 and former head of the General Electric Foundation. This working paper series is intended to permit faculty members to obtain feedback on research activities before the research is submitted to academic and professional journals and professional associations for presentations.

An award is presented annually for the most outstanding paper submitted.