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Artificial Intelligence Methods to Enhance E-Commerce in Product Planning in the Business Industry using Recurrent Neural Networks

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***Abstract*— The purpose of this study is to design a prototype for product planning using Artificial Intelligence (AI) methods. AI is a simulation of human intelligence in robots and machines designed to think like humans as well as imitate actions such as humans. As a rule, AI programs simply collect data and use different rules or mathematical methods to produce and respond with a view to enhancing professional judgement. Product planning in the business sector is a key step as it determines the future of the profit and growth of a company. In this stage, before choosing or selecting products, the product planning strategic aspects are taken into account. This process can usually take time, as product planners need to examine and study the market for information. This paper addresses the many types of AI application methods in e-commerce for the resolution of business challenges and proposes a solution for enhancing e-commerce product planning. A prototype for AI planning will be implemented on the basis of the proposed solution in order to demonstrate the RNN algorithm and how it can benefit enterprises. By conducing this research according to the research methodology, the existing AI methods used in product planning is studied to generate an improved approach for the product planning process. The proposed approach will be an RNN based recommendation system as RNN's are able to recall significant information from received data which will produce more accurate predictions. The datasets involved are Amazon phone dataset and GameStop product dataset. The results show the difference between the time consumed to train the model and the accuracy of the model to predict ratings.**

Keywords- Artificial Intelligence; Deep Neural Networks; Recurrent Neural Networks; Product Planning; E-Commerce

I. INTRODUCTION

Artificial Intelligence (AI) is the simulation of human intelligence in robots and machines that are programmed to think similarly to human beings as well as imitate similar actions like humans. Generally, AI programs simply perform data gathering and use various rules or mathematical formulae to produce and come up with a response with the intention of it to be used to enhance professional judgment [1]. Over the years, AI has evidently proven to be useful in all sorts of fields and industry so much so that it is even applied in everyday life. It is a known fact that even the most impressive and advantageous artificial intelligences produced displays somewhat of a restricted range of intelligent behavior seeing as not everything can be done or solved with AI. Currently, machine learning systems are heavily oriented towards one specific task which is to make accurate predictions [2]. The phrase that needs to be emphasized is that it "makes accurate predictions" which leads to the question of what kind of predictions will further benefit people all over the world. In this case, people in business industry could greatly benefit from such technology in which it would allow business revenues to increase by minimizing expenditures while increasing effectiveness and efficiency. This is possible with the use of AI by producing a program or system which will allow businesses to plan future product releases effectively and efficiently. By considering the suggestions and results obtained from the AI technology, the time for analyzing numerous amounts of data will be decreased

II. LITERATURE REVIEW

E-commerce is like any other kind of businesses in terms of conducted activities related to the business itself. The letter "E" in e-commerce simple implies that the use of the Internet and its connection is implemented to most of the business activities in e-commerce. Some products are not so compatible to be sold over the Internet as there are some cases where certain products require a lot of interaction between the seller potential buyers in terms of negotiation or mutual understanding.

A. Product Planning

Product planning is the ongoing process of producing one or multiples ideas of a product and following through with the idea until it is launched and released to the market. When it comes to product planners, these individuals should be inquisitively analytical while also being creative as creative product planning often leads to success [3]. Aside from that, it is not a one-time activity, and it does not stop after the product has been released as product planning also involves the strategies to improve the product to increase sales. There is always room for improvement in any case especially for developing a good quality product. Hence, product planning continuous and is not considered as a one-time activity.

Not every product uses the same technique in making decisions for the product planning process as each product is unique in many ways especially in terms of its functions. The scope of the product planning process becomes more comprehensible after considering the main activities proposed from the generation of ideas regarding the product to develop [4]. The idea itself allows product planners to define attributes, features, and the potential of the product in general which will influence the design stages followed by the product planning process. For instance, the brain storming process for creating clothing and a new beverage recipe will be distinctively different as each product has certain factors and requirements that will be considered to decide on the most beneficial product between the two respective examples.

B. Written Reviews in E-Commerce

Online reviews have a big impact on how a business is seen in the digital world. It can aid in the development of a brand, the attraction of new leads, the generation of additional money, and the education of businesses on how to grow and improve their operations. It is a valuable resource for a firm, and it is becoming more valuable by the day. Written reviews play an important role in a consumer's thought process on deciding to purchase a product and can lead to an increment of sales as well as build a business' reputation [5]. Consumers rely on product reviews and ratings to assist them in making purchases. These tactics are also beneficial to online stores that rely on rating systems to build trust and reputation in the online marketplace. Quantitative ratings, textual assessments, or both are common in online marketplaces. A research study has stated that online reviews are evaluated as vital or very important by 74.04% of participants, whereas reviews are rated as unimportant or not important by 4.80% [6]. Reviews help businesses stand out, increase sales, enhance search engine results, educate customers, and persuade them to engage more with the business.

C. Artificial Intelligence

According to Oxford Languages, artificial intelligence is defined as the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages. In the period of mankind intellectual ability, AI is part of the complex teleological records whereby representational AI rises from hundreds of years in an attempt to reduce human reasoning to a logical formality [7] . Cognitive human faculties at varying times were hypothesized, partitioned, valued, and devalued in varying methods.

Artificial intelligence has been used in decision support for purposes such as assisting decision makers in selecting actions in real-time and stressful decision-making problems; reducing information overload, enabling up-to-date information, and providing a dynamic response with intelligent agents; enabling information exchange for collaborative decisions; and dealing with ambiguity in decision making problems [8]. AI Planning may be well positioned to overcome the problems that motivated the Defense Advanced Research Projects Agency (DARPA) AI project: planners can ultimately be trusted; planners can allow more simple human interaction; planners are understandable to an extent that at least their programmers understand the rationality of the decisions made [9].

D. Recommendation System

Software tools and techniques that offer proposals for items to assist and aid user are known as recommender or recommendation systems. The recommendations are intended to support their users in identifying and making decisions. It has consistently proven to have essential aspects for online users to deal with overloading information and has become one of the most successful and influential e-commerce tools [10]. Different techniques for generating recommendations were therefore suggested and many of them were also effectively used in commercial environments over the last decade. Recommendation is an AI technology that has successfully been applied in various business contexts. Seeing as the algorithm and heuristics of recommendations are viewed as a massive intellectual property of a business, recommendation systems are often not designed based on standardized solutions, but instead are based on proprietary solutions customized to the company's particular case [11].

E-commerce software that gives users recommendations for products or services they might like is known as a recommender system. Web-based recommender systems are the most well-known example of personalization, or the practice of customizing a web site to individual users' features or preferences. To generate novel scenarios for human-to-human and human-to-machine interaction, today's recommender systems employ a wide spectrum of AI technologies. The ultimate goal is to provide each individual user with a more customized one-to-one solution, allowing them to more effectively and efficiently meet their needs [12]. The fundamental goal of e-commerce recommendation systems is to offer products to customers in what are known as smart shop windows or recommendation windows. They can be found on the front page of the website, product pages, and in the shopping basket. Some e-commerce businesses that use one or more types of recommendation system technology on their websites are Amazon, eBay and Levis.

Recommendation systems support consumers in scientific libraries, enabling them to explore more besides catalogue searches. Therefore, it is crucial to emphasize the need for reliable and precise recommendation techniques within a system that provides users with credible and appropriate recommendations [13]. The first step in choosing a suitable algorithm is by deciding on which properties to focus on in the application. Figure 1 shows a general mapping for the

basic recommendation techniques which consists of three different approaches; Content-based filtering technique, Collaborative filtering technique, and Hybrid filtering technique.

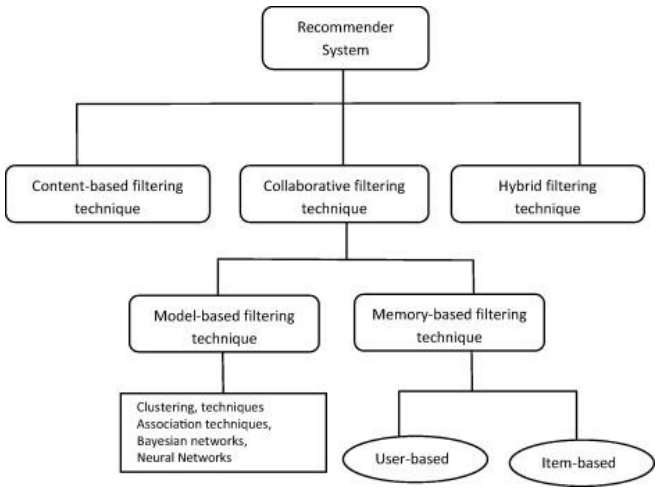

Figure 1. Recommendation techniques.

E. Product Planning Methods Using AI

In e-commerce, AI is often used to advise users on the products they want to examine or buy through the Internet. As there are no real people to advise consumers on the Internet, this type of advice is in high demand [14]. This piece of advice comes in handy when handling a wide variety of product details. In contrast to that, the process of product planning can be greatly enhanced in terms of efficiency with the assistance of AI. Continuous progress in production planning may be achieved by incorporating machine learning and artificial intelligence into the equation. This is because, unlike humans, AI can handle much larger amounts of data and analyses it effectively, quickly, and in real time. However, in order to implement AI, data must first be accessible and in a usable format. On the other hand, AI does not require stamina and can work for longer hours compared to humans. As quoted by Colin Kessinger, Ph.D., Managing Director of End-to-End Analytics, LLC, “Machine intelligence paired with human knowledge significantly lowers forecasting error even in situations of product transitions.”.

In these dynamic knowledge spaces, recommendation systems assist people in making decisions. Recommendation systems recommends things to the customer based on their awareness of her and the room of available items. For example, a news service may remember which articles a user has read. The system will suggest new articles to her the next time she visits the site based on the ones she has already read [15]. The design of these recommendation engines is determined by the domain and the specific characteristics of the data. On Netflix, for example, viewers often rate films on a scale of 1 (disliked) to 5 (liked). This type of data source keeps a record of the consistency of user-item interactions [16]. Recommendation systems help users address the issue of information overload by supplying them with tailored, unique content and service recommendations.

In general, algorithms for recommendation systems depend on previous transactions and page views. Furthermore, several providers now provide in-the-moment suggestions, as they employ artificial intelligence for the purpose of analyzing consumer experiences and identify visually appropriate items that would appeal to any given customer [17]. Recommendation engines use artificial intelligence to make fast and to-the-point recommendations that are customized to each customer’s needs and preferences. The advancement of computer vision technology has benefited recommendation systems. In recommendation systems, image recognition and deep learning neural networks work together to produce exceptional results [18].

F. Artificial Neural Networks

Artificial neural networks, or "neural networks," are computer systems that are modelled after the organic neural networks that make up animal brains. Artificial neurons are a collection of connected units or nodes in an ANN that loosely mimic the neurons in a biological brain. In a nutshell, each neuron receives a multiplied version of inputs and random weights, which is coupled with a static bias value (which is unique to each neuron layer) and delivered to an appropriate activation function, which decides the final value to be output by the neuron. Different activation functions are possible depending on the nature of the input values. The loss function (input vs output) is computed after the final neural net layer's output is formed, and backpropagation is used to alter the weights to minimize the loss. The main goal of the process is to find the best weight values. Some types of ANN which are currently being used in machine learning are feedforward neural network, multilayer perceptron, convolutional neural network, recurrent neural network, long short-term memory, etc.

One of the breakthroughs of mankind is the ANN, which is inspired by the neuronal structure and helps computers and machines behave almost like humans. RNNs are a class of artificial neural network that utilizes sequential or time series data. The key difference between AI and neural networks is that AI refers to technologies that are able to imitate human cognitive skills whereas neural networks refer to a network of artificial neurons or nodes that is loosely modelled after the biological neural networks that make up an animal's brain. As part of Artificial Intelligence, neural networks comprise technologies like deep learning and machine learning as a part of AI. Vanishing gradients are a problem usually found with a standard RNN. As a result, we used the RNN with long-short term memory (LSTM) units, which was created specifically to solve the problem involving the vanishing gradients [19].

LSTM is a deep learning architecture based on artificial recurrent neural networks (RNNs). The key distinction between an LSTM and a normal RNN is that the LSTM is more advanced. It is made up of so-called gates, which are designed to better govern the flow of information through the unit. LSTM networks are a modified version of recurrent neural networks that make it simpler to recall information from the past [20]. LSTMs have a chain-like architecture as well, however the repeating module is distinct compared to a regular RNN. Instead of a single neural network layer, there are four, each of which interacts in a unique way. A recommendation is a major

predictor of a good sentiment score, and vice versa, according to the findings. Ratings in product reviews, on the other hand, are shaky indications of sentiment scores [21].

Recommendation systems are useful tools that make it easier to browse content. A good recommendation system can also help consumers find goods they wouldn't have looked for otherwise. As a result, recommendation technologies have the potential to significantly increase e-commerce income. By implementing RNN in the recommendation system, it could outperform other models. There are many techniques in designing a recommendation system such as content-based, matrix factorization or training a model to predict the interaction likelihood. By using neural networks, some advantages include achieving a higher accuracy and when a neural network is increased, the model will be able to improve its performance with more data.

Deep learning has had a substantial impact on recommendation structures, giving recommenders more opportunities to improve their performance. Deep learning-based recommender systems (DLRS) have recently received a lot of attention for their ability to overcome the constraints of classic models and produce high-quality suggestions. Deep learning can capture non-linear and non-trivial user-item interactions, allowing more complex abstractions to be codified as data representations in higher layers. It is shown that predicting a user's preferences based on their reviews is effective in neural network models and it is believed that the performance of a model can improve significantly using RNN implementation that can withstand variable review length as increasing data size will surely improve the accuracy of predictions in recommendation systems [22]. With the ignorance of combination factors, collaborative filtering or model-based algorithms have limits in providing a better outcome. Other studies have used RNN models in recommendation systems such as applying the RNN model to compare different songs according to its similarity to allow recommendation systems to rank scores [23].

III. Experimental Design

In this section, all the phases involved during the experiment are briefly discussed. Overall, there are five phases involved in this research. Figure 2 shows the research workflow for this research.

For the first phase, the goal is to identify the use of AI in e-commerce on a worldwide scale and to study about the existing AI methods in e-commerce to enhance the existing methods. The phase begins with searching for related works and journal articles to identify the uses of AI in e-commerce as well as the existing product planning methods.

For the second phase, the goal is to study and compare the existing AI methods in product planning. The phase begins with searching for related works and journal articles to identify the existing AI methods in product planning. Next, the collected information regarding the existing AI methods in product planning will be tabulated to compare between the other systems.

For the third phase, the research goal is to study the implementation of recommendation systems. The phase begins with searching for related works and journal articles to identify the implementation of recommendation systems in similar works and research. Then an AI method to be implemented in the recommendation system will be selected which is Recurrent Neural Network (RNN).

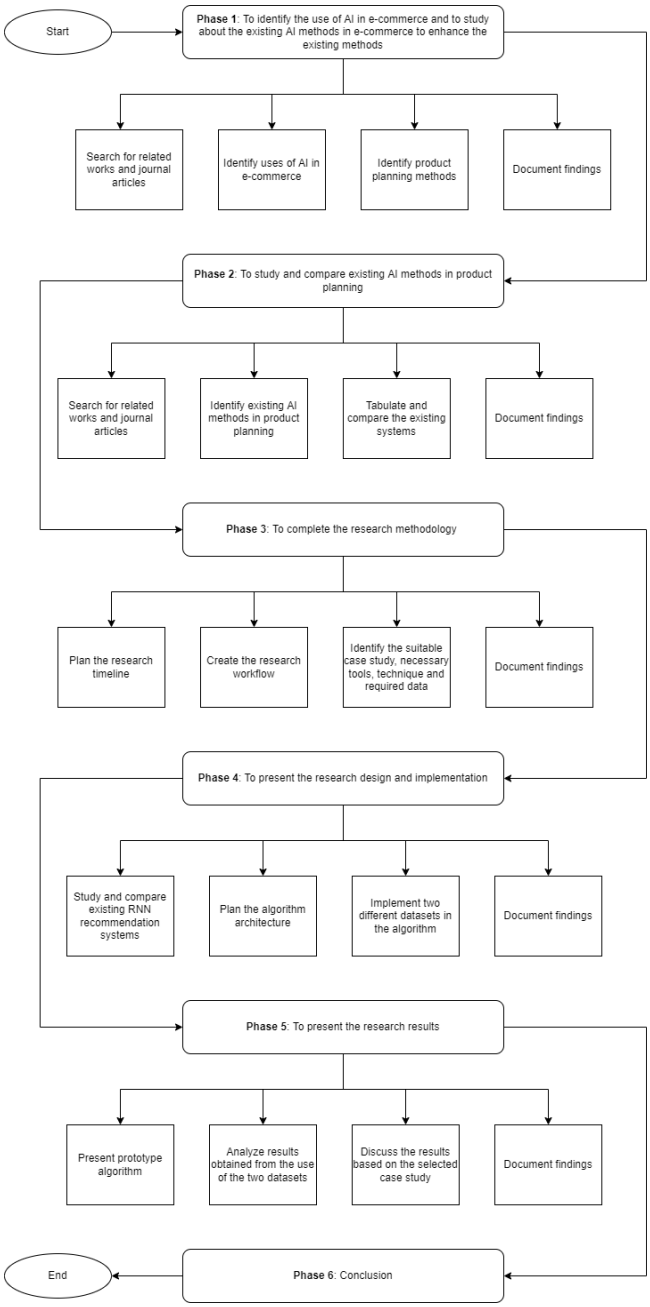

Figure 2. Research workflow

For the fourth phase, the goal is to study the existing RNN based recommendation systems to improve product planning. The phase begins with searching for related works and journal articles to study architecture and models of existing systems to be related to the selected case study.

For the fifth phase, the findings will be concluded and the plan for the implementation phase will be explained regarding how the data will be used to implement the prototype. This will be included in the final report of the research.

The architecture or modeling strategy of the prototype was designed based on some of the existing RNN based recommendation systems above. The prototype is then developed using a RNN model designed as shown in Figure 3.

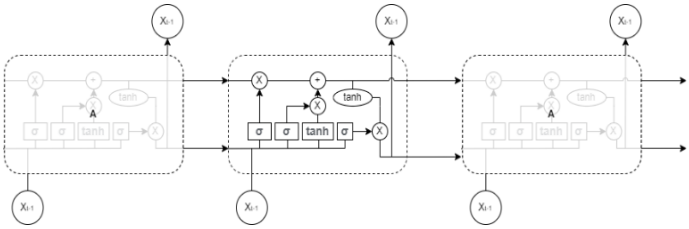

Figure 3. RNN Model for the recommendation system.

The steps involved in the recommendation system are as follows:

i. Data collection
ii. Data processing
iii. Data cleaning
iv. Sentiment Analysis of the text reviews of the data
v. Implement RNN and train the model
vi. Print model summary

IV. Result and Discussion

A. Amazon Mobile Phones Reviews Dataset

The chart pie in Figure 3 shows the sentiment polarity distribution for the Amazon phone dataset with 73.5% for the positive sentiment, 13.6% for the neutral sentiment and 12.9% for the negative sentiment while Figure 4 shows the model summary for the Amazon phone dataset that reports the layer type, output shape and parameter number. Aside from that, it also reports the total parameters, trainable parameters, and non-trainable parameters.

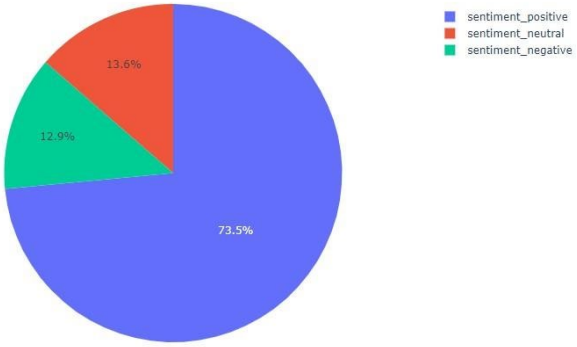

Figure 4. Amazon phone dataset sentiment polarity distribution.

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 20)]              0

 embedding (Embedding)       (None, 20, 100)           865200

 lstm (LSTM)                 (None, 128)               117248

 dense (Dense)               (None, 3)                 387

=================================================================
Total params: 982,835
Trainable params: 117,635
Non-trainable params: 865,200
_________________________________________________________________
None
```

Figure 4. Model summary for Amazon phone dataset.

B. GameStop Products Reviews Dataset

The chart pie in Figure 5 shows the sentiment polarity distribution for the GameStop product dataset with 85% for the positive sentiment, 5.8% for the neutral sentiment and 9.24% for the negative sentiment while Figure 6 shows the model summary for the GameStop product dataset that reports the layer type, output shape and parameter number. Aside from that, it also reports the total parameters, trainable parameters, and non-trainable parameters.

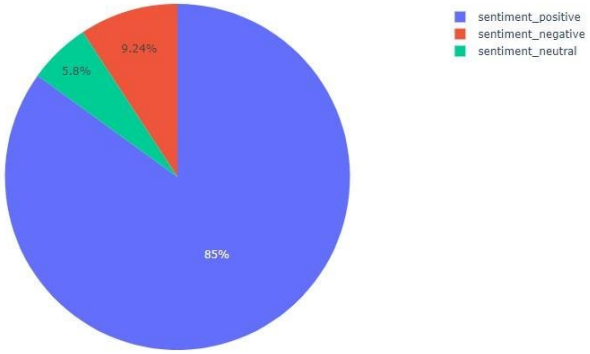

Figure 5. GameStop product dataset sentiment polarity distribution.

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 30)]              0

 embedding_1 (Embedding)     (None, 30, 100)           802300

 lstm_1 (LSTM)               (None, 128)               117248

 dense_1 (Dense)             (None, 3)                 387

=================================================================
Total params: 919,935
Trainable params: 117,635
Non-trainable params: 802,300
_________________________________________________________________
None
```

Figure 6. Model summary for GameStop product dataset.

Based on the selected case study [24], it highlights on the utilization of a set of strategies that allow e-commerce websites' recommendation system to make the most of customer reviews. In terms of feature and opinion mining, the case study states that it defines various elements of written reviews such as the product features, review contexts, review sentiments, feature specific sentiments and comparative opinions. These features were implemented in the prototype algorithm. Aside from that, the case study also mentions the use of deep neural network architectures such as recurrent neural network to include review texts in recommendation algorithms. Based on the obtained results (as shown in Table I) from the experimentation of the algorithm using the two different datasets, it can be concluded that this algorithm will be able to bring profit to a business if they have a large database able of customer reviews. Therefore it may not be suitable for small e-commerce businesses as this may lead to results with low accuracy and weak reliability.

TABLE I. COMPARISON OF RESULTS AND EXPERIENCE OF THE ALGORITHM IMPLEMENTATION USING TWO DIFFERENT DATASETS.

Dataset	Amazon Mobile Phones Reviews Dataset	GameStop Products Reviews Dataset
Training time/speed	From 20 minutes to an hour	From 5 to 15 minutes
Sentiment Positive	73.5% Total = 22504	85% Total = 3981
Sentiment Neutral	13.6% Total = 4172	5.8% Total = 272
Sentiment Negative	12.9% Total = 3936	9.24% Total = 433
Accuracy	High accuracy	Low accuracy
Reliability	Strong reliability	Weak reliability

V. CONCLUSION

From this research, it can be concluded that the RNN based recommendation system is an enhanced approach for e-commerce product planning in the business industry. Based on the discussion above, the proposed algorithm can be implemented, it is shown that a larger dataset is required for the best results in terms of accuracy and reliability.

The next step in the future will be to implement the algorithm in a prototype or system for e-commerce business to identify and predict top selling products based on customer's written reviews. It is also important to keep in mind that the algorithm would work best with a larger database to maintain high accuracy and reliability.

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