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Abstract

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INTRODUCTION

The meaning of electronic commerce, popularly known as e-commerce, has changed over the last 30 years. In current times, a lot of transactions take place online, for the purchase of variety of products like a mobile phone. In such purchases often the buyers end up buying more products than the main item, like mobile accessories, in this case. The paper would make an attempt to provide a methodology which will be able to predict which item the purchaser of a product may be interested in after a purchase of a certain product, in an online transaction. This will be achieved by using Artificial Neural Networks for the purpose of pattern association. This paper makes no attempt to investigate the causes that leads to associative purchases.

This paper identifies the major contributions in the area and lists them, chronologically, especially in the area under focus. The objective of this paper is to provide a deeper insight of the work done till date in data mining in the field of data or pattern association and then use an existing pattern association algorithm involving a rare technique with neural networks, for the implementation of the same in a new business setting. This proposed methodology can provide key information to the marketer who can provide information regarding such associated purchase products to the customer, and thus affect the recall value of such items, in the mind of the customer, immediately at the point of purchase. This would have a huge impact on the total sales generated by the vendor. Thus having such key insights would have a huge impact on the cross selling efforts of the marketer.

1. LITERATURE REVIEW OF MAIN CONCEPTS

2.1 Pattern association

From the early 1970s, pattern association was primarily studied in the context of market research model development. Perhaps the most common precursors to the exploration of the associative relationship between two variables in marketing involve the use of bivariate cross-tabulations or multivariate analysis (DeSarbo and Hildebrand 1980; Green 1978; Perreault and

Barksdale 1980). Several alternative measures are available for assessing the extent of association in a contingency table.

Current pattern association studies in data mining started developing from 1993. Agrawal, Imielinski, and Swami (1993); Park, Chen and Yu (1995); Holsheimer, Kersten and Mannila (1995); Houtsma and Swami (1995) studied association in mining approaches and are highly cited works. The Apriori algorithm (Mannila, Toivonen, and Verkamo, 1994; Agrawal and Srikant, 1994) was shown to have superior performance to previous methodologies and is one of the most referred (cited) algorithm. Another major contribution in the area is the development of the partition algorithm (Savasere, Omiecinski, and Navathe, 1995) which minimizes I/O by scanning the database only twice. In the first pass it generates the set of all potentially frequent item-sets and in the second pass their global support is obtained.

2.2 Analysis with dynamic data

All these previous studies focused on static data only. There had been few studies in the field of neural continuum models in a 1-d or a 2-d cortical domain in associative memory focused studies like those of Weiner and Rosenblueth (1946); Beurle (1956); Griffith (1963); Coleman (1971); Wilson and Cowan (1973); Boylls (1975); Ellias and Grossberg (1975); Stanley (1976); Amari (1977); Amari and Arbib (1977); Erment, Rout and Cowan (1980). These were the precursor to studies in associative memory research of more recent times and focused more on pattern generation, pattern retrieval and visual invariance and not on the generation of association rules.

Hopfield (1982 and 1985) proposed methodologies for neural networks to express collective computational capabilities. These methodologies were used later in other studies to develop rules for pattern association using neural networks. Cohen and Grossberg (1983) studied pattern association and focused their efforts on the process whereby input patterns are transformed and stored by competitive cellular networks, besides focusing on the stability of the pattern rules and their parallel memory storage in competitive neural networks. Carpenter and Grossberg (1985) proposed the adaptive resonance architectures (ART) for neural networks that self-organize stable pattern recognition codes in real-time in response to arbitrary sequences of input patterns, for adaptive pattern recognition. In 1987, Carpenter and Grossberg proposed a parallel architecture with neural networks for pattern association. In the same year, they presented a methodology to form invariant pattern recognition rules with ART architecture for a dynamic data. In the same year, they proposed the ART 2 architecture, a class of adaptive resonance architectures which rapidly self-organize pattern recognition categories in response to arbitrary sequences of either analog or binary input patterns. Again in 1989, they proposed the ART 3 model to implement parallel search of compressed or distributed pattern recognition codes in a neural network hierarchy. Bart Kosko (1988) proposed a methodology for creating associative rules in bidirectional memories using the algorithms for Hebbian learning and extended the studies by Grossberg to propose the model. Joydeep Ghosh and Hung Jen Chang studied pattern association in a continuous neural system in 1992 after referring their work and proposed a neural model with a noise reduction equation with a visual cortex model to achieve pattern association invariant to scaling, translation and mirror reflection. Aumann, Feldman and Lipshtat (1999) presented a new algorithm BORDERS, with 3 variants, for generating associations in dynamic databases. Very little work has been done in the field of incremental and dynamic databases using neural networks.

2.3 Market basket data analysis

A particularly well-studied problem in data mining is the search for association rules in market basket data (Agrawal 1993; Klemettine 1994; Mannila 1994; Agrawal and Srikant 1994; Han and Fu 1995; Houtsman and Swami 1995; Park 1995; Srikant and Agrawal 1995; Savasere 1995; Agrawal 1996; Toivonene 1996). There has also been some work on extending this paradigm to numeric and geometric data (Fukuda 1996). While Piatetsky, Shapiro and Frawley (1991) define an association problem as the general problem of finding recurring patterns in data, much of the recent work on mining of large-scale databases has concerned the important special case of finding association rules. Association rules are primarily intended to identify rules of the type, “customer purchasing item A is likely to also purchase item B.” Most of this research in data mining from large databases has focused on the discovery of Boolean association rules (a=>b). Agrawal (1996) has demonstrated the need for quantitative rules ([a, b] => [c, d]) in the domain.

Silverstein, Brin and Motwani (1997) moved the research and developed pruning strategies based on the closure property and thereby devise an efficient algorithm for discovering dependence rules. What has not been extensively studied is the formation of association rules in market basket data obtained from e-commerce settings, during the online purchase of products from web-sites or e-Stores selling the same. In this paper, previously proposed algorithms have been suitably modified and proposed for the creation of pattern association rules when a customer shops in online stores, so as to enable the marketer invest suitably to obtain better results for his cross-selling efforts.

2.4 Micro-economic aspects of association rules

Kleinberg (1998) proposed that the utility of extracted patterns such as association rules in decision-making can only be addressed within the microeconomic framework of the business. This implies that a pattern in the data is interesting only to the extent in which it can be used in the decision-making process of the enterprise to increase utility. A major disadvantage of association discovery is that there is no provision for taking into account the business value of an association (Cabena, 1998). Brus, Swinnen, Vanhoof and Wets (2004) tackled the problem of product assortment analysis and introduced a concrete microeconomic integer-programming model for product selection based on the use of frequent item-sets. Their studies indicated the relevance of the rules of pattern association in providing greater returns for the marketing investments for a marketer. In this study, the proposed methodology tries to provide economic profit to the marketer using the generated rules where economic profit is defined as the increase in wealth that the seller has from making a transaction, taking into consideration the revenue generated from the transaction and all the costs associated with that transaction.

2.5 Virtual market conceptualization

Although these studies focused on dynamic databases which were created and evolved over time, none of them focused on mining association rules for basket data in online shopping business models based on "Virtual market" conceptualization of the business. Virtual markets refer to settings in which business transactions are conducted via open networks based on the fixed and wireless Internet infrastructure. Dutta and Segev (1995) examined the ways commercial organizations are exploiting the Internet and established that such markets are characterized by high connectivity and dynamism that improves their overall effectiveness above static markets. Balakrishnan, Kumara, and Sundaresan (1999) suggested that these newly created markets have a greater focus on transactions and that the new environment facing manufacturing enterprises will involve more customer engagement, transitory partnerships with global companies, and greater emphasis on agility, which will affect overall revenue for the business. This study helps to realize the importance of customer focus on individual transactions and thus, the necessity of pattern association rules in such a business setting can be well understood. According to Amit and Zott (2001) virtual market conceptualization of businesses have enabled the ease of extending a business' product range to include complementary products, improved access to complementary assets, new forms of collaboration among firms and customers, the potential reduction of asymmetric information among economic agents through the Internet medium, and real-time customizability of products and services. The stress on each o these aspects being equally important establishes the need for generation of pattern association rules for this newly developing "market". Thus, with the virtual market conceptualization of businesses catching up, businesses will have to depend more and more on the "web-shops" to reach out to new customers. So cross-selling will be a major driver to boost the total revenue from each customer.

2.6 Product classification

For classifying different products, several different standards and formats were developed over the years. Classification schema have classically focused primarily on consumer response variables, such as convenience, shopping and specialty goods (Copeland, 1923), or on specific characteristics of the product such as durability or frequency of purchase (Aspinwall, 1962). Nelson (1970, 1974) classifies experience goods as experience durable (low frequency of purchase goods) and experience nondurable (high frequency of purchase goods) and tests for significant differences in the advertising sales ratios for search, and the two experience good classifications. In this study, the focus has been limited on such products whose frequency of purchase are low and as such are experience durables, as defined by Nelson, which would include consumer electronics, apparel, accessories, foot-wear and home appliances. Web enabled transactions for these products will create value for the customers in terms of lowered transaction costs, and has been established as being more preferred products in online purchases in an IBM study "Understanding consumer patterns and preferences in multi-channel retailing", conducted in 2008. These product categories have been selected due to the high preference of customers for online transactions for the same.

2. RESEARCH FOCUS AND JUSTIFICATION

In this study, a methodology has been adapted for usage in the data obtained when customers shop online for consumer durables from online "web-stores" or "e-tailers" following the virtual market conceptualization of businesses for the generation of association rules. The focus of the proposed methodology has been on web enabled transactions since in such business setting, the product ranges and transaction volumes tend to be very large and dynamic. Thus existing association rule generating methodologies often fail to address such a business setting effectively although they can address the same in a static business setting or a normal store setting. The focus has been on products whose purchase frequency is not too high, since such products often are more sought for in a web enabled business setting. The proposed methodology would address generation of dynamic pattern association rules using neural networks from online shop data on individual customer transaction. This methodology would enable a marketer to post suitable advertisements of products, which would be based on the associative rules generated by the proposed methodology. An algorithm has also been proposed that would filter out association rules which would not provide economic value to the marketer and maximize the profit for the marketer. This would enable improved returns on cross-selling efforts of a marketer. The study limits itself to the techniques needed to generate association rules and does not look into the issues of consumer behavior that leads to associative purchases. Nor does it look into how existing information about the customer may be used effectively to predict preferences using segmentation techniques post classification.

3. METHODOLOGY PROPOSAL

So based on previous research done in the field of pattern association, a methodology is being suggested for the usage of pattern association in the field of online purchase of consumer durables from an e-shop, which often is realized as an unit of business entity in a virtual market conceptualization of a business. For the generation of association rules, each purchased item or to be purchased item, be it a mobile phone or a mobile phone accessory, for example, would be considered to be a product. Each product purchase or transaction is to be treated as an individual vector in this system using the neural network mesh and would have a unique serial number.

Thus say an individual purchases a product of model ABC-123. Say, purchaser of that particular model of the mobile phone often buys another mobile accessory XYZ-123. So, the purchase of the item ABC-123 can be associated with the purchase of the accessory XYZ-123. In this paper, both purchases would be represented as separate transactions and each transaction would be encoded as a vector. Let **x** be the vector for the purchase of the original item, ABC-123, in this case. Then **t** would be the vector for the purchase of the associative product, XYZ-123, in this case.

Thus each associative purchase pair can be represented as an input-output vector pair, say ***x-t***. If each vector ***t*** is the same as the vector ***x*** with which it is associated, then the net is called an auto-associative memory. If the ***t***'s are different from the ***x***'s, the net is called a hetero-associative memory. In both types, the ANN not only learns from the specific pattern pairs that were used for training, but also is able to recall the desired response pattern when given an input stimulus that is similar, but not identical, to the training input. This is the part that gives it the pattern recognition capability.

For training the system for pattern association, we use the extended form of the Delta rule, as proposed by Widrow and Hoff (1960), for pattern association since this rule may be used for input patterns that are linearly independent but not orthogonal. We denote our training vector pairs as ***x-t*** and then denote our testing input vector as x. Let **α** be the learning rate, ***x*** be the training input vector and ***t*** be the target output for input vector ***x***.

The original Delta rule assumes that the activation function for the output units is the identity function; or, equivalently, it minimizes the square of the difference between the net input to the output units and the target values. An analogy can be drawn from this as the minimization of RMS error. That the delta rule will produce the least squares solution when input patterns are not linearly independent was established by Rumelhart and McClelland (1986). Using this process, we are able to compute the initial output node values, being referred here as y.

Using y as the computed output for the input vector x, y is calculated as follows:

$\mathbf{y_j = \sum(x_i * w_{ij})}$ for all i.

and the weight updates are: $\mathbf{w_{ij}(new) = w_{ij}(old) + \alpha(t_j - y_j)x_i}$ for all (i = I, ... , n; j = I, ... ,m)

Or we can denote the same in terms of weight change as $\mathbf{\Delta w_{ij} = \alpha\, (t_j - y_j)\, x_i}$

Now, we use the extended Delta rule, which allows for an arbitrary, differentiable activation function to be applied to the output units. The update for the weight from the I-th input unit to the J-th output unit is as follows:

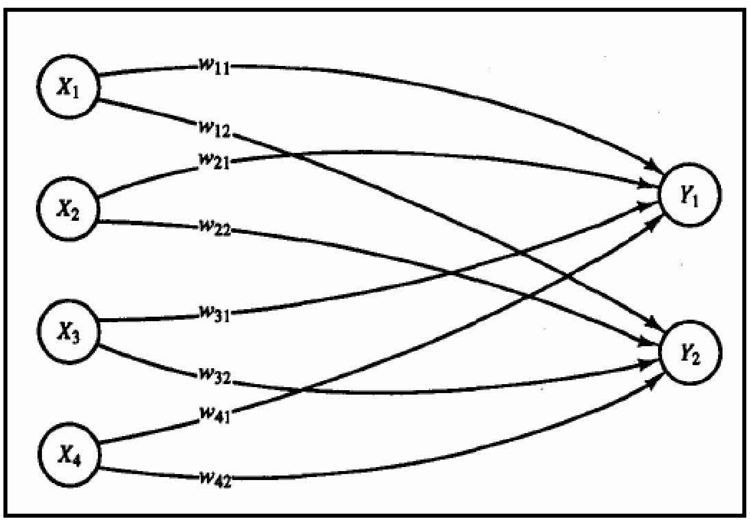
$$\mathbf{\Delta W_{IJ} = \alpha\, (t_J - y_J)\, x_I\, f'(y\_in_J)}$$

Now a hetero-associative memory neural network is being used for the next step. Associative memory neural networks are nets in which the weights are determined in such a way that the net can store a set of P pattern associations. Each association is a pair of vectors (x(p), t(p)), with p = 1,2, ... ,P. Each vector x(p) is an n-tuple (has n components), and each t(p) is an m-tuple. The weights of the network are determined by the extended Delta rule as mentioned earlier in the paper.

The algorithm to find out the association between the vectors is as follows:

- **Step 1**: For each input vector X_i, do Steps 2 to 4.
- **Step 2**: Set activations for input layer units equal to the current input vector X_i.
- **Step 3**: Compute net input to the output units: $y\_in_j = \sum X_i W_{ij}$
- **Step 4**: Determine the activation of the output units:
    - $Y_j = I$ if $y\_in_j > 0$
    - $Y_j = 0$ if $y\_in_j \leq 0$

Here, X_i denotes the inputs to the neural network mesh. Y_i denotes the output of the neural network mesh, and would provide the final association rules, that would indicate whether association exists between the products. W_{ij} denotes the weights of the interconnecting network branches of the neural network mesh, and would be initialized in the beginning with the extended Delta rule, as indicated earlier.



The network is denoted along with its symbols in the following diagram [Figure 1: ANN-Pattern Association].

A threshold function has been used here to generate the final association rules by the proposed methodology. The utility of the threshold function would be to minimize the implications of cross-talk, unless the same is not too high.

The output unit Y_j denotes a positive association if $Y_j = 1$, which would indicate, for the concerned pair of vectors, X_i and Y_j. This means that if transaction X_i happens, Y_i can be inferred to happen by the rules of association. Thus in such a scenario, a purchase of the product corresponding to X_i would infer a strong probability of purchase of the product corresponding to Y_i, following the rules of association. The output unit Y_j denotes a negative association if Y_j = 0, which would indicate, for the concerned pair of vectors, X_i and Y_j. This means that if transaction X_i happens, the probability of the transaction Y_j happening can be inferred to be low, or if product corresponding to X_i is purchased, the probability that the buyer would also be interested to purchase the product corresponding to Y_j is rather low, following similar rules of association.

Now, the rules generated needs to be further tested before actual implementation to see whether they create economic profit for the firm where economic profit is defined as the increase in wealth that the seller has from making a transaction, taking into consideration the revenue generated from the transaction and all the costs associated with that transaction. For the same, the strength "α" of each generated rule would need to be tested on a continual basis. For doing so, the ratio of the transactions that lead to a success of the association rule generated, to the total number of transactions involving the 1^{st} product which may or may not have led to the purchase of the secondary product (as predicted by the association rule) needs to be calculated. This would be used to determine which rules would finally be used on a regular basis, and which would need to be rejected, based on the profit that may be generated by the association rule to the business.

Now, in this study, the economical value of each generated association rule is evaluated using the mentioned algorithm.

- **Step 1**: Do step 2 to step 4 until all association rules (X_i–Y_j) have been evaluated.
- **Step 2**: Calculate the profit that may be generated on successful completion of the transaction, i.e. profit = $Y_{j\text{-Val}} * \alpha_{(Xi - Yj)} - C_{(Xi - Yj)}$
- **Step 3**: If ($Y_{j\text{-Val}} * \alpha_{(Xi - Yj)} - C_a$) > 0, keep the association rule
- **Step 4**: If ($Y_{j\text{-Val}} * \alpha_{(Xi - Yj)} - C_a$) ≤ 0, reject the association rule

Here, in this algorithm, every association rule is referred as (X_i–Y_j). $Y_{j\text{-Val}}$ is the revenue generated on completion of the transaction $Y_{j.}$ The strength of the association rule (X_i–Y_j) is depicted as $\alpha_{(Xi - Yj)}$. C_a is the cost of converting a customer through targeted advertising into buying incurring transaction Y_j and in this scenario, would involve the cost of advertising. Finally only those rules are finally kept which propose economical value to the business.

Now, on the actual purchase of product X_i, a profit maximization algorithm is being proposed where the objective function represents the goal of a profit maximization problem and therefore reflects the microeconomic framework of the marketer.

- **Step 1**: For transaction Y_j, do steps 2 to 3 for all values of j.
- **Step 2**: For each Y_j, calculate C_{Yj}.
- **Step 3**: For all Y_j, find maximum $(Y_{j\text{-}val} – C_{yj}) * \alpha_{(Xi – Yj)}$
- **Step 4**: Choose Y_j for which $(Y_{j\text{-}val} – C_{yj}) * \alpha_{(Xi – Yj)}$ has the maximum value.

Here, C_{Yj} represents the cost of sales of Y_j which would include the sum of the cost of the product, the transaction costs and the logistic costs for the transaction. $Y_{j\text{-}val}$ represents the monetary value of the transaction Y_j. The strength of the association rule (X_i–Y_j) is again depicted as $\alpha_{(Xi – Yj)}$.

With this algorithm, the associated rule which will generate the maximum expected profit for the marketer for the transaction Y_j after X_i has taken place, will be generated eventually, and thus will address the profit maximization objective of the marketer. Thus, with this approach, a business will be able to predict after a customer makes a transaction, which purchase would he be interested in, next, and whether attempting to convert such a purchase would create economic value for the business.

4. SUMMARY

In this proposed methodology, the focus has been on the generation of association rules in one of the most modern business context, that in the "virtual market" conceptualization of business. Virtual markets are characterized by much greater focus on transactions where both the number of transactions, the variety of the products and the reach to customers is much higher than in the traditional store setting. Traditional methodologies to generate such association rules have not been proposed for the process, since neural networks offers exciting dynamic benefits in addressing the same problem domain. Another key reason for utilizing the methodologies using neural networks is that pattern association studies have not been studied with neural networks at large. Pattern association and generation of association rules itself is not too well developed an area of research and is still in its infancy.

Given these reasons, an attempt has been made to propose a methodology with existing algorithms of separate studies to generate pattern association rules from data obtained from web enabled shops and evaluate each rule to check whether it could create economic profit for the firm. The proposed methodology used an extended form of the Delta rule for the initial training of the network and a hetero-associative neural network for generating and storing the associative rules. Also, a methodology has been proposed to filter out all rules which do not add economic value to the firm and then solve the profit maximization objective of the marketer. This would enable web-stores not only to generate more profit from higher conversion of cross-selling efforts, but also do so effectively so that maximum economic profit may be generated from the transaction.

5. FUTURE RESEARCH

An area of concern would be whether the proposed methodology is suitable for an ever increasing and dynamic database system, and how the complexity of such a methodology be minimized. Future research should also look into the issue of how many patterns can be stored (or pattern pairs learned) before the net starts to "forget" patterns it has learned previously. Also another area of concern would be whether the generated rules are able to propose greater economic value for the business as compared to other association rules generating methodologies.

6. REFERENCES

1. Agrawal R. and Srikant R., (1994), “Fast algorithms for mining association rules”, 20th Int'l Conf. on Very Large Data Bases, Santiago, Chile.

2. Agrawal R., Imielinski T. and Swami A., (1993), “Mining association rules between sets of items in large databases”, ACM, SIGMOD Intl. Conf. Management of Data, Washington.

3. Amari and Arbib M. A., (1977), “Competition and cooperation in neural nets”, In J. Metzler (ed.), Systems Neuroscience, Academic Press, pp 119-165.

4. Amari, (1977), “Dynamics of pattern formation in lateral-inhibition type neural fields”, Bio-logical Cybernetics, vol. 27, pp 77–87.

5. Amit R. and Zott C., (2001), “Value creation in e-business”, Strategic Management Journal, Vol. 22, pp 493–520.

6. Aspinwall L. V., (1962), “The Characteristics of Goods Theory and Parallel Systems Theories”, Marketing Theory-Classic and Contemporary Readings, South-Western Publishing Company, Chicago, IL.

7. Aumann Y., Feldman R. and Lipshtat O., (1999), “Borders: An efficient algorithm for association generation in dynamic databases”, Journal of Intelligent information Systems, Vol. 12, pp 61–73.

8. Balakrishnan A, Kumara S. R. T. and Sundaresan S., (1999), “Manufacturing in the digital age: exploiting information technologies for product realization”, Information Systems Frontier, Volume 1, Number 1, pp 25-50.

9. Beurle L, (1956), “Properties of a mass of cells capable of regenerating pulses”, Philosophical Transactions of the Royal Society London B, Vol. 240, pp 55–94.

10. Boylls C., (1975), “A theory of cerebellar function with applications to locomotion: the physiological role of climbing fiber inputs in anterior lobe operation”, COINS Technical Report Univ. mass. at Amherst.

11. Brus T., Swinnen G., Vanhoof K. and Wets G., (2004), “Building an Association Rules Framework to Improve Product Assortment Decisions”, Data Mining and Knowledge Discovery, Vol. 8, Issue 1, pp 7-23.

12. Cabena P., Hadjinian P., Stadler R., Verhees J. and Zanasi A., (1997), “Discovering Data Mining: From Concept to Implementation”, NJ: Prentice Hall, pp 195.

13. Carpenter G. A. and Grossberg S .,(1987), “ART 2: Stable Self-Organization of Pattern Recognition Codes for Analog Input Patterns", Applied Optics, Vol. 26, Issue 23, pp. 4919-4930.

14. Carpenter G. A. and Grossberg S., (1985), “Category Learning and Adaptive Pattern Recognition: a Neural Network Model", Proceedings, 3rd Army Conference on Applied Mathematics and Computing, ARO Report 86-1, pp. 37-56.

15. Carpenter G. A. and Grossberg S., (1987), “A Massively Parallel Architecture for a Self-Organizing Neural Pattern Recognition Machine", Computing and Vision Graphics Image Processing 37, pp. 54-115.

16. Carpenter G. A. and Grossberg S., (1987), “ART 2: self organization of stable category recognition codes for analog input patterns”, Applied Optics, Vol. 26, issue 23, pp. 4919-4930.

17. Chang H., and Ghosh J., (1992), “Pattern Association and Retrieval in a Continuous Neural System”, University of Texas, Biological Cybernetics, Vol. 69, Number 1, pp 77-86.

18. Cohen M. and Grossberg S., (1983), “Absolute stability of global pattern formation and parallel memory storage by competitive neural networks”, IEEE Transactions on Systems and Cybernetics, SMC-13 (15), pp. 815-826.

19. Coleman B. P., (1971), “Mathematical theory of lateral sensory inhibition”, Archive for Rational Mechanics and Analysis, Vol. 110, Number 4, pp. 377-384.

20. Copeland M. T., “The Relation of Consumers' Buying Habits to Marketing Methods”, Harvard Business Review, (April 1923), pp. 282–289.

21. DeSarbo W. S. and Hildebrand D. K., (1980), "A Marketer's Guide to Log-Linear Models for Qualitative Data Analysis", Journal of Marketing, Vol. 44 (summer), pp. 40-51.

22. Dutta S. and Segev A., (1999), “Business transformation on the Internet”, European Management Journal, Vol. 17 No.5, pp. 466-476.

23. Ellias S. and Grossberg S., (1975), “Pattern formation, contrast control and oscillations in the short-term memory of shunting on-center off-surround networks”, Bio. Cybernetics, Vol. 20, Number 2, pp. 69-98.

24. Fausett L., “Fundamentals of Neural Networks: architectures, algorithms and applications”, Prentice Hall.

25. Green P. E., (1978), "An AID/Logic Procedure for Analyzing Large Multi-way Contingency Tables", Journal of Marketing Research, Vol. 42, No. 4, pp. 92-100.

26. Griffith J. S., (1963), “A field theory of neural nets”, Biophysics, Vol. 25, pp. 111-120.

27. Holsheimer M., Kersten M., Mannila H. and Toivonen H., (1995), “A perspective on databases and data mining”, In 1st Intl. Conf. Knowledge Discovery and Data Mining

28. Hopfield J. J. and D. W. Tank, (1985), “Neural computation of decisions in optimization problems”, Biol. Cybernetics, Vol. 52, Number 3, pp. 141-152.

29. Hopfield J. J., “Neural networks and physical systems with emergent collective computational abilities”, Proceedings, National Academy of Science, USA, vol. 79, no. 8, pp. 2554-2558.

30. Houtsma M. and Swami A., (1995), “Set-oriented mining of association rules in relational databases”, proceedings, 11th Intl. Conf. Data Engineering.

31. IBM Global Business Services, (2008), “Understanding consumer patterns and preferences in multi-channel retailing”, market research report.

32. Kosko B., (1988), “Bidirectional Associative Memories”, IEEE transactions on systems and Cybernetics, Vol. 18, No. 1, pp. 49-60.

33. Mannila H., Toivonen H., and Verkamo I., (1994), “Efficient algorithms for discovering association rules”, AAAI Workshop, Knowledge Discovery in Databases, pp. 181-192.

34. Nelson P., (1970), “Information and consumer behavior”, Journal of Political Economy, 78 (2), 311-329.

35. Nelson P., (1974), “Advertising as information”, Journal of Political Economy, 82 (July/August), 729-754.

36. Norton, S.W. and Norton, W. Jr., (1988), "An economic perspective on the information content of magazine advertisements", International Journal of Advertising, Vol. 7 No.2, pp.138-48.

37. Perreault, W. D. and Barkswale H. C., (1980), "A Model-Free Approach for Analysis of Complex Contingency Data in Survey Research", Journal of Marketing Research, Vol. 17, pp. 503-515.

38. Rumelhart D. E., Mcclelland J. L. and the PDP Research Group, (1986), “Parallel Distributed Processing, Explorations in the Microstructure of Cognition”, MIT Press: Cambrige, Mass.

39. Savasere A., Omiecinski E., and Navathe S., (1995), “An efficient algorithm for mining association rules in large databases”, 21st VLDB Conference, Switzerland.

40. Stanley J. C., (1976), “Simulation studies of a temporal sequence memory model”, Bio. Cybernetics, Vol. 24, Number 3, pp. 121-137.

41. Toivonen H., (1996), “Sampling large databases for association rules”, 22nd VLDB Conference, pp. 134-145.

42. Widrow B. and Hoff M. E., (1960), "Adaptive Switching Circuits", IRE WESCON Convention Record, pp. 96-104.

43. Wiener N. and Rosenblueth A., (1946), "The mathematical formulation of the problem of conduction of impulses in a network of connected elements, specifically in cardiac muscle", in Wiener, N. (Eds),Wiener's Collected Works, MIT Press, Cambridge, MA, Vol. 4, pp.511-71.

44. Wilson H. R. and Cowan J. D., (1973), “A mathematical theory of the functional dynamics of cortical and thalamic nervous tissue”, Biological Cybernetics, Vol. 13, No. 2, pp. 55-80.

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