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Hybrid Adaptive Markov Chain Monte Carlo Tree Search and Bayesian Lipschitz Optimization for Recommendation system in Online Social Network

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Abstract
The effectiveness of the program's suggestions has been severely compromised by the high scarcity of comparable quality. Some models based on Convolutional Neural Networks (CNNs) have made maximum use of textual information to increase predictive performance, mitigating problems associated with data scarcity. In this article, the researchers proposed a Hybrid Adaptive Markov Chain Monte Carlo Tree Search (HAMCMTS). Where it extends the ability of the permutation conversion model by counterbalancing the surface to the CNN with a novel Recommendation System (RS). The researchers then proposed methods using the presumption of Lipschitz coherence traditional Bayesian Optimization (BO) processes, which the researchers consider to be Bayesian Lipschitz Optimization (BLO). This method does not extend the asymptotic run time and, in some situations, leads to significantly improved performance. Researchers use the HAMCMTS in conjunction with embeds to collect background data for the article and enhance a hidden framework to maximize the reliability of suggestions. The researchers perform extensive tests on global sets of data, & the outcome shows that HAMCMTS & BLO has exceeded standards.

Keywords: Sparsity; CNN; Adaptive Markov Chain Monte Carlo Tree Search; Lipschitz Bayesian optimization

1. Introduction

Requests for choosing people for merchandise have been made easier thanks to mobile apps. The urbanization process would be a type of service that has become more popular, and it is typical for users to share rides themselves. The benefits of this product were tied to benefits for urban transportation, such as lower costs and reduced environmental destruction [1-3]. Sharing consumerism emphasizes the importance of having more experience than having anything at all. Consumers are now trying to satisfy their real needs with intangible experiences rather than with the products or services offered by a commercial arrangement. The sharing economy appears to be a reinvention of traditional market behavior, such as transfer and communication, trading and leasing, using new scales and new technology forms never seen before [4]. The rideshare business benefits from the convenience & accessibility of some personal vehicles, lowering the prices of personal transport [5]. In the instance of automobiles & homes, the modifications of traditional forms of transport have progressively generated a shared transportation industry & the idea of the sharing economy. Not only is Quality of Service (QoS) crucial in a data network, but the customer Quality of Experience (QoE) also is important to take into account [6]. The customers' QoE is a metric for assessing the level of enjoyment experienced while checking out a service or product. As a result, the QoE idea could be extended to ride-sharing services [7].

According to research [8], several people like to share goods with people who have comparable traits. The RS which seems to be a method that involves a database of customer attributes the services or products offered to the customer [9], was used to advise sharing services. In the recent decade, RS solutions have become increasingly popular in both academic & business settings. Among the benefits of RS was its ability to provide consumers with more customized choices, and it can even be used for ride-sharing ideas [10].

It's worth noting that the user information must be present for an acceptable recommendation to be made. Companies have discovered Online Social Networks (OSN) to be quite popular in this instance, and have played a vital role in RS remedies. The correct interpretation of this data could provide valuable information for building models or user information, & more accurately propose information [11]. As the number of internet retail sites has grown, so have the types & amounts of services and products offered by merchants. Even though it provides customers with more options, this becomes increasingly hard to manage a great deal of information, resulting in sparser & sparser rating data [12-13]. Some of the most popular e-commerce sites, like eBay, Taobao, & Amazon, for instance, have a significant number of customers & merchandise.

The sparseness of the rating data, logically, has a significant impact on the prediction performance of the grade in the classification method. Using supplemental textual information to enhance the precision of the classification method has been one of the ways for solving the issue of sparse rating data [14]. To delve further into the user data, several scientists used context-aware Collaborative Filtering (CF). The CF method systems, on the other hand, have two main shortcomings. They have two flaws: one was that it is extremely difficult to make suggestions to a customer who has a particular preference, and the other is that they are hard to interpret. Natural language processing, pattern recognition systems, language processing, and image analysis seem to be just a few of the deep learning approaches based on deep neural networks which have recently been acknowledged used to resolve this issue [15]. The ability of a CNN to extract features from an article's text analysis has been demonstrated. Nonetheless, it is unable to overcome the two disadvantages listed above.

2. Related Works

The capability of CNN to represent geometric transformations was largely dependent on considerable data augmentation & the huge model capacity, among other things [16]. The difficulty of modeling phrase pairings in a range of contexts could be handled by a convolution neural network model, which has the generalization performance. The attentiveness technique was applied in the model developed to evaluate the connection between the initial separate phrases, and a different phrase structure with the contextual connection of the phrases was built [17]. Following its success in the field of picture identification, the Attention mechanism was extended to the field of natural language processing. CNN has been used to discover the best way of representing q&a phrases. The framework employs a spread paragraph prototype to encode several more complicated features linguistic, morphological, & logical of a statement, then computes different matches metrics among the characterizations acquired, & employs allotment phrases trying to match to solved an issue for linguistic message compare & the uses of extra D for raise embeds to solved an issue of a phrase overlapping in a particular sentence [18].

The generated feature mapping of a zero-filled, fully convolutional would be the same size as the input feature map, & it could also expand the quantization for the input featured location texture features. From the areas of language processed, question output systems, & retrieval of information, the new CNN variation performed well. As a result, it aids in the comprehension of the material & provides a good perspective factor structure. Without making assumptions about the underlying arbitrary function, optimization, technique of a genuine feature was difficult [19]. Lipschitz continuity would assume that the function cannot modify arbitrarily quickly as the input variables. This was among the most flimsy assumption in which it would be still possible to optimize an abstract representation. Lipschitz optimization (LO) takes advantage of the fact that the function's Lipschitz variable L has a restriction. This variable L sets a limit on the greatest amount that the algorithm could modify [20]. This constraint enables LO to narrow the searching area, according to select an optimal solution. Bayesian boost, on another hand, assumes that was manipulated variable was part of a recognized data structure, the most popular of which is the Gaussian process (GP) constructed with the Gaussian or Marten kernel. BO & LO may both be proven to be enormously quicker than randomized optimization algorithms under their own set of extra constraints. If the underlying value comes near to matching the higher BO criteria, BO has often been quicker than LO at optimizing circuits [21]. When these expectations here are not acceptable, though, BO may take longer to converge than merely attempting random numbers. LO, on the other hand, requires few expectations & merely prunes out model parameters that do not satisfy the Lipschitz condition and thus cannot be answered [22]. This could help efficient algorithms such as random checks run faster. When faced with a novel variable to optimize, it may be unclear which of these approaches would outperform the others.

3. Materials and Methods

3.1 CNN

On CNN, the input feature mapping, extracted feature chart, & inversion have all been 3D, but the deformed convolutional network modules were specified in 2D & subsequently extended to 3D for simplicity of explanation. Figure 1 depicts the construction of the flexible loop. Researchers suppose that the length, breadth, & height of the image convolution layer were C1, W1, & H1, correspondingly, & that the intensity, spacing, & height of the output feature map were C2, W2, & H2, including both, and the kernel size.

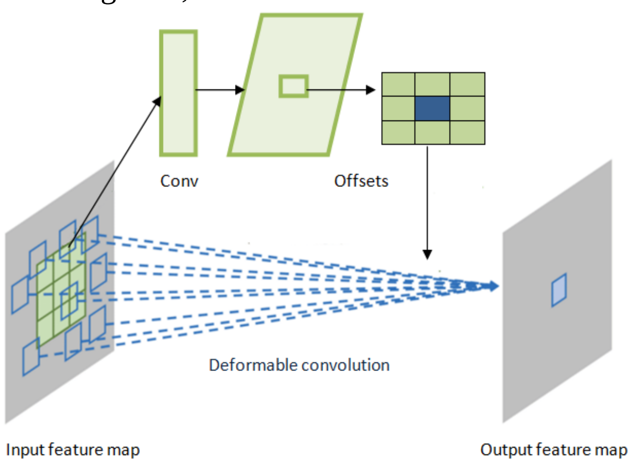


Figure 1. 3 x 3 deformable CNN

Word2vec would be a prototype that directly converts phrases for the languages in a text, vector representation, and this could train a forecasting model for the term coordinates from the corpus. There are 2 major methods: followed Bag by text & SkipGram. CBOW deduces a target text from the normal statement, whereas SkipGram deduces a target word from an original sentence. The Skip-Gram mode of word2vec was being used extensively in this research [23]. Word2vec was split into 2 parts: the 1st was to create a structure, & the next would be to extract an embedding vector representation of the system.

Word2vec's entire modeling technique was rather consistent with the idea for an autoencoder. To begin, the neural system was built using data for training. Researchers could retrieve the variables that the system learns from training examples based on the framework, such as hiding gradient weight matrices, which have been the phrase vectors we're looking to learn in word2vec. To put it differently, once the system training has been completed, the output layer would be removed, keeping only the hidden units. The input phrase reflects the characteristic graph with dimensions 9x6 as seen in Figure 2 in the embed of word2vec where input length was 9 & embedded characteristic depth was 6.

3.2 Chain Monte Carlo Tree Search

HAMCMTS were concise formulations of sequential decision-making problems with uncertainties. The status of the issue develops based on stochastic mechanics which were only influenced by the present state & actions. The operator in a HAMCMTS was supposed to have recourse to noisy condition measurements. The agent's purpose was to plan a line of behaviors that expend the sum of cumulative incentive across the issue horizons to use this information [24]. When resolving a HAMCMTS, it's customary to keep track of a belief b distributed over the environment.

The conviction was usually modified with a Bayesian updating filter every moment the creature performs an action and gets an observer

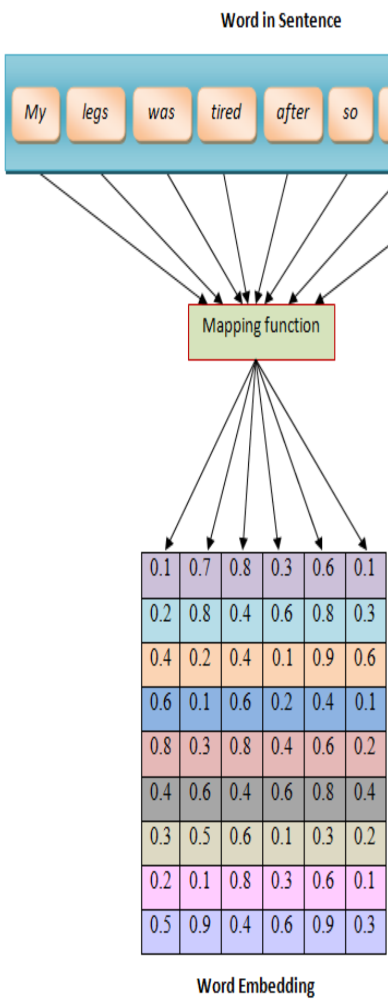


Figure 2: Representation of Word2vec 9 x 6

The majority of online HAMCMTS solutions use sample-based tree search algorithms, also known as Monte-Carlo tree searching. HAMCMTS techniques that are stochastic build searching trees by layering actions conducted & observation collected, with a root in the current belief. The tree could then be used to assess the cost of the activities that the agents could do based on its present condition. In a standard HAMCMTS procedure, the owner's present conviction is used to sample a condition. To model possible trajectories, the information was employed in a prediction model. Until a leaf destination was reached, the simulator goes down the tree, choosing the optimal action from the existing relations. Then it attaches a child node to the leaf & runs a rollout to predict the amount to use a base rule.

To refresh their worth estimations, the information gets transmitted back through the neighboring node to the root. The analysis provides the root act with the greatest average worth after a given variety of models have been done. Deeper trees have a greater chance of estimating the genuine optimum solution.

3.3 BO methods

Gaussian processes (GPs) were commonly used in BO techniques because they have attractive global coherence qualities across small subsets & allow for a closed-form likelihood function. BO approaches generally assume a homogeneous GP precondition just on arbitrary function & calculate a prior probability over the potential values at every point x using actual objective functions.

The fact that researchers don't know a genuine L in most cases would be a major limitation of Lipschitz optimization. We'll go over this case in more detail in the following chapter, but first, humans should mention that there have been situations in which we do get recourse to a legitimate L [25]. Alternatively, if we have minimum and maximum values on the stored procedure number of values, humans could use this information along with a size for the X for getting the excess of a minimal L rate.

3.4 Lipschitz Bayesian optimized

In this chapter, humans explain how the Lipschitz inequality constraints could be included in BO by making minor adjustments to the conventional acquisition methods. LBO [26] seems to be the name given to this method. BO was prevented from evaluating x t variables that were not awarded maxima, & the value of the f (xt) range examined in the acquisition method would be limited to those who have been consistently utilized the Lipschitz inequalities. The essential characteristics of BO, LO, & LBO were depicted in Figure 3. It's vital to notice that the Lipschitz constant L does have been the distinct meaning of the GP's distance scale. The constant L denotes a stored procedure maximum available speed of adjustment, whereas' denotes how fast a specified length between pairs of points alters a GP. Researchers were observed as employing a Lipschitz inequality has a computational burden of O (n^2), which was the same as (precise) inference in the GP

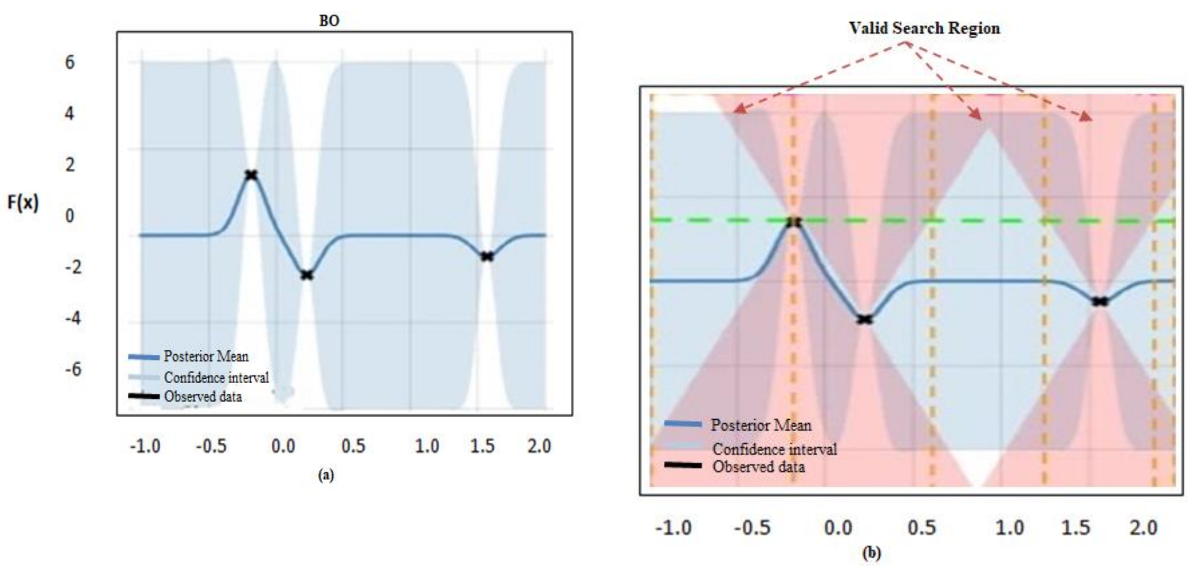


Figure 3: LBO influence and constraints

For calculating the increase, researchers could utilize the Lipschitz bounded to strict the bounds of the uncertain fitness range. An optimum value would always be $f^u(i)$ Whereas the lower bound L_f Would be determined by j^* Perceived worth. Researchers have had the examples provided in specific:

$$L_f = \begin{cases} j^*, & if\ j^* \in \left(f^l(i), f^u(i)\right) \\ f^u(i), & if\ j^* \in (f^u(i), \infty) \end{cases} \quad (1)$$

An accept-reject-based mixed acquire product seems to be an alternate technique for incorporating the Lipschitz constraints. Similar to LO techniques, this process utilized the Lipschitz limits for a reality asses to accept or decline a benefit produced by the normal acquisition procedure. If $\breve{g}(i)$ seems to be the result of the initial purchase functional, then the combined acquisitions role g(x) would follow:

$$\breve{g}(i) = \begin{cases} g(i), & if\ g(i) \in [f^{l}(i), f^{u}(i)]\ (Accept) \\ -\infty, & otherwise\ (Reject) \end{cases} \quad (2)$$

AR-UCB & AR-TS seem to be the accepted-reject whatever it acquisitions algorithms, accordingly. The accept-reject approach seems to be quite general, and that might be also used in any acquisition method which contains a range of a very similar magnitude to the functional. It's also conceivable that a valid point would be discarded while using an estimation of L because the estimation of L has become too low, but employing a rising estimation guarantees that such locations would be chosen again in successive iterations. During operation gradual broadening, LBO was added. Rather than choosing an act randomly from the available agent acting when a new action was introduced to the search tree, HAMCMTS employs the technique specified in method 3.

4. Architecture of HAMCMTS

Algorithms HAMCMTS

Step 1: Start the LBO **Proceduer** and set the input (a,P,A)

Step 2: X =0

Step 3: Y=0

Step 4: for (a,t) ϵ P uniom do

set the VECTORIZE (a,t) to X append u(a,b) to Y

Set the gp= Gaussian Process (X,Y)

€*, δ* = POSTERIOR(gp,l*)

end for

Step 5: retun the value

To identify the good X & Y, humans apply a coordinated descending approach. The parameter was optimized repeatedly by adjusting the surrounding parameter conver equilibrium has been reached. As a result, humans take the derivatives of Eq. (18) About u & set Y, We, & WC to zero. The optimum amount of X could then be calculated as follows:

$$L(X,Y,V) = \mathrm{Min}_{V,U,W_C,W_S}\left(\frac{1}{2}X\|R - XY\|_2 + \frac{\gamma U}{2}\|x\|_2 + \frac{\gamma V}{2}\|V - dcn(W, I_y)\|_2\right) \quad (2)$$

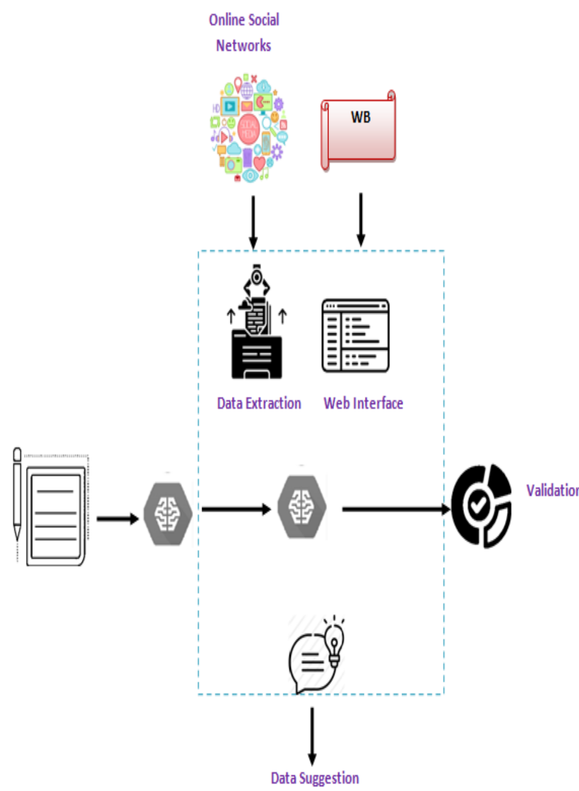


Figure 4: RS structure based on mobility

Figure 3 shows how the planned RS was executed. User information first was retrieved based on a questionnaire, shown by (1) in Figure 3, that would be administered by a team of volunteers. After the machine learning algorithms have been trained and tested, the one that produced great results has been used in the RS, as shown in Figure. 4. The RS applied in this paper was built in Hypertext Markup Languages & Cascading Style Sheets, with Hypertext Text Preprocessor & the social media software, and has been handled using information recorded from OSN. Lastly, the models validate the customer obtained data in OSN via testing (4).

4.1 Recommendation System

The usage of RS attempts to boost customer pleasure & fidelity; it must be utilized in a variety of industries, including book, film, and other service and product recommendations based on previous search results & transactions. Must provide personalized experiences without overburdening a platform with enormous amounts of information. Content-Based Filtering, Collaborative Filtering, & Hybrid Filtration seem to be the 3 primary diverse approaches in RS that have been dependent on the resemblance among objects. Come with me would be an RS that appears in ridesharing services. The RS has been used in carpooling programs to keep track of customers' activity. Moreover, no research has been done on how a patient's basic trait influences their rideshare selection.

5. Performance Evaluation

Figure 5 illustrates the proportion of instances UCT chooses the proactive steps & how often the correct move order was preserved at the roots. To demonstrate that a rise in confidence interval causes an increase in the chance of an improper ordering, humans display the likelihood that a stochastic process taken from N (1) was bigger than the one chosen from N (1/2).

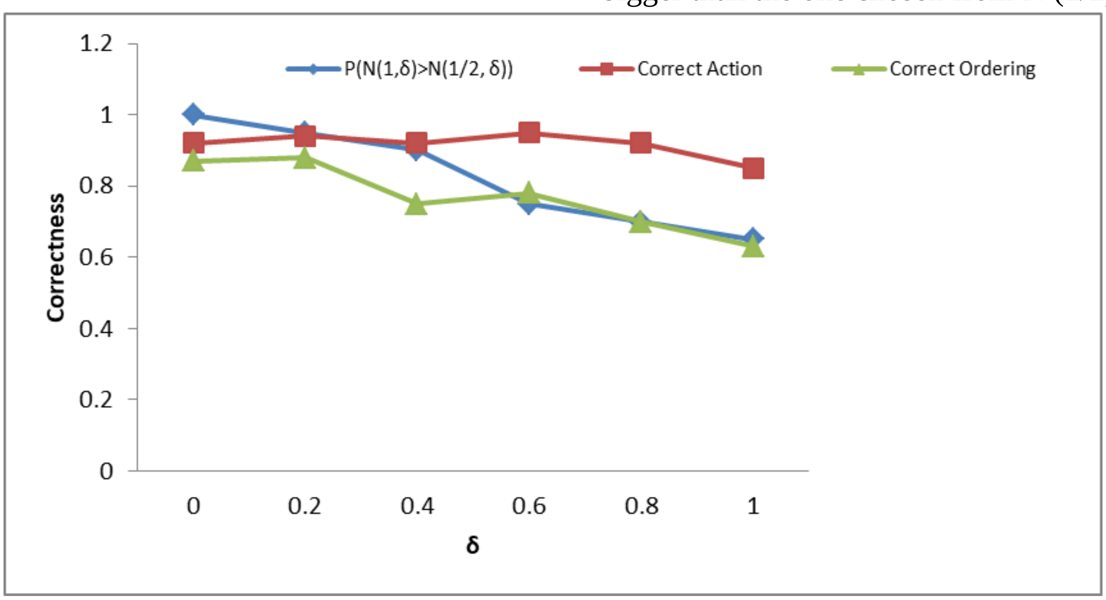


Figure 5: 2000 average runs

For all except the simplest settings, determining the smoothness of an MDP was hard. Humans address the job of determining the popularity and recognition of a function to design some way to control & display the smoothing. Pleasant surroundings were represented by the basic monotonic capabilities, & non-smooth environments were represented by advanced systems. The function g, from the other side, seems to be more difficult to solve, although got the same number of important moments as f. UCT's suggested safe period of the stored procedure scope has become suboptimal. UCT does have a hard time transitioning to the genuine ideal value in this scenario because it wants to utilize the smooth, inaccurate area.

Researchers utilized three publicly available databases that contained are based on users' reviews & ratings of things, & also data about the objects' deliver the documents. Table 1 shows the key characteristics of these 3 datasets after preprocessing. To acquire customer profile information, the RS uses a Facebook-based program. The OSN Application Programming Interface was used for a Software Development Kit library when the user permits the applications to view & retrieve her or his information from OSN.

Table 1: Real-world data chosen from OSN

Dataset	Users	Items	Ratings	Density
ML^{-1}m	6140	3801	1000351	4.387%
ML^{-10}m	70848	10687	1000052	1.465%
Amazon	10512	362	10984	1.5154%

The rating information on the three different datasets, particularly the ML-10m collection, seems to be quite low. The issue of sparseness could have a significant influence on the effectiveness of the recommendation system. In our studies, researchers use the well-known root mean square error of approximation to measure the performance of HAMCMTS (RMSE). The variance between the rating matrix R x 7 the Forecast Rating Matrix (FRM) was calculated using the RMSE method. The following is a formula for RMSE**:**

Researchers randomly divided every database into three sets: learning, verification, & test, with proportions of 80%, 10%, & 10%, correspondingly.

5.1 Experiments

The overall ratings forecast error of HAMCMTS & the other two methods for the 3 real-world sets of data when the training data set proportion was varied. When compared to the other two methods, which are using a conventional inversion for grade predictions, our model outperforms a considerable improvement. The advantages of HAMCMTS for the efficiency of RMSE above PMF to the ML^{-1}m & ML^{-10}m collections were 35.9% & 38.7%, correspondingly. Moreover, to the ML^{-1}m & ML^{-10}m sets of data, HAMCMTS improves RMSE efficiency above ConvMF by 21.6 percent & 27.2 percent, correspondingly.

In 2nd table shows the PMF & ConvMF are unable for collecting contextual information.

If enough evaluations were collected, though, these systems could show better performance. For Instagram, we would see that HAMCMTS outperforms PMF by 37.7 percent & 29.9 percent to 20 percent & 80 percent of the training dataset, correspondingly. However, for 20 percent & 80 percent of the training dataset, HAMCMTS outperforms ConvMF by 5.2 percent & 5.3 percent, correspondingly. The Facebook information has far fewer gains than the $ML^{-1}m$ & $ML^{-10}m$ sets of data. In conclusion, HAMCMTS outperformed all of the baseline methods in all three different datasets by a mean of 18.2 percent.

$$\textbf{Root Mean Square Error} = \sqrt{\frac{\sum_x^N \sum_y^M \left((\boldsymbol{R}_{xy})^2 - (\widehat{\boldsymbol{R}}_{xy})^2 \right)}{\|\boldsymbol{R}\|}}$$

Table 2: The proposed HAMCMTS existing methods

Dataset	**PMF**		**ConvMF**		**HAMCMTS**		**Improvement**
$ML^{-1}m$	3.65844	0.987121	0.956474	0.86156	0.78452	0.63548	22.1%
$ML^{-10}m$	2.62546	2.51323	0.97564	0.85434	0.768710	0.584647	27.5%
Amazon	0.945218	0.869207	0.619274	0.615847	0.567942	0.567910	5.3%
Ratio on training set	0.2	0.7	0.2	0.7	0.2	0.7	18.9%

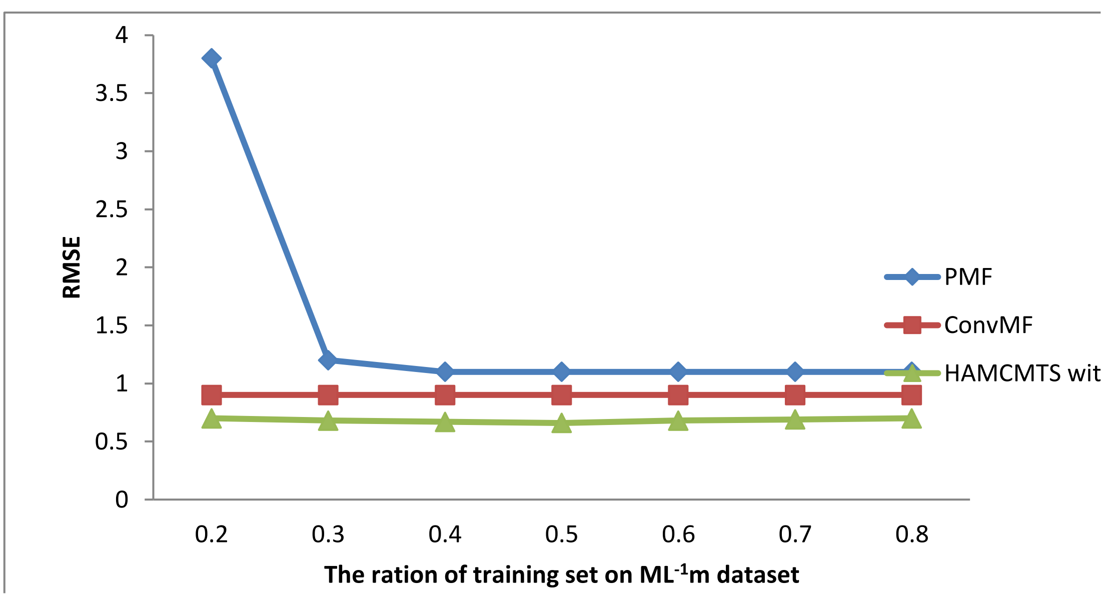
5.2 LBO

Researchers employ a Gaussian Process before the Morkov kernel for Bayesian optimization. To create the mixed acquisition functions, researchers changed the publicly available BO package. Depending on the open-source package Spearmint, all previous hyper-parameters were updated & established throughout the iterations. Researchers normalize the function values, similarly in Spearmint, to make the optimization invariant to the scale of the method range. Every iteration, researchers center an observed method range by removing the dividing & the mean by their normal deviation. Researchers next fit a GP for such rescaled divide & method range researcher Lipschitz constant estimation by the standard deviation to adjust for the Lipschitz constant estimate. Within every cycle, researchers utilize direct and optimized acquisition methods. Although this would be a common choice in current BO research, researchers believe that Lipschitz data might boost performance when utilizing different acquisition function optimization approaches like discretization, adaptive grids, & other gradient-based techniques.

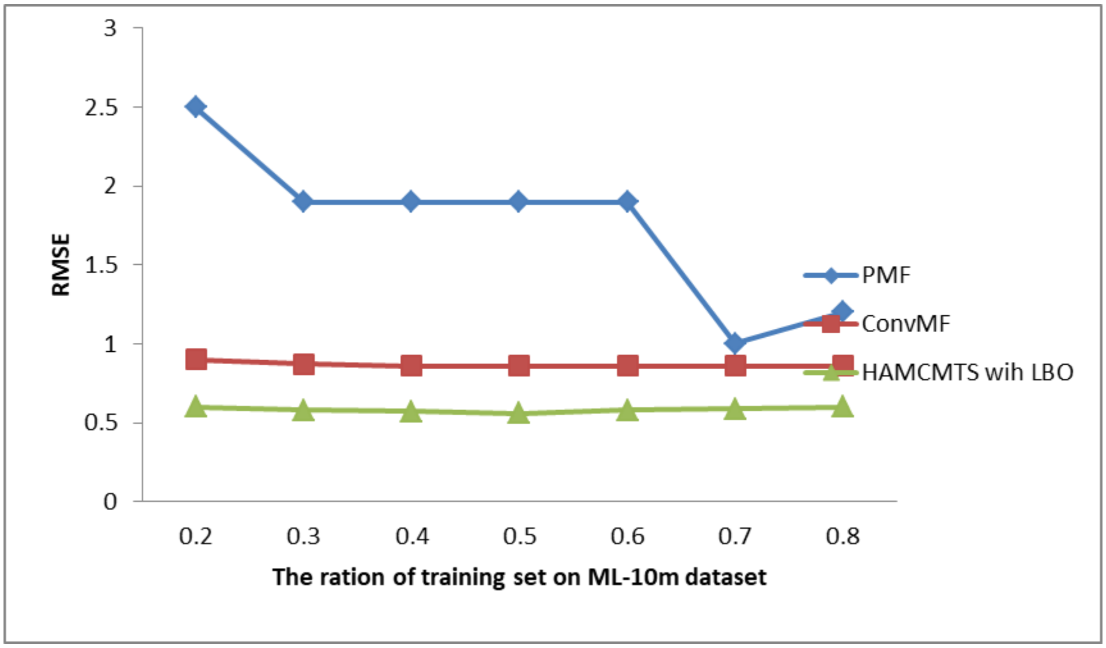
On every four iterations of BO, instead of improving the acquired product, humans should choose variables that are the effect to assess to guarantee that Bayesian optimization wouldn't get caught in sub-optimal maximum. As a result, the optimal technique was "harmless," in the view that BO does not outperform random checks. These have grown prevalent in current BO algorithms; therefore we've included an "investigation" stage for all of them to keep the comparisons equitable. That's worth noting that throughout the situation of LBO, humans might have to ignore sample points till one meets the Lipschitz inequality. In reality, researchers discovered that both randomized search standardization & repetitions were required for favorable performance. 4 The standard deviation of the error value vs the number of objective functions were plotted in every one of these images, which have been average across 10 different trials.

5.3 Performance Comparison

The effectiveness of HAMCMTS & the other 2 standards on RMSE could be seen in Figure 6(a). On average, HAMCMTS outperforms the other two sets of data. It shows that HAMCMTS could accurately capture the rising aspects of the items article's contextual information, resulting in greater suggestion effectiveness. PMF seems to be a participatory post-processing recommended system that would be widely used. By assessing rating information & excluding any extraneous information, CF-based methods could suggest things to a customer. As a result, giving suggestions to a customer with minimal scores was tough for CF. Even if the rating information & is HAMCMTS are incomplete, HAMCMTS greatly beats PMF, as seen in Figure 6(b) It demonstrates how product descriptions could be helpful info. ConvMF also utilizes a typical CNN method to recover a distinctive feature of the document, even though it may collect the context data of the product file by leveraging textual information to measure predictive performance Figure 6(c). HAMCMTS, in contrast to ConvMF, violates the CNN module's predefined geometry & achieves unconstrained structure morphing of the sample grids. To acquire a greater understanding of the product description, HAMCMTS could test characteristics at various positions in the product paper data sources. HAMCMTS provides the greatest results, as seen in Figure 6, suggesting that CNN seems to be a basic, effective deep network structure



(a)



(b)

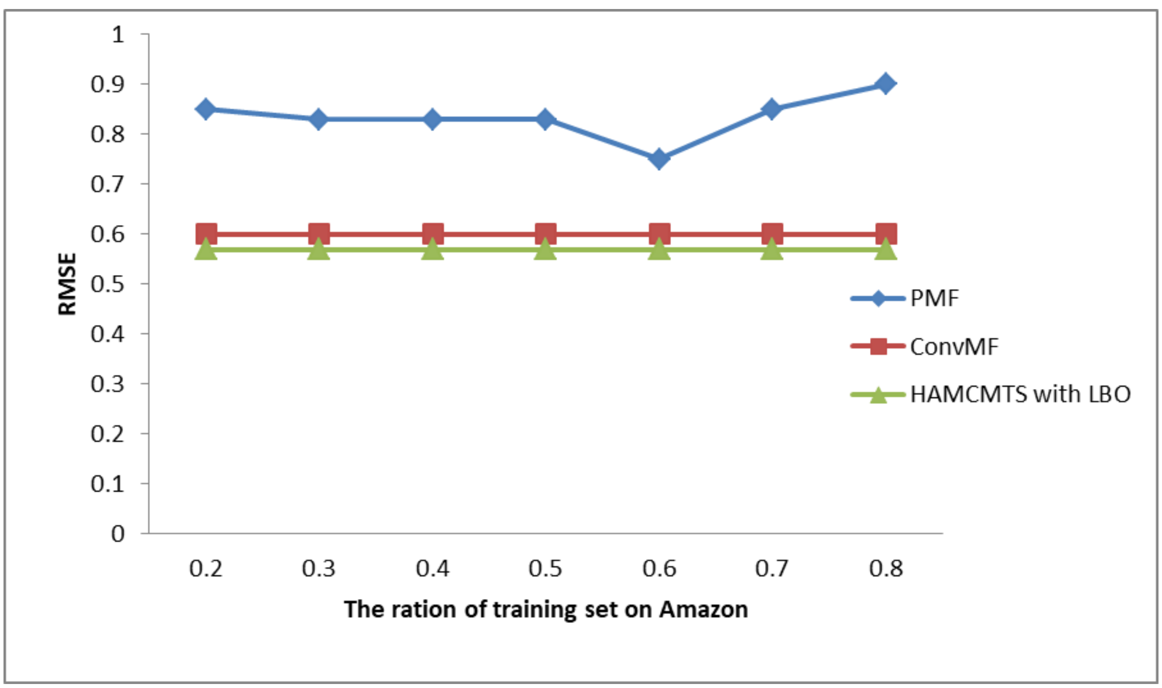
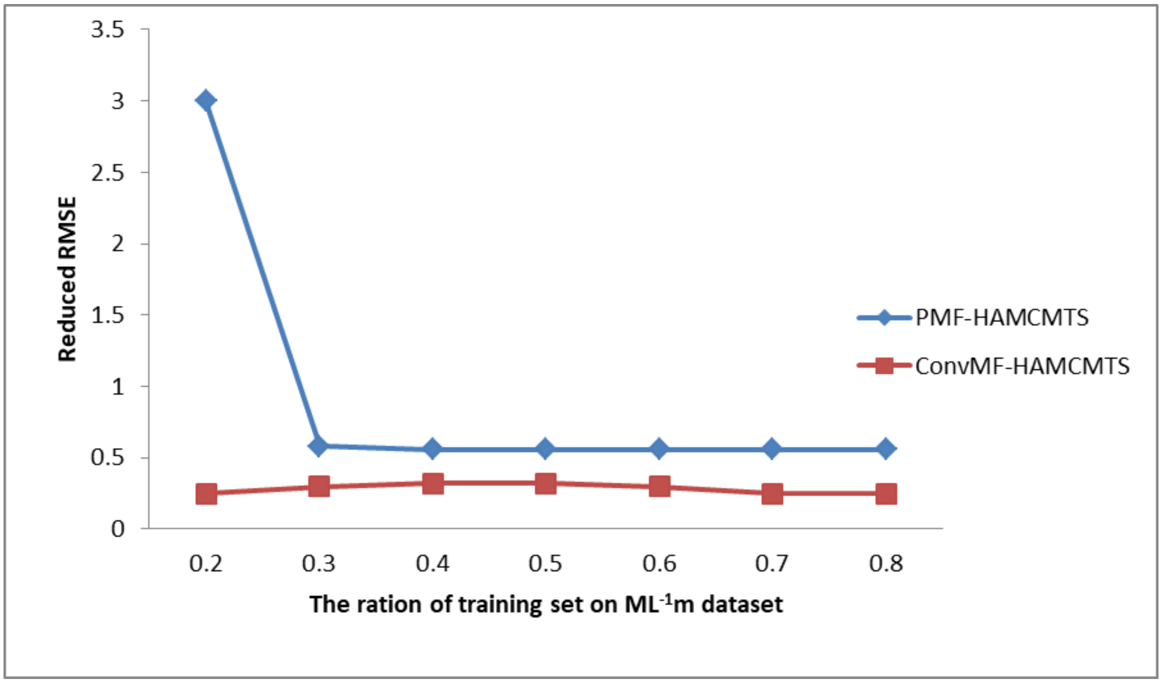


Figure 6: Comparison of RMSE Proposed method with other methods

With three different sets of data of ML^{-1}m, ML^{-10}m, and Flipkart, the lower RMSE of HAMCMTS relative to PMF & ConvMF was illustrated in Figure 7. The variation among the RMSE of PMF & the RMSE of HAMCMTS, as well as the differential among the RMSE of Comm. & the RMSE of HAMCMTS was referred to as the decreased RMSE. It shows that with fewer scores, a larger decrease may be achieved, demonstrating that HAMCMTS could solve the scalability issue.


Reduced RMSE
3.5
3
2.5
2
1.5
1
0.5
0
0.2
0.3
0.4
0.5
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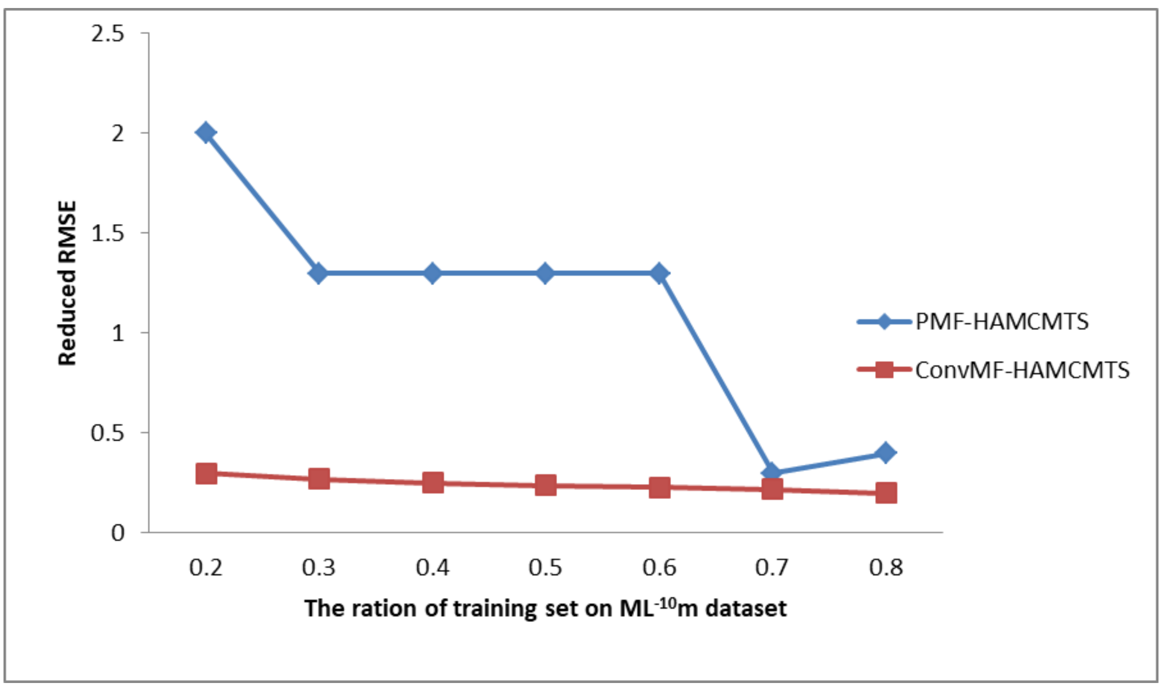
0.7
0.8
The ration of training set on ML-1m dataset
PMF-HAMCMTS
ConvMF-HAMCMTS


Reduced RMSE
2.5
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The ration of training set on ML-10m dataset
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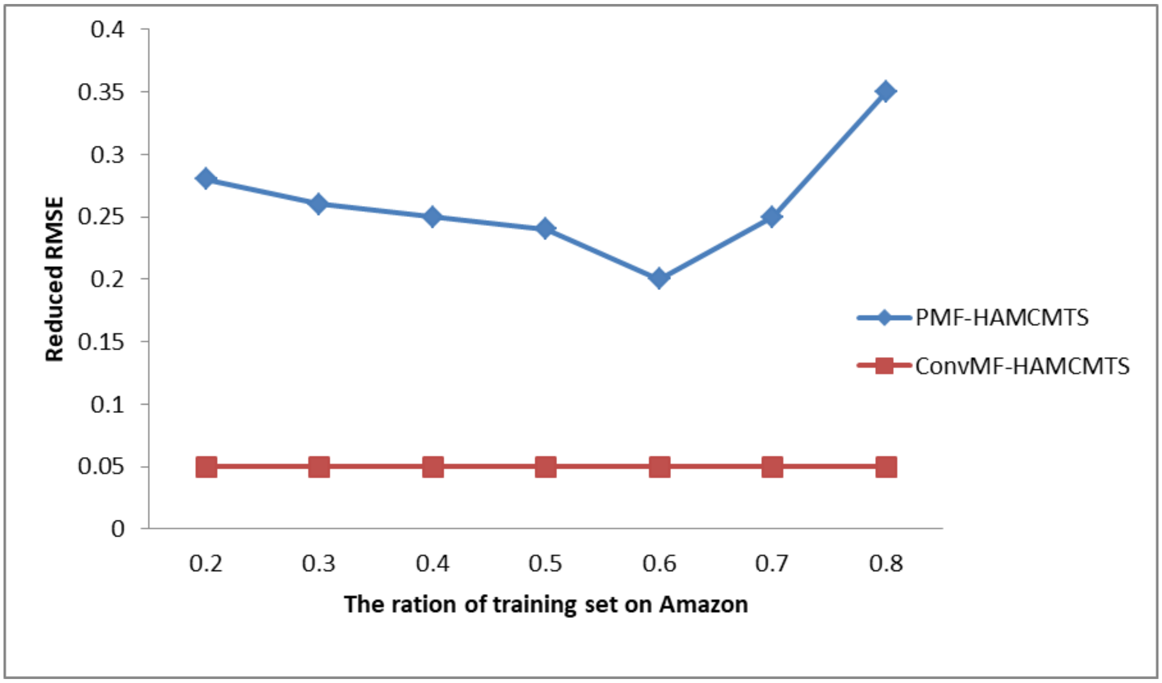

Figure 7: Proposed system with existing datasets

5.4 Discussion

In this study, researchers show how to integrate Lipschitz inequality to some of the most popular BO techniques in a simple approach. Our tests demonstrate that this frequently makes a significant difference, & in the worst-case scenario, an operates similarly to the normal BO technique. Even though they have just looked at four of the most basic acquiring processes, it appears that these disparities might be applied to additional acquisition features as well. Data acquisition methods like entropy searches & their latest modifications, for instance, rely on sampling a functionary from the GP, which was why researchers employed Thompson activities planned. A systematic investigation among those data learning processes was left to future studies. Researchers also predict the Lipschitz inequality to be useful in other situations, such as LBO with restrictions, LBO approach depends on other class labels, such as neural networks or regression trees, & methods that assess many xt at once. Lastly, 1st Bayesian optimization approaches have recently gained popularity. The descending lemma could be used to establish Lipschitz bounds that seem to be dependent on both response values & gradient if the gradient was Lipschitz continued. The RS provides a user-friendly experience by displaying customers who have similar interests & traits. On the OSN, however, the RS could locate the customer peers. In the RS, the PHP program code & JSON were employed. Since it records certain common user attributes retrieved from the OSN, like identity, gender, quality of interpersonal, & age, the customer must supply an OSN name to register.

6. Conclusions

A unique HAMCMTS method, was used to tackle this optimization challenge. Experiments demonstrated that AMCMTCS performs on a range of large scales, but at a much higher computing cost. These findings show that the existing AMCMTCS solution was better suited for issues involving computationally demanding rollout simulations. Using improved reaction sequencing, this research exhibited considerable improvements to HAMCMTS. Even with Gaussian Process assumptions, straight use of BO could result in a massive rise in processing cost, according to the research. More ways for reducing computing costs would be investigated in the coming, including through different distributional models. Researchers also looked into deforming able convolution extracting features at various positions for an input feature map, &humans suggested HAMCMTS for fully use context data of product documents. Researchers used CNN with phrase anchoring to combine with PMF to collect context data in delivering the documents for grade predictions. Rigorous testing on the three real-world sets of data revealed that HAMCMTS-LBO exceeds the standards considerably.

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