

A BINARY NEURAL NETWORK FRAMEWORK FOR ATTRIBUTE SELECTION AND PREDICTION

Victoria J. Hodge¹, Tom Jackson¹ and Jim Austin¹

¹*Department of Computer Science, University of York, York, UK
{ victoria.hodge, tom.jackson, jim.austin }@york.ac.uk,*

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Abstract: In this paper, we introduce an implementation of the attribute selection algorithm, Correlation-based Feature Selection (CFS) integrated with our k-nearest neighbour (k-NN) framework. Binary neural networks underpin our k-NN and allow us to create a unified framework for attribute selection, prediction and classification. We apply the framework to a real world application of predicting bus journey times from traffic sensor data and show how attribute selection can both speed our k-NN and increase the prediction accuracy by removing noise and redundant attributes from the data.

1 INTRODUCTION

Prediction is the assumption that the future trend of variations in the value of a time-series variable will mirror the trend of variations in the value of the same variable for similar historical time-series. There is a wide variety of prediction algorithms including: ARCH (Engle, 1982), ARIMA (Box & Jenkins, 1970), neural networks (Bishop, 1995) and support vector machine regression (Brucker et al., 1997). The prediction algorithms typically have two phases of operation: a training phase where the algorithm learns a representation of the data and a prediction phase where the algorithm generates predictions for new records using the learned model.

For prediction, the quality of the input data is critical; redundant and irrelevant attributes can slow execution and reduce accuracy. Redundant attributes also push the data to the tails of the distribution as the higher dimensionality spreads the data's convex hull. Attribute selectors reduce the dimensionality of data by selecting a subset of attributes (Kohavi & John, 1997). They remove irrelevant and redundant information, reduce the size of the data and clean it. This allows machine-learning algorithms such as predictors to operate more effectively.

There is a wide variety of attribute selection including: Correlation-based Feature Selection (Hall, 1998); Information Gain (Quinlan, 1986); Chi-square Selection (Liu & Setiono, 1996); and,

Support Vector Machines Selection (Guyon et al., 2002). There are two approaches for attribute selection (Kohavi & John, 1997). Filters are independent of the actual algorithm and tend to be simple, fast and scalable. Wrappers use the algorithm to select attributes. Wrappers can produce better performance than filters as the attribute selection process is optimised for the particular algorithm. However, they can be computationally expensive for high dimensional data as they must evaluate many candidate sets using the classifier.

Attribute selection is often used in conjunction with data mining algorithms such as k-NN. K-NN is a widely used algorithm (Cover & Hart, 1967; Hodge, 2011) that examines vector distances to determine the nearest neighbours. However, standard k-NN is computationally slow for large datasets. We have previously developed a binary neural network-based k-NN (Hodge & Austin, 2005) using the Advanced Uncertain Reasoning Architecture (AURA) framework. It is efficient and scalable, being up to four times faster than the standard k-NN (Hodge et al., 2004). We extended AURA k-NN to prediction in Hodge et al., (2011).

The main contribution of this paper is to: introduce the CFS attribute selector into the AURA k-NN framework and demonstrate the attribute selector's utility for prediction on a real world problem. Using attribute selection with prediction to reduce the data size will further speed processing.

2 AURA

AURA (Austin, 1995) is a set of methods for pattern recognition. AURA is ideal to use as the basis of an efficient k-NN predictor as it is able to partial match during retrieval so it can rapidly find records that are similar to the input – the nearest neighbours. It has a number of advantages over standard neural networks including rapid one-pass training, high levels of data compression, network transparency and a scalable architecture. These are enhanced with our robust data encoding method to map numeric attributes onto binary vectors for training and recall.

2.1 Time-Series

To estimate bus journey times, the system must incorporate a time component. In this paper, the vectors represent time-series of spatially-distributed sets of traffic sensors. To produce the time-series vector X_j , we buffer each sensor's readings for a preset time interval PT and concatenate the buffers to form the time series X_j^{TS} . Buffering always preserves the temporal ordering of the data. X_j^{TS} is $\{x_{1t-2}, x_{1t-1}, x_{1t}, x_{2t-2}, \dots, x_{yt-2}, x_{yt-1}, x_{yt}\}$ for PT of three time slices $\{t-2, t-1, t\}$ and y sensors.

2.2 Learning

AURA uses binary input I and output O vectors to store records in a CMM, M as in fig. 1. First, any numeric attributes must be quantised (binned) as the data to be trained into the CMM is binary. Quantisation maps a range of input values for attribute a onto each bin. Each individual bin maps to a unique integer. This identifies the bit to set in the AURA input vector and a unique row in the CMM (see Hodge & Austin (2005) for details).

Equi-width quantisation subdivides each attribute into b equal width bins across its range of values. The even widths of the bins ensures that the inter-bin distances are all equivalent and that the quantised data can be used to approximate the Euclidean distance. Once the bins and integer mappings have been determined, we map the records onto binary vectors to train into the CMM during learning. Each binary vector represents a pattern from the data set.

For an attribute with five bins, the five binary representations are then $bin_0 = 00001$, $bin_1 = 00010$, $bin_2 = 00100$ etc. The bins corresponding to the data values in X_j^{TS} are set to 1 and all other bins are set to 0. The binary representations for all attributes and their respective time slices are concatenating to form I_j . Thus, I_j is a learning pattern stored in the CMM to

allow the particular record to be stored and indexed.

The CMM, M , is initialised with all weights set to 0. Training stores the binary patterns for all N records in the data set in M . Each binary pattern I_j is associated with a unique identifier pattern O_j . Each O_j has a single bit set to index a unique column in M and to uniquely index I_j . At each training step, any matrix elements excited by both the input and output patterns are set to 1. This process is given in eq. 1.

$$M = \vee_j (I_j O_j^T) \text{ where } \vee \text{ is logical OR} \quad (1)$$

2.3 Recall

AURA recall is the dot product of a recall input vector R_k and M . R_k may be either a binary vector or an integer vector. For prediction, we use an integer vector to allow us to emulate Euclidean distance. For attribute selection (described later), we use a binary vector to count attribute values and co-occurrences.

For prediction, the integer recall vector R_k is generated for each new query using a set of concatenated parabolic kernels. The kernels represent scores which decrease in value with the distance from the query value and emulate Euclidean distance (see (Hodge and Austin, 2005) for details). Each kernel is centred on the bin representing each attribute value for the query record so that bin receives the highest score (the dotted values in Fig. 1). The best matching historical records will receive the highest scores. R_k is applied to M to retrieve the k best matches and the values in R_k multiply the rows of the matrix as in eq.2 and Fig. 1. The columns of M are summed according to the values on the rows indexed by R_k multiplied by the CMM weights to produce a summed output vector S_k as given in eq. 2.

$$S_k^T = R_k \bullet M \quad (2)$$

In Fig. 1, rows 0 to 4 represent traffic sensor $Sensor_t$, the variable is vehicle *flow* and the time slice within the time-series is $t-2$. For row 4, columns 2 and 3 (indexing from 0 on the left) score 9 as the set bits in columns 2 and 3 align with the score of 9 for row 4. In contrast, column 0 receives a score of 0 as the set bit in column 0 aligns with row 0 which scores 0 from the recall pattern R_k .

For partial matching, we use L-Max thresholding which retrieves *at least* L top matches. It finds the L highest values in the output vector S_k and sets the corresponding vector element to one in the binary output vector T_k . For AURA k-NN, L is set to the value of k ; the number of nearest neighbours.

count of the number of ones in T_k in Fig. 2. $Ent(b)$ in eq. 6 calculates the total count of data records for a particular attribute value b_j as per a_i .

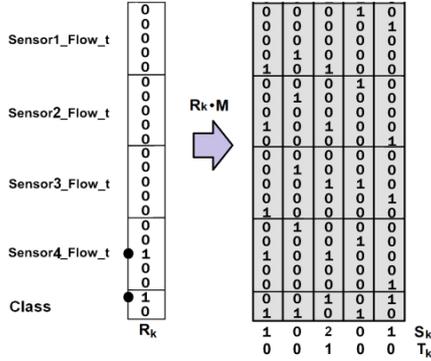


Fig. 2. Diagram showing the use of the CMM for attribute selection. The class attribute is included. The retrieval input vector R_k is binary for attribute selection whereas Fig. 2 has an integer retrieval vector. The dot is the value for each attribute (a quantisation bin).

$Gain(a, b)$ is based on the calculation of $Ent(a)$ and $Ent(a/b)$. $Ent(a/b)$ counts the number of co-occurrences of a_i with b_j . AURA excites both CMM rows corresponding to a_i and b_j as in Fig. 2. S_k has a two in the column of every record with a co-occurrence of a_i with b_j . By thresholding S_k at 2, we find all co-occurrences. The total co-occurrence count is the count of the number of ones in T_k .

3.3 Selecting the Attribute Subset

CFS uses Best First Forward Search (Hall, 1998) to search the attribute space, greedily adding individual attributes to the chosen subset. Search terminates when five consecutive fully expanded subsets show no improvement over the current best subset.

4 JOURNEY TIME ESTIMATION

We analyse our prediction framework to see if it could form part of a system to analyse mean bus journey times in York, UK. This system would provide an estimate of the level of congestion encountered by buses so other vehicles can be routed to less congested roads. We plan to estimate the bus journey times using other traffic sensor data to plug the gaps when actual bus data is not available.

To combine different bus routes along a road into an overall congestion estimate, we use journey time ratio. For buses, the bus journey time ratio is the journey time for a particular bus travelling the route

between a particular pair of bus stops divided by the 90th percentile historical journey time for that route. Mean journey time ratio is defined as the mean ratio across all buses travelling all routes along the road in a particular time period p as given by eq. 7.

$$mean_p = \frac{\sum_{r=1}^R \sum_{n=1}^N \frac{bjt_{(r;x,y)}}{bjt_{(r;x,y)}^{90}}}{N} \quad (7)$$

Where $bjt_{(r;x,y)}$ is the bus journey time for route r between stops x and y ; $bjt_{(r;x,y)}^{90}$ is the 90th percentile historical bus journey time for route r between stops x and y and N is the number of buses during the time period. $Mean_p$ will be <1 if the road is uncongested and ≥ 1 if the road is congested as bus journey times will exceed the 90th percentile journey times.

The sensors on the roads in York output vehicle flow (the number of vehicles passing over the sensor during a specific time period). The sensor data forms a pattern of the current traffic conditions for a time period p which we associate with the bus journey time ratio $mean_p$ for the same time period p , using the data's timestamps. AURA k-NN uses the sensor patterns as the input vectors and predicts the expected bus journey time ratio from the matching sensor pattern associations.

5 EVALUATION

The data comprises traffic sensor and inbound bus journey data from Fulford Road in York from 05/10/2010 to 28/03/2011. There are ten sensors each generating a flow value every five minutes. We use 12 time steps representing one hour's duration as our time series. There are five possible bus routes along the road section under investigation. Bus journeys are aggregated over five minute periods to match the periodicity of the traffic sensors.

We only consider time periods when two or more buses departed the final stop to smooth any anomalous readings. The data have been cleaned by removing erroneous bus journey times (80 seconds \leq valid \leq 2400 seconds). The data are still very noisy but will allow a thorough test of the algorithms and configurations under evaluation. The data set has 1932 records which we split 2/3 for training and 1/3 for testing giving 1288 training records and 644 test records. We perform the attribute selection on training data only. Each algorithm's parameters were optimised using only the training data: we evaluated a similar number of parameter sets for each

algorithm for fairness. The test data was applied to each learned model to get the prediction accuracy.

We produced three data configurations: all records in chronological order (**DataSet1**); all records in alphabetical order of date/time (**DataSet2**); and, all records in reverse alphabetical order of date/time (**DataSet3**).

The evaluation compares the RMSE of a multi-layer perceptron (MLP) used by Vlahogianni et al. (2005), a support vector machine (SVM) used by Labeeuw et al. (2009) and three configurations of the AURA k-NN: no time-series data (**AURA_{nts}**); time-series length 12 (**AURA_{ts}**) and time-series length 12 but only the sensors selected by CFS (**AURA_{CFS_{ts}}**). For CFS, we split the class ($mean_p$) into two bins (as in Fig. 2), if $mean_p < 1$ then map to $bin_{uncongested}$ otherwise map to $bin_{congested}$.

Each algorithm was applied to the three data sets using all attributes unless stated and a mean RMSE was calculated across the three data sets. The results are listed in table 1. In table 2, we compare the RMSE of the algorithms using just the chronological (true) order, DataSet1. Table 3 lists the parameter settings for AURA k-NN using CFS across the three data sets to demonstrate whether the variation in parameters is needed. Table 4 lists the training times on all of DataSet1 for AURA k-NN and AURA k-NN learning only the attributes selected using CFS.

6 RESULTS

We examine the attributes selected and the prediction accuracy of the various algorithms next.

6.1 Attribute Selection

For the three data sets, CFS selected:

DataSet1 : Sensor3, Sensor6, Sensor9

DataSet2 : Sensor1, Sensor2, Sensor3, Sensor6

DataSet3 : Sensor3, Sensor6, Sensor9

CFS has reduced the data dimensionality from 10 sensors to 3 for two of the data configurations and reduced the dimensionality to 4 for the other. This will speed both training and prediction for k-NN. The subsets for DataSet1 and DataSet3 are identical and sensors 3 and 6 are present in all subsets indicating some consistency. This data is noisy and temporal data is likely to have trends. These will affect the data when it is split into train and test sets which may explain the differences in DataSet2. Next we evaluate the prediction accuracy to ensure that this dimensionality reduction has not compromised the accuracy.

6.2 Prediction Accuracy

Table 1. Table comparing the mean RMSE (RMSE μ) for the prediction algorithms over the three data sets. The highest prediction accuracy is shown in bold.

Algorithm	MLP	SVM	AURA _{nts}	AURA _{ts}	AURA _{CFS_{ts}}
RMSE μ	0.1795	0.1722	0.1799	0.1750	0.1709

Table 2. Table comparing the mean RMSE (RMSE μ) for the algorithms over the chronologically ordered DataSet1. The highest prediction accuracy is shown in bold.

Algorithm	MLP	SVM	AURA _{nts}	AURA _{ts}	AURA _{CFS_{ts}}
RMSE μ	0.1826	0.1626	0.1695	0.1671	0.1603

Tables 1 and 2 show that CFS attribute selection coupled with time-series data improves the prediction accuracy of AURA k-NN. Thus, CFS has both reduced the dimensionality and increased the accuracy. Only the AURA k-NN using CFS attribute selection is able to outperform the SVM benchmark.

6.3 Parameters

Table 3. Table listing the parameter settings for AURA_{CFS_{ts}} across the three data sets. The three parameter variables are the number of neighbours retrieved (k), the number of quantisation bins and the range of values for quantisation.

Dataset	K value	Bins	Range
1	19	15	[0, 120]
2	24	15	[0, 120]
3	14	11	[0, 120]

Table 3 shows that across the three data sets the AURA k-NN parameters require tuning to maximise prediction accuracy. This variation also applied to the parameters of both the MLP and SVM. It is important that a prediction algorithm can perform this optimisation quickly and efficiently. Using CFS to reduce the data dimensionality will speed the parameter optimisation further as shown in table 4. Both standard MLPs and SVMs are slow to train as they require multiple passes through the data. Zhou et al. (1999) determined that the AURA k-NN trains up to 450 times faster than an MLP

6.4 Training Time

For AURA k-NN, the training time contributes the bulk of the processing time whereas retrieving the matches is much quicker (Hodge et al., 2004). Using attribute selection prior to training reduces the training time by almost half by reducing the data size. Attribute selection is a one off cost whereas the

AURA CMM must be trained each time the system is started so the key is minimising the training time.

Table 4. Table comparing the mean training time for AURA k-NN using time-series data compared to AURA k-NN with CFS on the same data. The mean was calculated over five runs.

	<i>AURA_{ts}</i>	<i>AURA_{CFS_{ts}}</i>
Training time (secs)	0.30	0.17

7 CONCLUSIONS

In this paper, we have introduced a unified framework for attribute selection and prediction. Classification is also available in the framework (Hodge & Austin, 2005; Krishnan et al., 2010).

Previously, we demonstrated two attribute selection approaches in AURA (Hodge et al. 2006). We have now added the multivariate CFS selector which is based on entropy. No attribute selector excels on all data or all tasks so we need a range of selectors to select the best for each task. We showed that CFS improved the prediction accuracy of the AURA k-NN on the real world task of bus journey prediction. We demonstrated that using attribute selection to reduce the dimensionality reduces the training time allowing larger data to be processed.

The AURA framework described is flexible and easily extended to other attribute selection algorithms. Ultimately, we will provide a parallel and distributed data mining framework for attribute selection, classification and prediction drawing on our previous work on parallel (Weeks et al., 2002) and distributed AURA (Jackson et al., 2004).

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