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Research Paper

Daily Product Purchase Predictions with E-commerce Recommendations Using a Continual Learning Neural Network System

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Abstract— In this research paper, we propose an intelligent recommender system suitable for E-commerce transactions. The system employs an emerging ANN method called the Hierarchical Temporal Memory (HTM) for continuous predictive recommendation basing on whether a user will actually make a purchase or not. The results considering highly limited data obtained from an open source data of an online store were reported considering the adjustments of HTM columns parameter. The findings of the result indicate that higher columns do not necessarily lead to enhanced performance. It was also found that using a smaller session dataset of 100 feature patterns resulted in better performances for the HTM model when compared with a bigger one of 500 feature patterns. For model validation purposes, the HTM technique is compared with the Long Short-Term Memory (LSTM) technique on the basis of classification accuracy, precision, recall and false acceptance rate metrics and considering the limited dataset of 100 sessions. The findings from this comparison revealed that both techniques will generate the same classification estimates. The proposed HTM-ANN is expected to be a promising alternative to existing feed-forward ANNs for real-time E-commerce applications.

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Keywords: *ANN, E-commerce, Continual Learning, Prediction, Recommender System.*

1. Introduction

Recommender systems are basically knowledge discovery agents that intelligently and accurately make predictions that match a given product or set of products to a potential customer (Usmani et al., 2017). It involves customer use-case profiling. It also solves the problem of missing items in cart. In recent times, they have been proposals regarding the use of intelligent recommender systems as advisory agents in e-commerce applications.

Intelligent recommender systems are automatic state machines that seamlessly acquire and operate on the transaction data so acquired in order to provide useful decision, advice, and solutions. On this basis, recommender systems may employ a classifier method to determine the appropriate actions or relevant state representations for the decision making process.

Recommender systems serve as engine rooms for a vast number of modern day automated goods and services. For instance, in the social media space, it is common to find several ads displayed on user's app based on certain behavioural patterns such as number of visits to a familiar set of commercial sites, number of likes for a given content or commodity on one or more related sites, and number of views for a particular content be it audio, video or pictures etc.

It has been hypothesized that without the use of intelligent devices or systems the modern day society based on manual recommender approaches will cease to exist (Abonamah et al., 2021; Usmani et al., 2017). In view of this, many intelligent recommender systems have been conceptualized and built to specifications. More recently, these systems have been further developed in ecommerce online marketing, in particular the sales market forecasting.

Several intelligent and statistical models have been used in forecasting online e-commerce markets like electricity price market, stock markets, crude oil markets, widget market etc., but they are lacking in the real ingredients of real-time processing in mammalian brains (Hawkins et al., 2011; Osegi, 2021).

This research presents an attempt at applying more bio-inspired neural computing approaches that exploit the principles of continual learning, hierarchical learning, and temporal (time) based processing with Sparse Distributed Representations (SDRS) for the task of learning sales feature patterns obtained from an online retail e-commerce site and in turn make a predictive recommendation to the site operator on the possibility of generating a revenue from the sale.

2. Related Studies

Du et al (2015) studied online market trends for product searches in market response modelling. They proposed the notion that feature search trends are positively correlated with feature importance trends. Hsu (2016) applied the adaptive neuro-fuzzy inference system (ANFIS) for e-commerce using customer cash flow service time series data in fashion industry. The company weekly revenue data served as data source while the MATLAB language was used for program coding. The results showed an acceptable error rate of about 5.6% when compared to baseline results from previous research works (see Lo, 2003 and Hosoz et al., 2011). Suchacka and Stemplewski (2017) proposed neural strategy for forecasting purchases in active user sessions on e-commerce websites. Low-level data obtained from earlier studies (Suchacka et al., 2015a; Suchacka et al., 2015b) were applied to training a feed-forward ANN. A total of 8 predictor (input) variables and 1 output (dependent) variable were fed to the ANN for training. Their simulated results showed promising results with a recall of about 88% and also a very high prediction accuracy of 97.7%.

Gangurde (2017) proposed an optimized neural predictive technique for Market Basket Analysis (MBA) in e-commerce site. The proposed approach is a modification of Apriori algorithm with the conventional neural technique. Guo et al (2018) used a combination of a Radial Basis Function (RBF) neural network weight recommender, the Dempster-Shafer Fusion personalization technique and the power spectrum recommendation estimation for building a mobile e-commerce sales forecasting/recommendation system. Massaro et al (2018) used multiple ANNs to forecast the Global Distribution (GDO) sales in e-commerce. In their proposed design each ANN makes sales forecast using a different set of attributes. Li et al (2019) proposed a non-linear utility function as evaluation (fitness) function and a Generalized Dynamic fuzzy neural network (GD-FNN) in a Multi-Agent System and Genetic Algorithm Optimizer (MAS-GAO) solution. The new neural solution allows the transformation of the full Nash non-linearity equilibrium solution to an approximate one using sample data. Thus, with this hybrid approach, the evaluation of complex contract multi-attribute negotiations for e-commerce applications can be attained from both the analytic (Non-linearity based on Nash equilibrium) and data-driven (Neural-Network based) approaches. Their results of experimental simulations for simple negotiation case showed high precision of the data-driven evaluation function approach in comparison with the non-linearity evaluation function approach. In (Kedia et al., 2019) a deep neural network is employed for prediction of product return probability in ecommerce transactions. Feature engineering of user products embedding's used in the prediction process were equally performed with a Bayesian personalization technique. Shekasta et al (2019) incorporated a deep learning technique based on Gated Recurrent Unit Neural Net (GRU-NN) to predict new product consumption. The deep learning technique was incorporated in a Purchase Intent Session (PIS) model framework. Comparisons revealed the proposed deep learning technique were better than the existing baseline and integrated models for large data on cold start-up. Zhang et al (2021) proposed hybrid Extreme Learning Machine and Moth Flame Algorithm (ELM-HMFO) for predicting volume of e-commerce transactions data obtained from China Internet Network Information Centre (CINIC) between 2009 and 2019. A sine coefficient and the Levy flight strategy is used to improve the Moth update process. An acceptable RMSE of less than 0.5 and a determination coefficient of 0.99 were reported when compared to the standard ELM-MFO and the SVM techniques.

Considering the aforementioned reviewed studies, it can be inferred that most are lacking the continual learning property existing in real mammalian brains and may not perform effectively when faced with real-world streaming data. Hence, this research seeks to approach the e-commerce sales/transactions problem from a continual learning perspective.

3. System Methodology

The proposed system is based on the integration of a continual learning neural method called the Hierarchical Temporal Memory (HTM) integrated within an E-commerce trade recommender system. The system exploits the unique temporal and spatial representation to evolve a reasonable estimate of a candidate state representation. To implement such a system, a description of the data needed its integration into a machine learning recommender system and the expected output response states are needed. In the sub-sections that follow, the E-commerce market data, the recommender system based on the HTM model and the operational details of the HTM are presented.

3.1. E-commerce Market Data

The market data is based on shoppers' behaviour during visits to an online store (Sakar et al., 2019). This data specifically describes features that most probably describe online shoppers' purchasing intention. Data is based on user shopping behaviour and patterns with a total of 12,330 sessions recorded and with no missing values. It was obtained from the UCI repository and also consists of about 18 key feature attributes. These data suffered from the data imbalance problem as a total of 10,422 sessions were found to belong to the negative (FALSE) class while the remaining 1908 sessions belonged to the positive (TRUE) class. Considering these data, it is important to emphasize that only categorical data are considered in the analysis in order to limit the feature space as well as make it more difficult for machine learning algorithms to solve. In particular, 4 out of the 8 attributes of the categorical dataset were considered for the first 100 samples yielding a highly limited dataset as shown in Table 1.

Table.1. Used Categorical Features (Adapted from Sakar et al., 2019)

Name of Feature	Feature Function	Size of Feature	Data Type
Region	Visitor session location	9	Integer
VisitorType	Identify new, returning or other kind of visitor	3	String
Weekend	Identify whether the day is weekend or not	2	Boolean String
Revenue	Signal whether purchase was made or not	2	Boolean String

3.2. Hierarchical Temporal Memory (HTM)

HTM refers to a revolutionary machine intelligence method, technology and tool that attempts to replicate certain aspects of the real model of a biological neuron (Hawkins et al., 2011). In particular, it seeks to exploit the structural and algorithmic properties of the neocortex based on the Vernon Mountcastle columnar concept (Mountcastle, 1997). The neocortex supports such tasks as vision, language, hearing, movement and has been regarded as the seat of intelligence mammalian brains (Hawkins et al., 2011). Originally, HTM was based on the Cortical learning Algorithm (CLA) which can be trained by continuous exposure to streaming data making it a novel type of ANN. With respect to the hierarchical viewpoint, the HTM is structured in terms of levels composed of smaller elements called nodes or columns (Hawkins et al., 2011); for a single hierarchical level, a region is formed. It is important to emphasize that at higher levels of hierarchy, fewer nodes are formed and this leads to less spatial resolvability. Higher levels of hierarchy can support feature pattern reusability by combining patterns learned at lower levels in order to memorize more complicated features.

In order to learn in an effective manner, the HTM CLA model reference columns inhibit neighbouring columns in the neocortex hence creating a sparse activation of HTM columns. Hence, a region is allowed to create a sparse representation from its original input, so that a fixed percentage of HTM columns are active at a particular time. A cortical column is understood as a group of artificial cells (neurons) that possess similar receptive fields. Each column has several cells that enable the recollection of several past states. Typically, a cell can be in one of three states: active, inactive and predictive state.

3.2.1. Spatial pooling

For a given set of regions, the receptive field of each HTM column is a pre-defined number of inputs that are randomly chosen from a much larger pool of columnar inputs. Based on the input feature pattern, certain columns will receive more activations. Spatial pooling is employed in the HTM ANN model to select a relatively constant number of the most active columns and inactivate (inhibit) other columns in the vicinity of the active ones. Ideally, similar input feature patterns tend to activate a stable set of HTM columns allowing for consistency in the learned representation. Furthermore, the amount of memory used by each region can be enhanced to learn more complex spatial patterns or decreased to learn simpler patterns making for a more robust ANN.

3.2.2. Representing the input in the context of previous inputs

For a given HTM region and at a given time step, if one or more cells in the active column are in predictive state, they become active in that current time step. On the other hand, if none of the cells in the active column are in the predictive state (during the initial time step or when the activation of this column was not expected), all cells are made active.

3.2.3. Predicting future inputs and temporal pooling

In the HTM learning paradigm, when a cell becomes activated it steadily forms connections to nearby cells that tend to be active during several previous time steps. Thus a cell will learn to recognize a known sequence by checking whether the connected cells are activated. If a great number of connected cells are activated, this particular cell switches to the predictive state in anticipation of one of the few next inputs of the sequence. The output of a region includes columns in both active and predictive states. Thus columns are active over longer periods of time, which leads to greater temporal stability seen by the parent region. The operational mode for making predictions in the HTM ANN model is as shown in Figure 2.

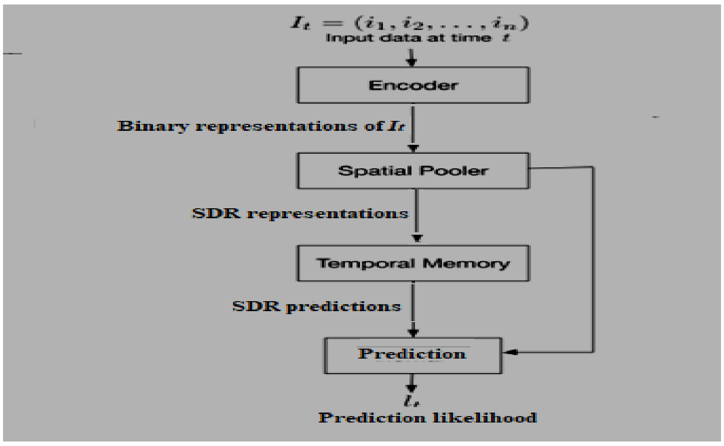

Figure 1. Sequence of Operations for making a prediction in the HTM

3.3. HTM Recommender Systems Model for E-Commerce Market Data Analysis

For the HTM to serve as a recommender system, it has to perform a predictive classification of the input streams. In this regard, the E-commerce dataset is processed in a sequential manner; this implies the encoding and overlap processing of one input feature pattern followed with another in a temporally structured manner such that a set of candidate patterns are formed. Typically, the feature patterns are uniform row-wise attributes (called feature pattern strings) but they need not be so at all times. The architecture of our proposed recommender system is as shown in Figure 2.

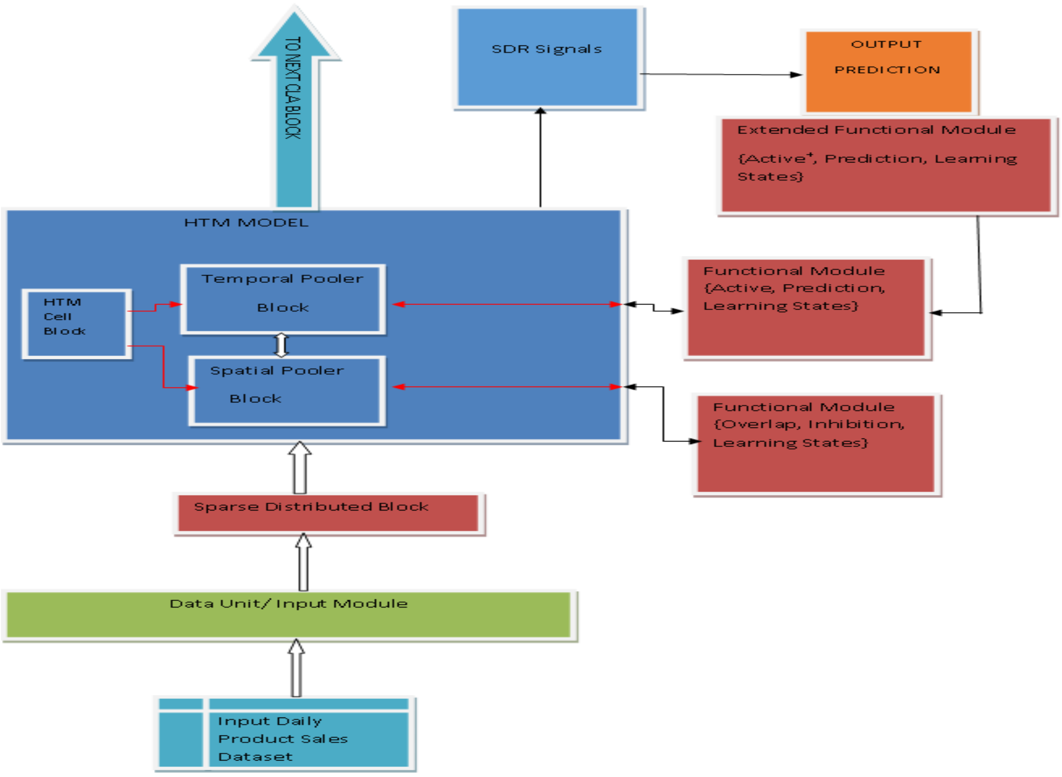

Figure 2. Proposed HTM Recommender System Model Architecture

Considering the system in Figure 1, the input daily product sales data is presented to an input module which sends the input to a Sparse Distributed Representation (SDR) block. Both input module and SDR blocks represent the input block of the HTM. The function of the SDR block is to create a uniform distributed representation such that there are more 0's than 1's in the re-formed input and that the formed patterns are consistent even when a similar new feature pattern is fed into the block. This process is temporally executed for any (new) feature pattern seen by the HTM model input processing block.

The SDR patterns formed in the prior stage is fed to an HTM model block which typically is a HTM-CLA block; this block performs spatial-temporal pooling operations such that learning of the feature patterns occur. This learning function is specifically handled by several functional module blocks tightly integrated to the HTM model block as shown in Figure 2.

Finally, once certain conditions are fulfilled, the HTM SDRs signal a prediction or several prediction states. One of such condition is achieved by adopting the overlap feature pattern match principle. This principle is formed on the basis of comparing a prior SDR pattern with the succeeding one such that if a matching threshold criteria is met, then that pattern is included in the bin of successful (winner) patterns otherwise it is discarded (destroyed). During testing, learning is turned off and the classifier signal is omitted in the input SDR presentation such that the previously formed HTM model performs predictive inference and in turn recommendations are made on the basis of these predictions.

In this research, our recommender logic is as follows:

Suppose an input signal state of E-commerce revenue is a failure implying a false (no-revenue) condition; then a true (Binary State 1) signal is assigned to that signal state in the HTM model. For a success condition, then the false (Binary State 0) signal is assigned. We may represent the success rate through the given number of SDR pattern observations as:

$$R_{win} = \left(\sum_{i=1}^{N_t} C_p \right) \Big/ N_t \tag{1}$$

where,

N_t = Number of temporal states

C_p =class prediction signal for the success condition

The success rate can be further simplified by fractionating the popular Classification Accuracy (CA) metric such that it falls between 0 and 1and then subtracting the CA from 1. This is clearly the same as the misclassification rate of the predictive model and can be computed as (Han & Kamber, 2006):

$$R_{win} = 1 - CA \tag{2}$$

By convention, the success rate cannot be greater than 1 or less than 0. Thus, we may safely assume a finite range between 0 and 1. In addition, for evaluating the level of recommendation, we may constrain a success requirement as meeting a positive threshold criterion as:

$$R_{sale} = \begin{cases} True, & R_{win} \geq t_h \\ False, & Otherwise \end{cases} \tag{3}$$

where,

t_h = threshold setting.

Considering the model in (2), we see that any success rate (R_{win}) greater than the stipulated threshold means a positive recommendation i.e. implying revenue will be generated for that input feature pattern. In this study, we set t_h = 0.85.

3.4. Tuning HTM Parameters and Simulation Experimental Details

In the HTM, there are several parameters that must be tuned to achieve reliable prediction accuracy or classification. The considered parameters and their corresponding values considered in the proposed HTM model include the permanence (both initial and connected), the permanence increment and decrement ratios, number of columns, stimulus threshold and boost factor. Typically, most of these parameters are fixated at some pre-specified values to minimize the need for hyper-parameter tuning with the hope that the HTM will give a general enough classification or prediction of the state signal (Osegi & Jumbo, 2021). The default HTM parameter specifications are as provided in Table 2. In this study, we adjust the HTM column parameter at values from a default of 256bits representation to 512bits and 1024bits representations. For each adjustment, we run a simulation of the HTM program provided in (Osegi, 2021) for a given number of intrinsic trial runs and then record the generated simulation performance results. This simulation is repeated for as many times as the designer so wishes or when the expected results are attained. In the next section (section 4), we present the results of using our proposed approach in solving the online sales orders recommendation and prediction problem.

Table.2. Parameter Specification Values of the HTM Model (Source: Osegi & Jumbo, 2021)

Parameter	Default Parameter Value
Initial Permanence	0.21
Connected Permanence	0.50
Permanence Increment	0.10
Permanence Decrement	0.01
Number of Columns	256
Stimulus threshold	10
Boost factor	10.1

4. Simulation Results and Discussions

Typically, in an HTM simulation, a data learning operation is performed continually and considering several intrinsic trial runs. In this study, initial visualization plots are performed to examine the behaviour of HTM ANN prior to results tabulation. The full and sparse visualization responses of HTM segment synapses during training are as shown in Figures 3 and 4 respectively.

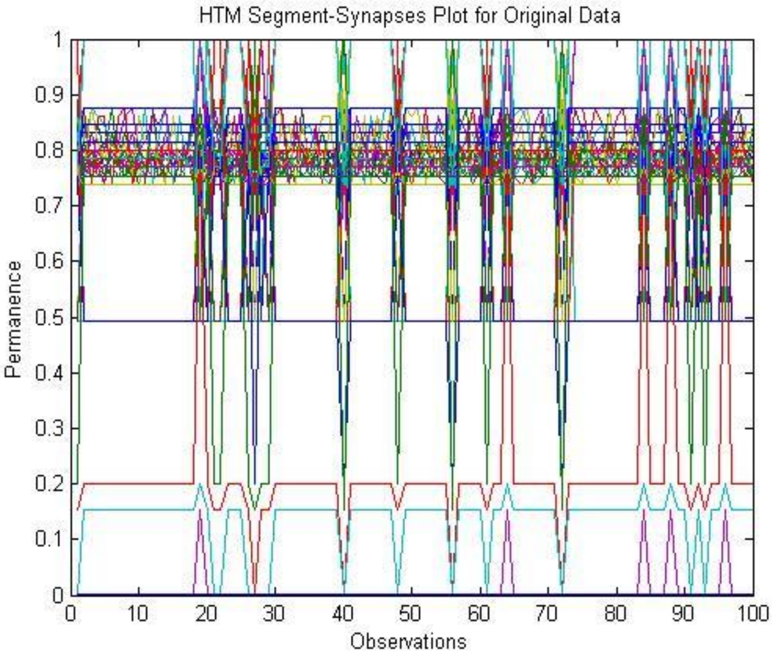

Figure 3. Visualization of Full HTM Segment Synapses of real-time data for Training

Comparing the generated visualization plots, we see that the plots are thinner at the bottom segments for permanence values between 0unit and 0.5units for the sparse representation (Figure 4) than for the full representation (Figure 3). This clearly shows the effect of sparsity on data in HTM learning systems.

4.1. Numerical Simulation Results Using the HTM on Limited Samples

We validate our proposed model on the recommendation task, using some very familiar metrics such as the Classification Accuracy (CA), Precision (Pr), Recall (Re) and False Acceptance Rate (FAR). For this task we consider a dual reduced dataset of 100 and 500 sessions as input data with a data split of 40% and 60% for the HTM model training and testing sessions respectively. The simulation results for the both cases are as shown in Tables 3 and 4 for the default HTM parameter values.

Considering the results using 100 data sessions (Table 3), the recommendation score is estimated to be 0.05 which is far less than the required threshold. Hence, the HTM recommends a halt in sales by signalling the alarm binary state 1. A similar scenario plays out for the second scenario (Table 4) as the recommendation score is 0.4250 which is still less than the design threshold. Also, as can be clearly seen, the *CA*, *Pre* and *Re* values of the HTM model using the 100 session's dataset are better than that using the 500 session's dataset; thus, limiting the data results in better estimates. However, the *FAR* for the HTM model when using the 100 session's data is extremely high at 100% (Table 3). This clearly shows the highly unbalanced nature of the problem. Using the 500 session's dataset improves the FAR but at the price of *CA* and *Re*.

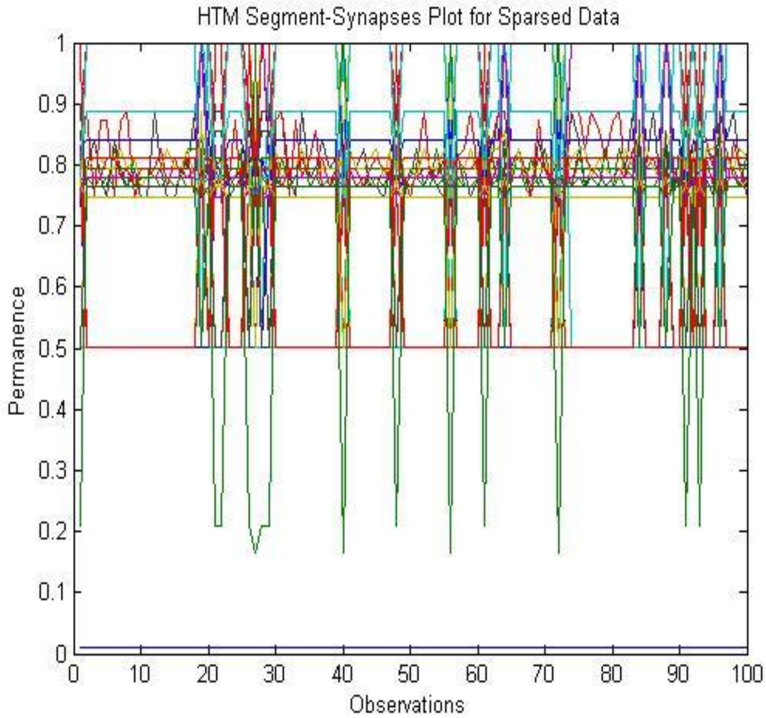

Figure 4. Visualization of Sparse HTM Segment Synapses of real-time data for Training

Table.3. Simulation Results for 100 data sessions using default HTM Parameter Values

Evaluation Metric	Score(%)	Recommendation Score
CA	95.0000	0.05
Pr	95.0000	NA
Re	100.0000	
FAR	100.0000	

Table.4. Simulation Results for 500 data sessions using default HTM Parameter Values

Evaluation Metric	Score(%)	Recommendation Score
CA	57.5000	0.4250
Pr	94.0678	NA
Re	58.7302	
FAR	63.6364	

4.2. Varying HTM Column Size Parameter

The results obtained with different column sizes ranging from 256bits, 512bits and 1024bits representations are as shown in Tables 5 and 6 for the 100 session's and 500 session's datasets respectively.

Table.5. Simulation Results for 100 data sessions using varying column sizes

Evaluation Metric	**Score(%) -** 256bits	**Score(%) -** 512bits	**Score(%) -** 1024bits
CA	95.0000	95.0000	95.0000
Pr	95.0000	95.0000	95.0000
Re	100.0000	100.0000	100.0000
FAR	100.0000	100.0000	100.0000

Table.6. Simulation Results for 500 data sessions using varying column sizes

Evaluation Metric	**Score(%) -** 256bits	**Score(%) -** 512bits	**Score(%) -** 1024bits
CA	57.5000	94.5000	94.5000
Pr	94.0678	94.5000	94.5000
Re	58.7302	100.0000	100.0000
FAR	63.6364	100.0000	100.0000

As can be seen from Tables 5 and 6, the results of the HTM model for the 100 session's data are consistent for all column size modifications while the results using 500 session's data is only consistent for the 512bits and 1024bits column settings. In general, we can see that using the HTM on smaller data leads to better results. Thus, HTM is especially useful in real-time applications where inference is required for minimal amount of data.

4.3. Comparisons with Long Short-Term Memory (LSTM)

The LSTM represents the state-of-the-art in temporal sequence-sequence classification tasks which equally be applied to recommender problems. To validate the efficacy of LSTM, we use the optimized code developed in (Fayek, 2018) and considering the default LSTM parameters. The results comparing our proposed solution with the LSTM approach are as shown in Table 6 for the 100 session's dataset.

Table.6. Comparative Simulation Results – HTM vs. LSTM

Evaluation Metric	**Score(%) - HTM**	**Score(%) -** LSTM
CA	95.0000	95.0000
Pr	95.0000	95.0000
Re	100.0000	100.0000
FAR	100.0000	100.0000

As can be clearly seen from Table 6, there was no significant difference between predictions for both the HTM and LSTM. Following from this result, it may be inferred that the recommendation score will be equivalent to 0.05 implying a signal to halt sales. Hence, the proposed system can be an alternative to the conventional one for recommender solution.

5. Conclusions and Future Work

This research has proposed a more bio-inspired ANN based method as trade recommender agent in e-commerce markets. The ANN is based on the technique called the Hierarchical Temporal Memory (HTM) which is based on the Cortical Learning Algorithm (CLA).

HTM ANN provides some important benefits that are closely tied to the working principles of the real mammalian brain such as sparse distributed representations, continual predictive hierarchical learning and spatial-temporal pooling. It offers promising benefits in dealing with real-time systems particularly when the data that needs to be processed is greatly limited.

This research applied the HTM-ANN to an open-source E-commerce purchase intent data from an online store with promising results. When compared to the state-of-the-art technique such as LSTM, the results obtained for a very limited dataset were equivalent validating the HTM model performance.

However, extensive results on a variety of data from real world E-commerce transactions needs to be investigated as this will provide a substantial basis for universal adoption. Alternative approaches such as the use of Particle Swarm Optimization (PSO) to tune the HTM and/or development of HTM variants/hybridization experiments to enhance (minimize) the FAR estimates are also an area for future explorations.

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