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A New Approach for Classification of Prices in the Electricity Market using Core Vector Machine

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Abstract

In this paper, an accurate and efficient classification of electricity prices using Core Vector Machine (CVM) has been presented. CVM is used to classify the prices into low and high classes efficiently. One of the most important aspects for an effective electricity price classification is the proper selection of training features. This paper investigates the use of a filter method for feature selection process. The CVM along with feature selection algorithm is tested for classification of electricity prices on Austria market and test results have been obtained. Simulation results obtained using CVM not only offer a very reliable price classification, but also provide a quantitative level of confidence for price classification.

Keywords: Core Vector Machine, Electricity Price Classification, Entropy based Feature Selection, Minimum Enclosing Ball

INTRODUCTION

Deregulation in electric power industry is a key issue in which the main objective is to increase the efficiency through competition [1]. With the development of power market, electricity price, especially, the forecasting of market clearing price is becoming more and more important. Electricity price forecasting has become a significant tool in competitive electricity market both for producers and consumers [2]. Government wants predictability as electricity is directly linked to the economic development; customers want protection from price variations and investors want confidence. Thus, the objective of a price forecasting model is to visualize future electricity market dynamics to assist in present decision making process [3]. The main objective of electricity market is to maximize the profit. Electricity price forecasting is one of the important functions in an electricity market since electricity has become an essential commodity in the modern society. Electricity price forecasting is very important to study because the electricity power market and electricity prices are highly volatile in nature. Since a single company no longer holds the entire supply chain, risk management has become an important issue. To manage such risks in the electricity market, forecasting of different market indicators has become necessary. Accurate forecast of the market prices is an important input to the decision making activities of a generating company for producing energy [4]. Price classification has become an important research area in Electricity Price Forecasting in recent years. Price classification is specifically useful when the exact value of future prices is not critically important. Most of the market participants expect electricity price classifications than the forecasting prices for making decisions [5].

In the last few years, numerous methods have been used to classify electricity prices. Conventional methods and many Artificial Intelligent (AI) techniques based on neural networks have been presented [5, 6] to solve price classification problems. Feed forward Neural Network (FFNN) [5], Cascade-Forward Neural Network (CFNN), Generalized Regression Neural Network (GRNN) [7], Discrete Cosine Transform with Neural Network (DCT-NN) [8], DCT-NN with Multilayer Feed forward Neural Network (MLNN) [6], Wavelet Transform, Particle Swarm Optimization (PSO-FFNN) [1], and machine learning classifiers such as Extreme Learning Machine (ELM) [9], Support Vector Machine (SVM) have also been reported in [10]. But, these procedures are found to be highly time consuming and infeasible for real time applications as they are based on the nature of inputs provided. Hence to overcome this problem, Core Vector Machine (CVM) is found to be the best method for solving price classification problems. The merits of CVM are that it is much faster than SVM and can handle much larger data sets than existing scale-up methods. Evading the similar patterns in the data set will enhance the performance of the proposed classifier. So, finding a finest feature selection algorithm is an additional apprehension in this paper.

Many feature selection algorithms are available such as Relief algorithm, Genetic algorithm, Particle Swarm Optimization, Sequential Forward Search, Chi-square test etc [11]. In this paper, the process of feature selection is performed by a simple approach called entropy based method [12].

The proposed CVM based classification approach is implemented in an Austria market. The simulation results prove that the CVM classifier gives an efficient classification, enhancing its suitability for on-line electricity markets with evidences of reduction in size of feature space and error rate by exploiting by way of an efficient feature selection method.

PROBLEM FORMULATION

Generation of Training and Testing Data Set

The process of making the dataset is an off-line process which should include data for all possible condition in the electricity market. The variation in prices of electricity is considered for whole dataset. For the hourly prices on daily basis, corresponding pattern vectors are obtained. Each operating condition has a number of operating variables called as pattern vectors. In this work, only prices in the electricity market i.e., market clearing prices have been considered. In this paper, the Austria energy price is taken from Austria market. The historical prices P_i have been used as inputs. Here, P_i indicates price at the i^{th} hour on daily basis.

The prices are classified based on a threshold value. The value of the threshold is based on the annual average of the prices in Austria for the year 2015. The annual average of the price threshold value is taken based on the average of the lowest price and highest price of the market. The minimum value for the whole year is -24.53 and maximum value of the price is 83.44. Evaluating each price, every pattern is labeled as low or high price. The class distribution based on price threshold is

Class 1: (prices between T_1 and T_2) = low prices

Class 2: (prices between T_2 and T_3) = high prices

Three classification thresholds are considered for the market: T_1=0, T_2 =31.65, T_3= 50 with all in euro per megawatt hour, where T_1, T_2, T_3 represent price floors, annual average price and price cap of the prices respectively. The dataset is split in such a way that 80% of data is taken for training phase and 20% of data is taken for testing phase.

Core Vector Machine

Recently, a number of procedures have been proposed in the literature for achieving multiclass classification, but data handling capacity still needs much attention. Several real-world applications typically deal with a massive collection of data and hence the main issue in using SVM is that of scalability. To overcome the problem of handling large dataset, CVM has been proposed. CVM is a technique for scaling up a two-class SVM [13] to handle large datasets. The proposed support vector data description computes a spherical boundary around the given data points. The diameter of the enclosing ball and there by the volume of the training data falling within the ball can be chosen by the user. Observations inside the ball are then classified as normal, whereas those outside the ball are treated as outliers.

Minimum Enclosing Ball Problem

Given a set of points $S = \{x_1, \ldots x_m\}$, where each $x_i \varepsilon R^d$, the minimum enclosing ball of S. Here, the approximate MEB algorithms based on core-sets. Let B(C,R) be the ball with center C and radius R. given $\varepsilon > 0$, a ball B(c, (1+ε) R) is an approximation of MEB(S) if $R \leq r_{MEB(S)}$ and $S \subset B(c, (1+\varepsilon) R)$. A subset $X \subseteq S$ is a core-set of S if an expansion by a factor (1+ε) of its MEB contains S.

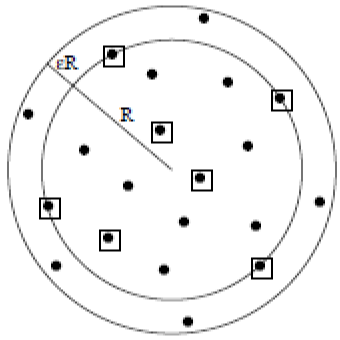

Figure 1: Inner circle is the MEB of a set of squares, and its (1 +ε) expansion (outer circle) coordinates all points and the set of squares represents each core set.

To obtain such an (1+ε) approximation, at the t^{th} iteration, the current estimate $B(c_t, r_t)$ is expanded incrementally by including the furthest point outside the (1+ε)-ball $B(c, (1+\varepsilon) r_t)$. Here, Figure 1 represents the Minimum Enclosing Ball, which consist of a set of squares in the inner circle, and outer circle is expanded to coordinate all points. Set of squares indicate each core set.

Classification based on CVM

The kernel method is formulated as a MEB problem, then the kernel k, is joined with associated feature space F, mapping φ and constant k= K(z,z). To solve this MEB problem, the ball is to be expanded by including the point furthest away from the current center. The core set, ball center and radius are denoted by S_t, C_t, R_t respectively. If $\varepsilon > 0$, then CVM works as follows [14]:

Step 1: Initialize S_0, C_0, R_0

Step 2: Terminate if there is no φ(z) (z is a training set) falling outside the (1+ε)- ball $B(C_t, (1+\varepsilon)R_t)$

Step 3: Find z such that φ(z) is furthest away from C_t.

Set $S_{t+1} = S_t \cup \{z\}$

Step 4: find the new MEB (S_{t+1}) from (7) and set $C_{t+1} = C_{MEB(St+1)}$ and $R_{t+1} = r_{MEB(St+1)}$

Step 5: Increment t by 1 and go back to step 2.

Initialization

In [15] an arbitrary point z ε S is used to initialize $S_0 = \{z\}$. z_a ε S that is furthest away from z in the feature space F is found. Then again the point z_b ε S, which is furthest away from z_a in F is found. The core set is set to be $S_0 = \{z_a, z_b\}$. MEB has center $C_0 = ½(\varphi(z_a) + \varphi(z_b))$. The initial radius

$$R_0 = ½||\varphi(z_a) - \varphi(z_b)|| = \frac{1}{2}\sqrt{2k - 2k(z_a, z_b)} \quad (1)$$

In classification problem, z_a, z_b is required to come from different classes. So R_0 becomes,

$$\frac{1}{2}\sqrt{2\left(k + 2 + \frac{1}{C}\right) + 2k(x_a, x_b)} \quad (2)$$

Where k and C are constants, the pair (x_a, x_b) maximizes R_0 that is equivalent to choosing the closest pair belonging to opposite class [16].

Distance computations

Step 2 and 3 involve computing $||C_t - \varphi(z_l)||$ for z_l ε S.

Now,

$$||C_t - \varphi(z_l)||^2 = \sum_{z_i z_j \epsilon S_t} \alpha_i \alpha_j k(z_i, z_l) - 2\sum_{x_i \in S_t} \alpha_i\, k(z_i, z_l), \quad (3)$$

Computing (3) for all m training points takes $O(|S_t|^2 + m|S_t|) = O(m|S_t|)$ time at the t^{th} iteration. This becomes very expensive when m is large. Here, the probabilistic speedup method is used. The idea is to randomly sample a sufficiently large subset S' from S, and then take the point in S' that is furthest away from c_t as the approximate furthest point over S. Instead of taking $O(m|S_t|)$ time, this randomized method only takes $O(|S_t|^2 + |S_t|) = O(|S_t|^2)$ time, which is much faster as $|S_t| << m$.

Adding the furthest point

Points outside MEB(S_t) have zero α_i. In classification case takes greedy approach by including the point furthest away from the center. In the classification case,

$$arg \max_{Zl\varepsilon B(C_t, (1+\epsilon)R_t)} ||C_t - \varphi(z_l)||^2 \quad (4)$$

$$arg \max_{Zl\varepsilon B(C_t, (1+\epsilon)R_t)} \sum_{z_i \epsilon S_t} \alpha_i y_i y_l (k(x_i, x_l) + 1) \quad (5)$$

$$arg \max_{Zl\varepsilon B(C_t, (1+\epsilon)R_t)} y_l(w'\varphi(x_l) + b)$$
(6)

The worst violating pattern is given by the equation (6). So for a pattern l currently outside the ball

$$(k\alpha)_l = \sum_{i=1}^{m} \alpha_i \left(y_i y_l k(x_i, x_l) + y_i y_l + \frac{\delta_{il}}{C}\right) \quad (7)$$

$$= y_l(w' \varphi(x_l) + b) \quad (8)$$

and $\alpha_l = 0$. Thus, the pattern in equation (6) makes most progress towards maximizing the objective.

Finding Minimum Enclosing Ball

The quadratic problem formulation is used for finding MEB. As the size $|S_t|$ of the core set is much smaller than m, the complexity of each Quadratic Programming sub problem is much lower than solving the whole QP. As only one core vector is added at each iteration, an efficient rank-one update procedure is used as only one point is added each time, the new QP is just a slight perturbation of the original. Hence, the MEB solution obtained from the previous iteration is used as starting point.

Thus, the new MEB is updated and based on the core set, the nearest points are added to both the opposite classes of z_a and z_b. This classification is indicated as high or low class.

The flowchart of CVM algorithm is presented in Figure 2. Here, step 1 gives the offline results of electricity prices used for classification procedure. The Step 2, manipulates the raw data into information and likewise raw data as input to produce information as output. It uses feature selection methods to deviate dimensionality of the feature selection. Step 3 shows all feature vectors and the corresponding classes are used to build the CVM. In last step, different indices are used to evaluate trained CVM.

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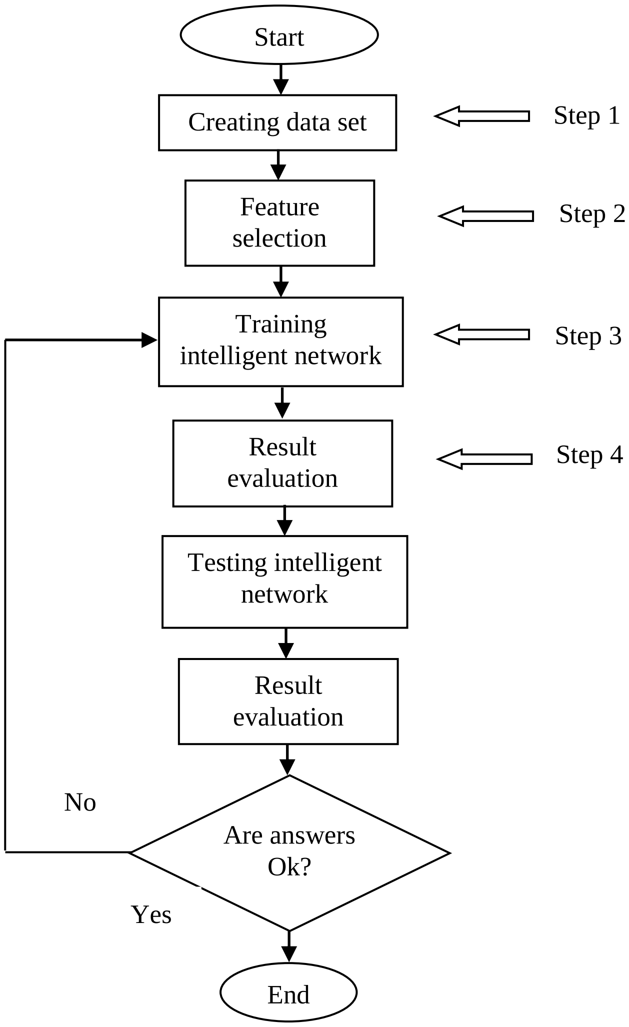

Figure 2: Flowchart of CVM method [17]

Feature Selection

Feature selection techniques have become an apparent need in classification of electricity prices in the electricity market. As many pattern recognition techniques were originally not designed to cope with large amount of irrelevant features, combining them with feature selection techniques has become necessary in many applications. The objectives of feature selection are manifold, the most important ones being a) to reduce the effects of curse of dimensionality b) to help in learning the model c) to minimize cost of computations d) to help in achieving good accuracy. The advantages of feature selection techniques come at a certain price, as the search for a subset of relevant features introduces an additional layer of complexity in the modeling task. In this work, the filter approach i.e., Entropy based feature selection [18] has been used.

Filter Method

It assesses the relevance of features by looking only at the intrinsic properties of the data. In most cases, a feature relevance score is calculated and low scoring features are removed. Afterwards, this subset of features is presented as input to the classification algorithm. Advantages of filter techniques are that they easily scale to very high dimensional data sets, they are computationally simple and fast, and they are independent of the classification algorithms. As a result, feature selection need to be performed only once and then different classifiers can be evaluated [18].

Entropy based Feature Selection

The basic idea of this method [19] is to filter out those features which are irrelevant. For the remaining features, this method can automatically find some cut points in these feature value ranges such that the resulting selected features can be maximally distinguished. If every cut point of a feature contain only the same class of samples, then this partitioning by the cut points of this feature has an entropy value of zero. This is an ideal case. The smaller a feature's entropy, the more it is discriminatory [20]. Entropy is a measure of disorder in physical systems and also a basic quantity with multiple field-specific interpretations. Entropy based feature selection used two methods to evaluate the features. First is information distance, which is used to evaluate the features based on the distance between feature and class label. In this method, the effect to classification accuracy is highly observed. Second, Pearson’s correlation [21] is used to evaluate the correlation between features. Then the minimum redundancy feature is selected according to the correlation. The feature which has small Pearson’s correlation value is selected and the remaining is eliminated. As in this method, the procedures are longer for the selection and it is complex, the information distance is used as it is reliable and consumes less time.

Information Distance calculation

Information Distance is based on information theory. The main concept of information theory is entropy, which measure the expected uncertainty or the amount of information provided by a certain event. The entropy of a random variable X is defined as follows:

$$H(X) = -\sum_{x} P(X=x)\log P(X=x) \tag{9}$$

Where P(X=x) is the prior probability of x

$$\text{Entropy } H(Y|X) = -\sum_{x,y} P(x,y)\log P(y|x) \tag{10}$$

Mutual information is a measure of how much the probability distribution for a random variable changes when the value of random variable is known. The mutual information between the two random variables X and Y is defined in the following:

$$I(X;Y) = \sum_{x,y} P(x,y) \log \frac{P(x,y)}{P(x)P(y)} \quad (11)$$

$$= H(X) - H(X|Y) \quad (12)$$

$$= H(X) + H(Y) - H(X,Y) \quad (13)$$

Information Distance adopts the conditional entropy to measure the relevance between a feature and the class label. The distance, d(X, C) of a feature and the class label is evaluated by

$$d(X, C) = H(X|C) + H(C|X) \quad (14)$$

Thus in Information Distance, feature selection is used to evaluate the distance between feature and class label. If a feature x_i has less distance $d(x_i, C)$ with the class label C, then it is considered as more relevant to class label. Then the cutoff distance is found based on standard deviation. These features with distance larger than mean distance plus cutoff value are regarded as irrelevant and are removed. As a result, the best candidate features are produced to improve classification accuracy. Then, these features selected are subjected to core vector machine classifier [21].

SIMULATION RESULTS AND DISCUSSION

The design of CVM based classifier model for prices of electricity is implemented and tested in an Austria market and the effectiveness of the proposed classifier has been demonstrated by using Tanagra software [22] and the results are compared with SVM and ANN. This data set is obtained by an hourly basis of the Austria market for a whole year.

The Austria market having daily prices on an hourly basis of electricity prices for the whole year of 2015 is considered. The patterns or variables are selected based on an appropriate feature selection technique. The data set generated for training and testing of CVM classifier is shown in Table 1. For a possible 365 days, 183 days are found to be in the class of low prices and the remaining 182 days are found to be a class of high prices. The training and testing samples are split at random by the ratio of 80 %(292 days) for training phase and 20 %(73 days) for testing phase.

Performance evaluation on feature selection for Electricity Prices

This paper describes a feature subset selector that uses an entropy based feature selection method to determine the goodness of feature subsets and evaluates its effectiveness with CVM classifier. An optimal set of patterns selected by using feature selection process is shown in Table 2.

Table 1: Data Set for Training and Testing phases

Days	Over all	Training	Testing
Total no of days	365	292	73
Low prices	183	146	37
High prices	182	145	37

In Table 2, all pattern variables are considered i.e., 24 hour variables on daily basis. Based on feature selection, only particular hours are selected, which increase the performance of the classifier. Thus, the dimensions of the features are reduced to 58.4%. The selected features based on the pattern variables are given below:

Table 2: Feature Selection Process

Case study	Austria market
No. of pattern variables	24
No. of features selected	14
Dimensionality reduction	58.4%
Selected features	P_8, P_6, P_{10}, P_{15}, P_{18}, P_{20}, P_{21}, P_{15}, P_1, P_7, P_9, P_{11}, P_3, P_{17}

Performance evaluation of CVM classifier for Electricity Prices

i. Accuracy: it defines the quality or state of being correctly classified.

ii. Misclassification rate: it defines the number of samples wrongly classified.

Based on the relevant definitions [12], the following formulations are obtained to compute the performance of CVM classifier.

Classification Accuracy (%) =

$$\frac{\text{No of samples classified correctly}}{\text{Total no. of samples in the data set}} x100$$

Misclassification Rate (%) =

$$\frac{\text{No of samples classified wrongly}}{\text{Total no. of samples in the data set}} x100$$

Evaluation

The proper selection of optimal values for CVM performance parameter decides the higher value of classification accuracy and minimal error rate. In this research paper, the following parameters listed below have been utilized for electricity price classification using CVM classifier. The optimal values of CVM performance parameters are provided in Table 3. The optimal value of 'gamma' is selected as 0.5. This value of 'gamma' forces to move the support vectors within their boundaries resulting in higher classification accuracy. The tolerance of termination criteria 'epsilon' is optimized as 0.0001.

Results shown in Table 4 prove that obtaining the useful support vectors from the whole data set is the fundamental part of this evaluation process. The number of support vectors for classification of low and high prices is presented. Moreover, support vectors are calculated based on the rule of radial basis kernel function that defines the boundaries between low and high classes. The performance of CVM classifier with 24 attributes is shown in Table 5. Based on this, the system is assessed for electricity prices with 93.24% of testing accuracy. .

The performance of CVM classifier with 12 attributes, after feature reduction, with 94.23% of testing accuracy, is shown in Table 6. From the simulation results, the classification accuracy of CVM classifier with feature selection is 94.23% as compared with accuracy of 93.24% without feature selection. It is clearly evident that the performance of the CVM classifier is improved with the selection of a good feature set and elimination of surplus data from the overall dataset.

Table 3: Parameters of CVM classifier

Parameters	Optimal values
Kernel type	Radial basis function
Degree of kernel	1
Gamma	0.5
Tolerance of termination	0.0001
C(complexity cost)	1

Table 4: Classifier characteristics during evaluation

Characteristic	Value
Number of classes	2
Number of support vectors	22
Number of support vectors for the class of low prices	6
Number of support vectors for the class of high prices	16

Table 5: Classification of Electricity Prices using CVM classifier without Feature Selection

Performance evaluation	Without feature selection (24 features)	
	Training	Testing
Accuracy (%)	96.55 (289/292)	93.24 (68/73)
Misclassification rate (%)	3.44 (3/292)	6.75 (5/73)

Table 6: Classification of Electricity Prices using CVM classifier with Feature Selection

Performance evaluation	With feature selection (12 features)	
	Training	Testing
Accuracy (%)	96.56 (290/292)	94.23 (70/73)
Misclassification rate (%)	3.43 (2/292)	5.76 (3/73)

Table 7: Comparative results of Electricity Price classification with Feature Selection (Testing phase)

Performance	CVM classifier	SVM classifier	ANN
Accuracy (%)	94.23	92.06	91.04
Misclassification rate (%)	5.76	7.93	8.95
Time in seconds	0.40	0.61	0.68

Evaluation of CVM Classifier with Feature Selection

The comparative study of CVM classifier with SVM and ANN for electricity prices is shown in Table 7. Results prove that CVM can handle large data sets and it is the finest classifier when compared with other classifiers. In addition, CVM-based price classification algorithm produces enough support vectors. Therefore, it is faster than the existing methods. Simulation results show that the proposed CVM-based price classification has small training time and small vector dimension compared to SVM and Neural Network.

CONCLUSION

The proposed CVM is a superior method adopted for constructing an optimal hyper plane via radial basis function kernel that separate the two classes with optimal margin in classification problems. The proposed entropy based feature selection algorithm is an efficient method to deal with the problem of high dimensionality in the design of machine learning classifiers. The result proves that the classification accuracy of CVM is equivalent to that of standard SVM. However, in the training of large scale data, CVM possesses fast training speed and takes up less space compared to standard SVM. Therefore, the overall performance of CVM is superior to that of standard SVM and it is applicable to the learning of large scale electricity market. The proposed model holds promise as a quick classifier for classification of prices in electricity markets.

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