Performance evaluation of health recommendation system based on deep neural network

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Abstract. Deep learning has developed as an innovative zone of machine learning and data mining exploration part. Controlled or unconfirmed methodologies which contain of a number of layers of handling which form a hierarchy are castoff for preparation in deep learning. Every succeeding layer mines an ever more intellectual depiction of the input data and shapes upon the depiction from the preceding layer, usually by calculating a nonlinear alteration of its input. The constraints of these alterations are adjusted by preparation of the prototypical on a dataset. A deep learning prototypical studies better depiction as it is delivered with more volumes of data. Key objective of using deep learning methods in recommender schemes is to lower time complexity and to increase the accurateness of formed expectations. In this paper, performance of planned HRS is evaluated by Arbitration Time, Latency Time, Jitter, Execution Time, Network Bandwidth Consumption, Power Consumption, Training Accuracy and Testing Accuracy.

1. Introduction

The explosive progress in the work of digital data and large count of people on internet has produced an impending task of data burden that obstructs well-timed entrance to things of importance on the internet. Recommender schemes are facts purifying arrangements which contract with the difficulty of data excess by clarifying vibrant evidence portion out of huge volume of vigorously produced data allowing to customer’s favorites, awareness, or practical activities around point. Next generation databanks and data learning implements are necessary due to rapid progression of statistics and information. Every business wants a service recommendation arrangement which can be used by many of customers. The number of consumers, goods and data is growing very speedily; service recommender systems face the big data exploration problematic. Traditional recommender facility arrangements suffer from shortage of scalability and effectiveness difficulties while handling or examination of this statistics on outsized scales [1]. A recommender arrangement must fulfill a right level of estimate correctness to develop desire capability and efficiency.
1.1 Overview of deep learning
Deep learning is referred as subclass of simulated neural systems has many management stages. Anyhow algorithmic progressions, the development in handing out capabilities, exploiting GPUs and the assortment of better-quality datasets are generally factors which assisted in the ongoing flood of deep knowledge.

1.1.1 What is deep learning?
- It comes under class of machine learning systems
- It uses hierarchy of nonlinear processing layers and complex model structures
- Layers learn to represent different representation of facts
- Advanced stage features are constructed from minor stage abstract features
- Trendy name for “Neural Networks with deep layers”

Deep learning has become increasingly more famous all through subfields of software engineering, for example, Natural language preparing, picture and video handling, PC visualization, and information withdrawal because there has not been such a typical way to deal with in taking care of various types of figuring issues previously. With such part of profound learning systems, they are not just exceptionally equipped for helping complex issues in numerous fields; however they additionally structure a mutual terminology and shared view for these exploration grounds. Deep learning strategies also assist these sub-fields to team up with one another wherever this was somewhat questionable earlier because of the assorted variety and unpredictability of used systems [2].

For whatever length of time that the personalization pattern stays famous, the recommender frameworks research will assume a basic job in data examining. In spite of the fact that the use of profound learning into recommender frameworks field guarantees noteworthy and empowering results, difficulties, for example, the precision and marketability are as yet open for upgrades and warrant future work.

1.1.2 Why Deep Learning for Search and Recommender System?
- Direct content Feature extraction instead of metadata
- Text, Image, Audio
- Better representation of users and items
- Hybrid algorithms and heterogeneous data can be used
- Better suited to model dynamic behavioral patterns and complex feature interactions.

1.1.3 Health Recommendation System
A health recommender system (HRS) is one of a specialization of a recommender system. The aim of an HRS is to deliver medical information to it’s user which is meant to be extremely pertinent to the medical enhancement of the associated patient.

2. Related work
Baldominos et al. [3] presented Data Care, a resolution for intellectual wellbeing administration. This creation is intelligent to recover and collect facts from dissimilar fundamental presentation signs in wellbeing hubs, however too to guess upcoming ideals for these strategic presentation signs and, by way of consequence, fervor initial warnings once objectionable standards are nearly to happen or offer endorsements to increase the excellence of facility.

Belle et al. [4] discussed few of key challenges with an emphasis on three future and encouraging regions of medical examination: image, sign, and genomics based analytics and current research which marks use of huge capacities of medicinal data while joining multimodal facts from dissimilar sources.
Georgia Koutrika [5] enclosed current progresses in recommendation techniques, concentrating on matrix factorization, multi-armed thieves, and approaches for merger recommendations. The author also described evaluation techniques, and outline open problems and challenges.

Konstan and Riedl [6] presented an analysis on important advances in collaborative filtering recommender schemes, concentrating on the development from investigation focused only on processes to investigation focused on the ironic set of queries around the customer involvement with the recommender. Author assessed the customer understanding of a recommender needs a wider set of actions that have remained normally castoff, and recommended extra actions that must confirmed operative.

Zhang et al. [7] projected a prototypical merging a collective clarifying commendation procedure with profound knowledge skill. These prototypical practices a feature demonstration scheme built on a quadric polynomial reversion prototypical, which gets hidden topographies further precisely by successful upon the old-style matrix factorization procedure. Formerly, these hidden features are considered as the contribution records of the profound neural system prototypical, and are castoff to forecast the assessment totals.

Riyazand Varghese [8] applied an innovative recommendations scheme by collaborative filtering procedure in Apache Hadoop leveraging Map Reduce model for giant data. Apache Hadoop is an exposed structure for scattered dealing out arrangements and can route huge capacities of records. This can be castoff for disconnected handling and inefficient for small inactivity analytics. This harbor statistics on top of the subsequent collection catalogues alike HBase and enhance the presentation of it. For the creation commendations the Amazon dataset is castoff. Planned Structure has substantial upgrading 3 in performance compared to conventional implements.

Jooa et al. [9] planned and applied a recommendation scheme which examines by configurations and individual tendencies of consumers by exhausting relationship instruction examination and collaborative filtering for composed client statistics on staying customer businesses with NFC. The commendation procedure castoff in planned scheme castoff the statistics examination outcomes plus remoteness facts from GPS to mention native productions that persons are greatly expected to stay.

Sahu et al. [10] exploited Content Centered Clarifying, Collaborative Grounded Clarifying, Mixture Contented-Cooperative, k-mean grouping and Naive Bayes categorizer to their great in direction to attain the finest conceivable exactness and ensure a complete reasonable examination. The strong point of altogether procedures can be obviously understood by the noteworthy improvement in accurateness, showed by the investigational exploration compelling unkund start problematic into attention.

Luis et al.[11]examined the probability of construction a content centered reference scheme which associates wellbeing customers to trustworthy fitness informative web links from Medline Plus for a particular well-being audio visual from YouTube. The database for this training contains a gathering of fitness linked audiovisual and their obtainable metadata. Semantic tools were castoff to endorse wellbeing web links from Medline Plus.

Abdiet al. [12] showed an intensive literature analysis to classify research documents on Recommender Schemes in the Healthcare in the last ten years. The important conclusions of this review are that the submission of Recommender Systems in Healthcare is growing. The integration of appropriate data is restricted although it has been recommended as a key element to refining the superiority of the recommendations and the accurateness of the predications.
Wang et al. [13] presented the Content centered Papers& Consultations Recommender Arrangement on computer discipline and its network facility at http://www.keaml.cn/prs/. This scheme mentions appropriate papers or consultations through a precedence direction grounded on the intellectual of a manuscript.

Ayyaz et al. [14] suggested a Mixture Content centered Indistinct Conformal Recommender Arrangement. Content centered clarifying system with fuzzy interpretation system. The author used two datasets Movie Lens and Movie Tweetings for experiment to recommend shows to the customers and assessed and then matched with further advanced reference schemes. The suggested procedure provided improved outcome than the old-style approaches.

Fazazi et al. [15] presented a recommender e-learning methodology which make use of commendation practices for informative data taking out precisely for recognizing e-Learners’ education inclinations. The suggested method is centered on three components, a field component which covers completely the information for a specific zone, a beginner component that practices to detect beginners’ education likings and actions and a commendation unit which practices records to make an appropriate reference list and guessing performances.

Batmaz et al. [16] analyzed collected readings in four extents which are profound knowledge prototypes used in reference arrangements, preparations for the tests of reference arrangements, attentiveness and dominance above endorsement fields, and the purposive assets. Author too provided a complete quantifiable valuation of journals in the field and concludes by deliberating added visions and conceivable upcoming effort on the topic.

Sahoo et al. [17] proposed smart HRS by means of (RBM)-(CNN) profound knowledge technique, which delivers an vision into in what way large statistics analytics can be castoff for the execution of an operative fitness reference device, and explains an prospect for the wellbeing maintenance productiveness to changeover from an old-style situation to a further adapted standard in a tele-health situation.

Nouh et al. [18] suggested a nifty recommender arrangement built on the procedures of cross knowledge for individual comfort facilities, named a clever reference scheme of mixture knowledge. The important fitness feature is deliberated to be individual routine, with the benefit of a life threatening inspection of several restraints. Incorporating the reference scheme efficiently gives to the avoidance of sickness, and it too clues to a decrease in cure fee, which adds to an enhancement in excellence of lifecycle.

3. Proposed work

Deep learning has developed as an innovative zone of machine learning and data mining exploration part. Controlled or unconfirmed methodologies which contain of a number of layers of handling which form a hierarchy are castoff for preparation in deep learning. Every succeeding layer mines an ever more intellectual depiction of the input data and shapes upon the depiction from the preceding layer, usually by calculating a nonlinear alteration of its input. The constraints of these alterations are adjusted by preparation of the prototypical on a dataset. A deep learning prototypical studies better depictions as it is delivered with more volumes of data. Key objective of using deep learning methods in recommender schemes is to lower time complexity and to increase the accurateness of formed expectations. Figure 1 demonstrates the process of machine learning.

![Diagram of machine learning process](image-url)
Figure 1. Machine Learning

Extracting features manually from a dataset, strong knowledge of the subject as well as the domain is necessary. It is an extremely time-consuming process. With Deep Learning, we can automate the process of Feature Engineering as shown in figure 2.

Figure 2. Deep Learning

Figure 3. Proposed Architecture

In this paper, deep neural network architecture for recommender scheme is designed as shown in figure 3. In feature extraction, all the required features are extracted and in feature selection, the important features that improve the performance of deep learning model are selected. The neural network is used for classification. The multilayer perceptron (MLP) is used to categorize linearly attached data. The MLP neural networks are feed forward networks with one or more layers of components between the input and output layer. The output components signify a hyper plane in the input space. In this the training procedure of the MLP neural networks uses the back propagation (BP) algorithm based on the generalized delta rule. The BP algorithm is enhanced by relating the momentum technique which suggests addition a span $\alpha$ with a worth between (0, 1] to alter the weights. A typical value for constraint $\alpha$ is 0.8. The back Propagation procedure with
gradient and momentum has a comparable intricacy to the BP algorithm but is improved concerning the merging speed and the capability to evade local minima.

3.1 Dataset used

In this paper, the proposed recommendation methodology is evaluated on real datasets [19].

3.1.1 Tool used

In this paper all evaluations are performed using Python 3.10. Highly-productive interface Keras are used for solving machine learning complications. Keras is a deep learning API written in Python, running on top of the machine learning platform. It is extensively used to speedily develop new training techniques or striking model architectures. In this paper, proposed churn prediction technique in Python programming language and Keras library for planned deep neural network architectures is implemented.

| Table 1: Evaluation Parameters |
|--------------------------------|
| Name                          | Description                                                                 |
| Arbitration Time              | It is the time to settle the differences between client and Cloud.            |
| Latency Time                  | Time interval between a client request and cloud service provider’s response.|
| Jitter                        | Latency variability, it is a measure of network and CPU congestion.           |
| Execution Time                | It is completion time of the task.                                            |
| Network Bandwidth Consumption | It is the capacity of a wireless network communications to transmit the maximum amount of data from one point to another over an internet connection in a given amount of time. |
| Power Consumption             | It is energy intake by device per unit time.                                  |
| Training Accuracy             | It is the accuracy when applying the model on training data.                 |
| Testing Accuracy              | It is the accuracy when applying the model for testing data.                 |

4. Results and discussion

In this paper, performance is evaluated of planned HRS by Arbitration Time, Latency Time, Jitter, Execution Time, Network Bandwidth Consumption, and Power Consumption. Table 2 and figure 4 demonstrates arbitration time in different scenarios.

| Table 2. Arbitration Time in different scenarios |
|-----------------------------------------------|
| Master Node | Node-1 | Node-2 | 2-Nodes-Ensemble | Cloud |
| 1            | 26     | 1377   | 3034             | 2122   | 61   |
| 2            | 39     | 1322   | 2799             | 2806   | 53   |
| 3            | 211    | 1456   | 3132             | 3115   | 89   |
| 4            | 179    | 1493   | 2954             | 4150   | 121  |
| 5            | 165    | 1411   | 2910             | 3315   | 254  |
| Avg          | 124    | 1411.8 | 2965.8           | 3101.6 | 115.6 |
Table 3. Latency in different scenarios

|      | Master Node | Node-1 | Node-2 | 2 -Nodes-Ensemble | Cloud |
|------|-------------|--------|--------|-------------------|-------|
| 1    | 10          | 27     | 19     | 27                | 2585  |
| 2    | 11          | 25     | 17     | 34                | 2750  |
| 3    | 14          | 21     | 24     | 23                | 2650  |
| 4    | 25          | 19     | 19     | 25                | 2555  |
| 5    | 21          | 17     | 20     | 36                | 2672  |
| Avg  | 16.2        | 21.8   | 19.8   | 29                | 2642.4|

Table 4. Jitter in different scenarios

|      | Master Node | Node-1 | Node-2 | 2 -Nodes-Ensemble | Cloud |
|------|-------------|--------|--------|-------------------|-------|
| 1    | 10          | 27     | 19     | 27                | 2585  |
| 2    | 11          | 25     | 17     | 34                | 2750  |
| 3    | 14          | 21     | 24     | 23                | 2650  |
| 4    | 25          | 19     | 19     | 25                | 2555  |
| 5    | 21          | 17     | 20     | 36                | 2672  |
| Avg  | 16.2        | 21.8   | 19.8   | 29                | 2642.4|
Table 5. Total Execution Time in different scenarios

|     | Master Node | Node-1     | Node-2     | 2-Nodes-Ensemble | Cloud  |
|-----|-------------|------------|------------|------------------|--------|
| 1   | 2215        | 3718.5     | 4944       | 6307.5           | 242    |
| 2   | 2315        | 3709.5     | 3637.5     | 6277.5           | 391    |
| 3   | 2490        | 3757.5     | 3408       | 6082.5           | 512    |
| 4   | 2450        | 3744       | 3307.5     | 5955             | 1600   |
| 5   | 2420        | 3784.5     | 3381       | 4492.5           | 1028   |
| Avg | 2378        | 3742.8     | 3735.6     | 5823             | 754.6  |

Figure 6. Jitter in different scenarios

- Table 5 and figure 7 demonstrate total execution time in different scenarios.
Figure 7. Execution Time in different scenarios

- Table 6 and figure 8 demonstrate network bandwidth in different scenarios.

Table 6. Network Bandwidth in different scenarios

|          | Master Only | Node-1 | Node-2 | 2-Nodes-Ensemble | Cloud |
|----------|-------------|--------|--------|------------------|-------|
| 1        | 4.1         | 5      | 13     | 19               | 18    |
| 2        | 4.1         | 5      | 14     | 16               | 17    |
| 3        | 4.1         | 5      | 25     | 18               | 21    |
| 4        | 4.1         | 6      | 8      | 29               | 19    |
| 5        | 4           | 7      | 9      | 21               | 14    |
| Avg      | 4.08        | 5.6    | 13.8   | 20.6             | 17.8  |

Figure 8. Network Bandwidth in different scenarios

- Table 7 and figure 9 demonstrate energy (power) consumption in different scenarios.

Table 7. Energy in different scenarios

|          | Master Node | Node-1 | Node-2 | 2-Nodes-Ensemble | Cloud |
|----------|-------------|--------|--------|------------------|-------|
|          | 2.75        | 2.83   | 3.4422 | 4.1545           | 17.935 |
Figure 9. Energy in different scenarios

Figure 10. Training Accuracy with number of edge nodes
Figure 11. Network Bandwidth with number of edge nodes

- Figure 10 shows Training Accuracy and Figure 11 shows Testing Accuracy of HRS.

5. Conclusion
Simple assessment rules centered and complex grouping models for healthcare recommendation tasks have been discussed in the literature. These approaches are capable to execute recommendation jobs but make use of manual feature selection and are more time consuming and error-prone. In this paper, deep neural network based healthcare recommendation system is created to automate feature selection engineering process. Experiment is conducted using real world datasets.

6. Future scope
Other learning techniques can also be used as upcoming research to improve the performance. In addition, hybrid procedures can be used to offer more assessment.

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