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Efficient and Scalable Matrix Factorization Transfer with Review Helpfulness for Massive Data Processing

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Abstract We explore the sparsity problem associated with recommendation system through the concept of transfer learning (TL) which are normally caused by missing and noisy ratings and or review helpfulness. TL is a machine learning (ML) method which aims to extract knowledge gained in a source task/domain and use it to facilitate the learning of a target predictive function in a different domain. The creation and transfer of knowledge are a basis for competitive advantage. One of the challenges prevailing in this era of big data is scalable algorithms that process the massive data in reducing computational complexity. In the RS field, one of the inherent problems researchers always try to solve is data sparsity. The data associated with rating scores and helpfulness of review scores are always sparse presenting sparsity problems in recommendation systems (RSs). Meanwhile, review helpfulness votes helps facilitate consumer purchase decision-making processes. We use online review helpfulness votes as an auxiliary in formation source and design a matrix transfer framework to address the sparsity problem. We model our Homogenous Fusion Transfer Learning approach based on Matrix Factorization HMT with review helpfulness to solve sparsity problem of recommender systems and to enhance predictive performance within the same domain. Our experiments show that, our framework Efficient Matrix Transfer Learning (HMT) is scalable, computationally less expensive and solves the sparsity problem of recommendations in the e-commerce industry.

Keywords: *fusion, transfer learning, sparsity, helpfulness*

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1. Introduction

Massive data analytics is aimed at making sense of data by applying efficient and scalable algorithms on big data for its analysis, learning, modelling, visualization and understanding. this requires the design of efficient and effective algorithms and systems to integrate the data and uncover the hidden values from it. It also requires methodologies and algorithms for automatic or mixed-initiative knowledge discovery and learning, data transformation and modelling, predictions and explanations of the data [1,2]. Online purchasing at various e-commerce sites like amazon, Netflix are crowded with chunks of data. Consumer purchasing decision making of such online products are immensely affected by their reviews and its associated information in such massive data environments [3,4], in such a way that, information overload has now become a constraint to consumers daily [5]. In this paper we focus on the sparsity problem that arises with review helpfulness giving rise to sparse matrix. the sparsity problem originates when available data are insufficient for identifying similar users or we can say neighbours and it is a major issue since it limits the quality of recommendations and the applicability of collaborative filtering in general. The main objective of our work is to develop an effective approach that provides high quality recommendations even when sufficient data are unavailable [6]. We use matrix factorization integration to reduce the sparsity using homogenous transfer learning paradigm. This on one hand must provide valuable product related information for consumers which in the long run affect the quality of recommendation system algorithms [7]. Consequently, researchers from diverse fields have explored the most efficient and effective ways of predicting quality recommendations. One of such paradigms in recent times has been transfer learning [8,9,10] from a psychological point of view, transfer learning is the study of the dependency of human conduct, learning, or performance on prior experience [11]. For instance, if one is good at coding in object oriented programming coding, may learn python programming language principally. Our main motivation for application of transfer learning in the recommender system field is the need for machine learning methods that retain and reuse previously learned knowledge such that intelligent agencies can adapt to new environment or novel tasks effectively and efficiently with little human supervision [12]. A lot of work on transfer learning has concentrated on the use of rating scores to make their arguments. We make our arguments on review helpfulness which is defined as the extent to which an online review helps facilitate consumer purchase decision-making processes [13]. Generally, consumers often seek online product reviews to help make purchase decisions [14]. So how do they judge whether a review is helpful or not? [15] Suggests that, consumers tend to judge review helpfulness based on two important features; the extent to which the provided information in a review familiarizes consumers with the product and the perceived credibility of the provided information. This idea presupposes that, if one wants to know the impact of transfer learning in a customer data from social networks, modelling with review helpfulness is worthwhile [16]. [17] used uncertain ratings for the transfer by integrating factors. In this paper, we go one step beyond and study a new problem with indecisive review helpfulness via homogenous transfer learning techniques. This research contributes to literature on review helpfulness in a fact that, to the best of our knowledge, this study is among the first to explore reviews' helpfulness effects from the perspective of transfer learning. Our findings suggest that review helpfulness is an important predictor for recommendation prediction efficiency in solving the sparsity problem.

1.1. Related Works

Transfer learning as an intelligent component in recommender systems has gained extensive interest in both academia and industry, and have been applied in the recommender system field. There are numerous existing works that are relevant to ours. Transfer learning approaches are proposed to transfer knowledge in latent feature space [18,19,20]. Convolutional Neural Network (CNN) to explore breast mass Lession in classification in mammograph through transfer learning was proposed by [21] and proved effective. [22] proposed in-domain collaborative filtering which successfully improved the predictive performance of collaborative filtering (CF) for sparse data by transferring patterns across domains. Other related transfer applications in the collaborative filtering field which is not limited to the field are; compressed rating patterns [23], Behavior prediction [24], personalized e-learning [25], and they all relate to our research. In collaborative filtering, transfer learning methods can be adaptive [26,27] which tends to use auxiliary social relations and extend the rating generation function in a model-based collaborative filtering method. [28] proposed optimized measures through transfer to solve a recommendation problem reduce GHG and pollutant emissions through a LUTI modeling approach. [17] on the other-hand used point-wise virtual ratings from sentimental polarities of users reviews on items.

[29] mined effective video social recommendation through transfer learning, which are then used in memory-based collaborative filtering methods for video recommendation. [17] proposed TIF which can be considered as a rating instance-based transfer for uncertain ratings in collaborative recommendation of which our research falls in line with though we are more concerned about indecisiveness with regards to review helpfulness within the same domain of a high involvement product; automotive in a social network platform; Amazon. Transfer learning applications include the paper by [30] which uses transfer learning for atmospheric dust aerosol particle classification to enhance global climate models. Being able to identify areas of low income in developing countries is important for disaster relief efforts, food security, and achieving sustainable growth.

Matrix Factorization models are in recent times applied in the domain of transfer learning and has improved recommendation algorithms; [41,42,43,44,45]. Matrix Convolutional Network was used for document context-aware by [32] that integrates convolutional neural network (CNN) into probabilistic matrix factorization (PMF) framework to solve sparsity issues. The work by [33] proposed a deep learning algorithm for transfer learning called a stacked denoising auto-encoder (SDA) to resolve the marginal distribution differences between a labeled source domain and an unlabeled target domain. Deep learning [34] algorithms learn intermediate invariant concepts between two data sources, which are used to find a common latent feature set.

The paper by [46] exploited meta- data in matrix factorization models for cross meta- data using fast alternating least squares to solve the sparsity problem of recommendation and was effective.

[47]. Hybrid of Particle Swarm Optimization and Gravitational Search Algorithm with Neural Networks all improved recommendation accuracy. The survey paper by [49] has it all. This motivates us to use matrix factorization model to explore transfer learning in a homogenous domain with our review helpfulness scores dataset.

However, it is evident that, these works do not address the indecisiveness associated with review helpfulness for recommendation problems with Matrix Factorization. We address the issue of Indecisiveness in a situation where a customer gives a review helpfulness score based on motivation from a friend or based on reviews posted by social relations. This implies that, reviews or rating scores are most at times positively motivated or induced by close relations or by related rating or reviews so for a high involvement products [50] like a house, an automotive or a computer system, such decisions are highly influenced by the outlined problem of indecisiveness. Product involvement refers to a consumer's perceived importance of, and interest in, a product [51], which is a consumer-specific concept [52,53]. A product can also be classified as high or low-involvement based on some of its characteristics such as cost and complexity which contribute to consumer's involvement in the product. [54] posit that durable products with complex functionality, high price and long life generally have higher levels of consumer involvement in the purchase decision, thus a wrong purchase decision leads to a high sunk cost. For such reasons, they are normally classified as high-involvement products.

We are more concerned about indecisiveness with regards to review helpfulness within the same domain of a high involvement product; automotive in a social network platform; Amazon. Social network application in transfer learning is a gap as far as we know and we wish to fill that gap. In this paper, we develop a novel approach known as Homogenous Matrix Transfer (HMT) to transfer supplementary data consisting of indecisive review helpfulness as constraints to improve the predictive performance in a target collaborative filtering problem within the same domain. Our contributions are as follows;

Most transfer learning papers in the recommendation system field are often limited to the transfer of homogeneous user feedback.

1. We propose a new framework to combine supplementary review helpfulness votes as constraints into the target matrix factorization problem efficiently through Homogenous transfer methodology.
2. An expected helpfulness for each review helpfulness is automatically learned for transfer.
3. The constraints and a penalty term for those violating the constraints are relaxed, then an optimization problem via stochastic gradient descent (SGD) is solved with convergence guarantee. We conduct empirical baseline comparison of HMT over other baseline frameworks

1.2. Motivation

A lot of work on Transfer learning has concentrated on rating scores to make their arguments leaving an important Review helpfulness is defined as the extent to which an online review helps facilitate consumer purchase decision- making processes. In general, consumers often seek online product reviews to help make purchase decisions. So how do they judge whether a review is helpful or not? A survey on literature suggests that consumers tend to judge review helpfulness based on two important features; the extent to which the provided information in a review familiarizes consumers with the product and the perceived credibility of the provided information. However, online shopping is actually becoming expedient to consumers as it helps them to choose products based on their reviews. The remainder of this paper is organized as follows. In the next section (2) present factor effect of online reviews whiles introducing the methodology applied. Section (3) talks about problem formulation and introduction of our learning algorithms. Section (4) involves Experiments and discussion of results. The last section gives the conclusion and suggestion for future work.

1.3. Methodology

The big data environment makes it possible for homogenous transfer methodology to be applied. The numerous and available big data repositories are available to such an extent that, there is a desire to use this abundant resource for machine learning tasks, avoiding the cost and time involved in collection of new data. If there is available dataset that is drawn from a domain that is related to, but does not exactly match a target domain of interest, then homogeneous [55] transfer learning can be used to build a predictive model for the target domain [56,57,58] as long as the input feature space is the same.

A survey paper [35] has it all, explaining in-domain and heterogeneous transfer domains. This dataset used in this paper contains product reviews and metadata from Amazon (https://snap.stanford.edu/data/), including 142.8 million reviews spanning May 1996 - July 2014 [59] which is about 4.5 GB of data. We preprocess the automotive datasets as follows; the helpfulness data sets were in this format; [0.5], [10,32]. We reformatted the data and converted all figures into decimals numbers for the purpose of our research.

We thus obtained figures ranging between (0.0-1.0.). The data was found to be really sparse. One of the challenges facing big data processing is scalability. Thus parallel processing is required and our data partitioning algorithm solves that problem in 2. In the processing of massive the datasets as it is in our case, we imperatively employ data partitioning strategy of breaking down data into various modules for easy processing, which makes it computationally less expensive. Data is divided into 3-parts for such purpose, algorithm (2) shows our splitting algorithm.

2. Problem Formulation

In the context of this work, we wish to state that, the helpfulness matrix is sparse, we formulate our problem as follows;

a. Helpfulness Matrix of target –user;

$$H = [\mathrm{h}_{ui}]_{n\times m} \in \{0.1-1.0, \kappa\}^{n\times m}$$

Where κ is the missing values?

Indicator Matrix; $D = [\mathrm{x}_{ui}]_{n\times m} \in \{1.1 \le \mathrm{x} \le 5\}^{n\times m}$

Denoting whether entry (u,i) is observed, $(y_{ui} = 1.1)$ or not $(\mathrm{y}_{ui} = 5)$ and $\Sigma_{u,i} y_{ui} = t$

b. Supplementary user-item indecisive Helpfulness Matrix ; $\tilde{H} = [\tilde{\mathrm{h}}_{ui}]_{n\times m} \in \{\lfloor a_{ui}, \mathrm{b}_{ui} \rceil, \kappa\}^{n\times m}$

With $\tilde{t}$ observations, the entry $[a_{ui}, b_{ui}]$ denotes the range of a decisive distribution for the corresponding helpfulness located at (u,i), where $a_{ui} \le b_{ui}$. κ is the missing value . The corresponding indicator Matrix; $\tilde{H} = [\tilde{\mathrm{h}}_{ui}]_{n\times m} \in \{1.1 \le \mathrm{x} \le 5\}^{n\times m}$ with $\Sigma_{u,i}, \tilde{\mathrm{h}}_{ui} = \tilde{t}$ is one by one mapping between users and items of $H, \tilde{H}$.

The main objective is to predict the missing values of H by exploiting indecisive helpfulness votes in $\tilde{H}$.

We propose to solve the optimization problem;

$$\sum_{u=1}^{n} \sum_{i=1}^{m} y_{ui} (\Sigma_{ui} + \mathrm{H}_{ui}) \text{ s.t.}$$

$$\hat{\mathrm{h}}_{ui} \in C(\mathrm{a}_{ui}, \mathrm{b}_{ui})$$

$$\forall\, \mathrm{x}_{ui} = 1, u = 1, \ldots \mathrm{n}, \mathrm{i} = 1 \ldots, \mathrm{m}$$

where the supplementary domain knowledge involving indecisive ratings is transferred to the target domain via fusion of constriants into the target matrix factorization problem;

$$\hat{\mathrm{h}}_{ui} \in C(\mathrm{a}_{ui}, \mathrm{b}_{ui}), \mathrm{y}_{ui=1}$$

The optimization problem with hard constraint $\hat{h}_{ui} \in C(a_{ui}, b_{ui})$ is intractable, so additional penalty term is introduced

$$\min u_u, v_i, b_u, b_i, u \sum_{u=1}^{n}\sum_{i=1}^{m}\begin{bmatrix} x_{ui}(\Sigma_{ui} + H_{ui}) \\ +\lambda\, \tilde{h}_{ui}(\tilde{\Sigma}_{ui} + \tilde{H}_{ui}) \end{bmatrix}$$

$\tilde{\Sigma}_{ui}$ involves predicted helpfulness, $\hat{h}_{ui}$ and the indecisive helpfulness $\lfloor a_{ui}, \overline{b_{ui}} \rfloor$. λ is the trade-off parameter to balance the two loss functions for target data and supplementary data.

2.1. Stochastic Gradient Descent Modelling

$$g_{ui} = \min_{u_u, v_i, b_u, b_v, \mu} \sum_{u,i}[x_{ui}(\tfrac{1}{2}(h_{ui} - \hat{h}_{ui})^2 + \frac{\alpha_u}{2}\| \mu_{u|} \|^2$$

$$+\frac{\alpha_v}{2}\| v_i \|^2 + \frac{\beta_u}{2} b_{u^2} + \frac{b_v}{2} b_{v^2} + \lambda \tilde{h}_{ui}(\tilde{\Sigma}_{vi} + \tilde{H}_{ui})]$$

Where $\hat{\gamma}_{ui} = \mu + b_u + b_i + u_u v_i^T$

Finding the partial derivatives,

$$\begin{aligned} \frac{\partial g_{ui}}{\partial u_u} &= \{x_{ui}[-(\gamma_{ui} - \hat{\gamma})v_i + \alpha_u u_u] \\ &= \{\tilde{h}_{ui}[-(\tilde{\gamma}_{ui} - \hat{\gamma})v_i + \alpha u_u].\lambda \end{aligned} \tag{4}$$

$$\begin{aligned} \frac{\partial g_{ui}}{\partial u_u} &= \{x_{ui}[-(\gamma_{ui} - \hat{\gamma}_{ui})\, u_u + \alpha_v v_i] \\ &= \{\tilde{h}_{ui}[-(\tilde{\gamma}_{ui} - \hat{\gamma}_{ui})\, u_u + \alpha v.v_i].\lambda \end{aligned} \tag{5}$$

$$\begin{aligned} \frac{\partial g_{ui}}{\partial u_u} &= \{x_{ui}[-(\gamma_{ui} - \hat{\gamma}_{ui}) + \beta_u b_u] \\ &= \{\tilde{h}_{ui}[-(\tilde{\gamma}_{ui} - \hat{\gamma}_{ui}) + \beta_u . v_u].\lambda \end{aligned} \tag{6}$$

$$\begin{aligned} \frac{\partial g_{ui}}{\partial u_u} &= \{x_{ui}[-(\gamma_{ui} - \hat{\gamma}_{ui}) + \beta_v b_v] \\ &= \{\tilde{h}_{ui}[-(\tilde{\gamma}_{ui} - \hat{\gamma}_{ui}) + \beta_v . v_v].\lambda \end{aligned} \tag{7}$$

$$\frac{\partial g_{ui}}{\partial u_u} = \{x_{ui}[-(\gamma_{ui} - \hat{\gamma}_{ui})] = \{\tilde{h}_{ui}[-(\tilde{\gamma}_{ui} - \hat{\gamma}_{ui}).\lambda. \tag{8}$$

For $u_u = u_u - \eta.\frac{\partial g_{ui}}{\partial u_u}$

$$v_i = v_i - \eta.\frac{\partial g_{ui}}{\partial v_i}$$

$$b_u = \ldots$$

$$b_v = \ldots$$

$$\mu = \ldots$$

η denotes the learning rate

2.1.1. Algorithm 1

1. Input the target Helpfulness Matrix H,
the supplementary user-item indecisive helpfulness Matrix $\tilde{H}$
2 Output the expected latent feature vector u_u and bias b_u ,latent specific feature vector v_i and bias b_i the global average , where u = 1; : : : ; n, i = 1,…, m.
For t = 1; : : : ; T
For iter = 1; : : : ; f + ~f
a. Pick a helpfulness vote randomly from H or $\tilde{H}$
b. If x_{ui} = 1, estimate the expected helpfulness vote γ_{ui} as shown in Eq.(4);
c. Calculate gradients.
d. Update parameters.
End for.
Reduce the learning rate η and indecisive factor Γ
End for

2.1.2. Experiments and Analysis

The experiments are performed as follows: The prediction performance of HMT, and TIF are shown in Figure 1 and in Table 1. We can have the following observations, HMT is significantly better than TIF in the data sets, which clearly shows the advantage of the proposed transfer learning approach in leveraging auxiliary indecisive review helpfulness; and HMT, values between (0.5) and (1) made impressive performance.

To address the sparsity problem of Collaborative Filtering, many researchers have effectively improved and proposed such methods based on single domain framework. However, we think such frameworks are subject to quality of the target domain. In that, there is the possibility of being matched to sparse target data. In our sparsity scenarios, we solve the problem during transfer where knowledge learnt are transferred from the supplementary data to the target data. Our preprocessing criteria removes all negative transfers which is a challenge for transfer learning and makes it ideal for homogenous transfer in an efficient manner. This also ensures more knowledge are transferred from the supplementary data to the target data ensuring scalability in the massive data era. From the results, it is evident that; HMT performs best on all user groups; and are more useful for users with fewer review helpfulness, which shows the effect of sparsity reduction of transfer learning methods in collaborative filtering. The results of RMSE (Table 1) is calculated over HELPFULNESS instances of users in the same group.

2.1.3. Algorithm 2

Input; $H \in T^{x,y,z}, S$
Output; $H^S \in T^{\frac{x}{s} \times y \times z}$
a. Initialize; $x = 0$
b. For $S = 1, \ldots, s$, do
c. $x = \lfloor S\frac{x}{s} \rfloor$
d. $H^S \leftarrow H(\text{xfirst}, +\text{x}; \text{xfirst};,;)$
e. returnH^S
f. End for

We further generate five copies of training data and test data, where in each copy 2/3 are used for training and 1/3 for test. For each copy of training data, we take 50% helpfulness as supplementary data, and the remaining 50% helpfulness as target data for each copy of supplementary data. We compare the TIF results with our algorithm.

Table 1

ITERATIONS	RSVD	TIF	HFTLEARN
20	0.84	0.83	0.81
40	0.83	0.82	0.79
60	0.82	0.79	0.77
80	0.81	0.78	0.75
100	0.8	0.77	0.73

Thus HFTLEARN performed very well above the named baselines.

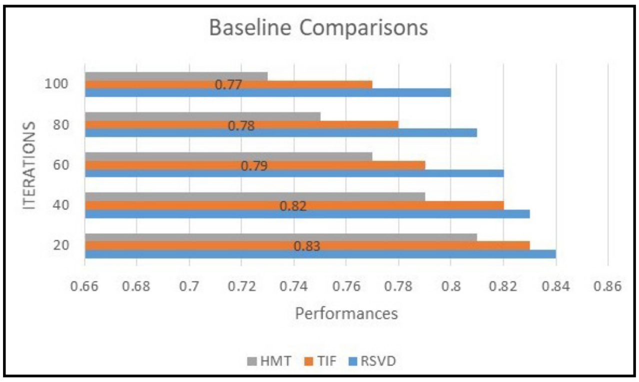

Figure 1.

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2.2. Root Mean Squared Error

We randomly select x as the training set and report the prediction performance on the remaining 1 - x testing set. The metric root mean squared error (RMSE) for Helpfulness Prediction is defined as

$$\sqrt{\sum_{vi,vj\in T} I(R_{i,j} - \hat{S}_{i,j} / |\mathrm{T}|}$$

where T and |T| is the test set and its cardinality. A smaller RMSE means a better prediction performance. The results from (comparison table), HMT giving higher prediction performances than other baseline algorithms. Thus HMT performed very well above the named baseline algorithms**.**

3. Conclusion

This paper presented a new framework of transfer learning in an e-commerce set up. It is usually customary in the field of recommender systems to define collaborative filtering" as a method of making predictions. Which implies "filtering" information regarding the interests of a user by collecting or, more precisely, "collaborating" between many people with similar interests, and subsequently making recommendations based on this. More generally, collaborative filtering" refers to the process of "filtering" information and or patterns using techniques involving "collaboration" among multiple viewpoints. In this sense, it is clear how transfer learning can be utilized for collaborative filtering, as was demonstrated in this research. TL based pattern sharing filters the relevant users and products, then fuses the information of the entities in the groups. We have applied an existing theory of transfer learning paradigm in recommendation prediction. Our data split mechanism is also scalable. This research contributes to literature on review helpfulness as far as we are concerned holding to the fact that, to the best of our knowledge, this study is among the first to explore review helpfulness from the perspective of Transfer Learning and it solves the sparsity problem in a simple manner. Our findings suggest that review helpfulness is an important predictor in the recommender system field, and so propose that, if we want to improve prediction performance, such information on review sides must be explored. Our proposed framework "MT" solves the sparsity problem and improves prediction in recommendation system as depicted in the experiments (Comparison Table and Graph). Review helpfulness made impressive performance in terms of prediction accuracy and thus must not be ignored in any recommendation decision making. We therefore propose homogenous matrix factorization transfer with parallel processing which is a challenge in the massive data era through our data partitioning mechanism Algorothm 2.

Conflict of Interests

As far as this research paper is concerned, we declare that, there is no conflict of interest whatsoever to any organization or person towards it's publication.

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