Personalized recommendation for extremely sparse and large scale data

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1. Introduction

Recommendation systems is a primary example of the mainstream applications of large scale data mining. Applications such as online adversiting, e-commerce website, personalized search, social network and etc, make use of similar techniques to mine very sparse and large scale data to better match users needs in a personalized fashion. How to provide effective personalzied recomendation for large scale and sparse data, becomes one of the most important research topics in the past few decedes.

Online adverstising, one typical application of recommendation systems, is a multi-billion dollar business which accounts for majority of the revenue for companies like Google and Facebook. It is a very complicated ecosystem, and involves multiple players, including advertisers, publishers, end users and many others. It allows publishers in the network of content sites to serve automatic advertisements (for text, image, videos, or interactive media), which are targeted to site content and audience.

Take Google Adsense system [4] as an example, Figure 1 illustrates how it works in a netshell: *Publisher* posts content on the Internet, and insert a code snippet into its web pages. *User* visits the web page, which triggers the code snippet to pull relevant advertisements from Google Adsense servers, and show them on the same web page. If user click on the advertisement, the *advertiser* who created it will pay Google certain amount of money, and Google will share majority of that payment with the content publisher.

Google Adsense system generates billions of dollars each year, supports hundreds of millions of publishers on the Internet eco-system, and can reach more than 80% of all Internet users worldwide in more than 30 languages and over 100 countries.

Delivering the right marketing messages to the right users at the right time is of great importance to the success of online advertising system. It requires the advertisers to provide a good list of keywords, to match advertisements with web contents precisely, to increase the click through rate and get a better advertisement performance.

However, the reality is most advertisers are lack of experience to provide good keywords for their advertisements. Therefore, how to make best use of historical data to provide effective personalized keyword recommendations is crutial

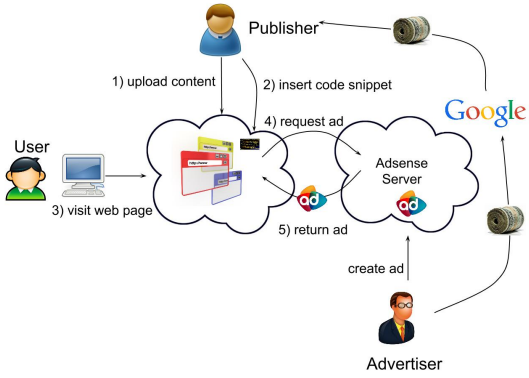

Figure 1. Google Adsense system work flow.

to the success of Adsense. There are mainly two types of approaches: A/B-testing and model based solutions.

A/B-testing [1] is widely used in online advertisement. It splits the web traffice into two parts: majority of the traffic uses the original keyword list to match advertisement, and the other small fraction of the trafic uses the new keyword list, which combine original keyword list along with some semantically relevant keywords. The experiments would be executed for some period of time, usually in days or weeks, and then compare the statistics. If the new list performs significantly better, we would surface this recommendation to the advertiser. The main drawback of this approach is the long turnaround time. Lots of business opportunities may be lost after days or weeks of experiments.

Model based solutions using collaborative filtering [2], [3] comes into the picture soon, which makes use of machine learning technology and predicts the performance of the new keyword list without running experiments. There are three type of collaborative filtering models that are commonly used, user neighborhood model (considering the similarity between users, in our case will be advertisers), item neighborhood model (considering the similarity between items, in oursecase will be keywords), and matrix factorization based model []. The matrix factorization based model has drawn a lot of attention recently due to its success in the Netflix Challenge []. It's proven to produce better estimates than user neighborhood or item neighborhood models, and can

handle sparse data set like the data in Netflix Challenge.

However, the data set we deal with is more than 100 times sparser than the Netflix data. We observe significant overfitting even with very strong regularization.

In this paper, we design a novel machine learning model (Similarity powered Pairwise Amplifier Network, SPAN for short), which is resilient to extremely sparse data set and doesn't need long turnaround time in experiments. First, the complexity of the model (a.k.a. the number of parameters) grows with respect to observed data, not to the number of advertisers and number of keywords like matrix factorization based models. This makes our model resilient to extremely sparse data. Secondly, our training algorithm is based on gradient descent, which is easy to parallelize, and thus can handle very large scale data set. Thirdly, our model combines the user neighborhood and item neighborhood ideas in collaborative filtering smartly, where similarities are "learned" from training algorithm other than defining a global similarity metric for neighborhood. All these makes our model can efficiently handle extremely large scale sparse data in an cost-effective way.

In summary, our main contributions in this paper include:

- We successfully exploit the potential of improving personalized recommendation for extremely sparse and large scale data.
- We develop a nodel model which uses gradient descent to combine user based and item based recommendation in a multi-dimension way, hence control the complexity with respect to observed data with short turnaround time. We have implimented a distrubted training system that can handle large scale data set.
- We apply our model successfully to personalized keyword recoomendation system in Google Adsense. The solution can be easily leveraged in all other online recommendation applications.
- We conduct extensive comparison experiments with matrix factorization based methods and demonstrate that SPAN can effectively make personalized recommendation for extremly sparse and large scale data.

The remainder of this paper is organized as follows. We first formulate the problem in Section 2.1. Then we describe the details of our model, including the high-level workflow, intuition and assumptions, as well as different components of the model in Section 2. After that, we introduce the training algorithms in Section 3. We evaluate the effectiveness and robustness of the proposed approach in Section 4. The related works are reviewed in Section 5. Finally, Section 6 concludes the paper and discusses future directions of this study.

2. SPAN Model

Add section overview here

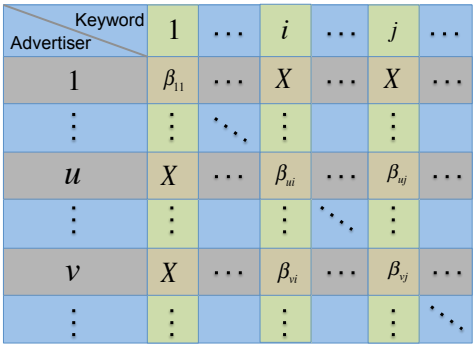

Figure 2. Matrix ??

2.1. Problem Formulation

We take same settings as other Colleborative Filtering algorithms, where the input keyword traffic data can be viewed as a matrix, as shown in Figure 2. Each row represents an advertisement and each column represents a keyword. If a keyword i is already associated with advertisement u, then we have some observed traffic value β_{ui}. Otherwise, no value is observed (noted as X). For convenience, we define the notations we will use through out this paper in Table 1. Specially u and v will be used for advertisers, while i and j will be used for keywords.

Notation	Description
N_a	total number of advertisements
N_k	total number of keywords
u	the uth advertisement, $u \in [1, N_a]$
i	the ith keywords, $i \in [1, N_k]$
Λ	missing values in data matrix M
$\Lambda_{(*,i)}$	missing values in the ith column of matrix M
$\Lambda_{(u,*)}$	missing values in the uth row of matrix M
Γ	observed (known) values in the matrix M
$\Gamma_{(*,i)}$	observed values in the ith column of matrix M
$\Gamma_{(u,*)}$	observed values in the uth row of matrix M
β_{ui}	observed value for cell (u,i) of matrix M
$\hat{\beta}_{ui}$	model estimated value for cell (u,i) of matrix M

TABLE 1. NOTATIONS FOR SPAN MODEL

The quality of the model is evaluated by the standard root mean square error (RMSE), which is

$$\sqrt{\frac{1}{N_a \times N_k} \sum_u \sum_i \left(\beta_{ui} - \hat{\beta}_{ui}\right)^2}$$

2.2. Model Intuition

Our model is inspired by the similar idea of collaborative filtering that the preference of a user on an item is predicted based on the preferences of other users with similar interests. There are mainly two categories of collaborative filtering, either in user-centric or item-centric manner:

- item-based collaborative filtering: build an item-item matrix determining relationships between pairs of items, then infer the tastes of the current user by

examining the matrix and matching that user's data, e.g. users who bought x also bought y

- user-based collaborative filtering: look for users who share the same rating patterns with the active user (the user whom the prediction is for). Then use the ratings from those like-minded users found in step 1 to calculate a prediction for the active user, e.g. people also looks at the following items

Both item-based and user-based models are trying to emphasize only one perspective of the problem, but did not consider the correlation cross them.

Is it possible to use the information from both dimensions to further improve the model's prediction performance?

The answer is positive. We approach this problem by mining the homogeneous similartiy across advertisement and keyword dimentions, in another word, similarity ratio of different keywords between similar advertisement should be close to each other. Instead of using only item-based or user-based method, it is a synthetic multi-dimension model, which evaluates the similarity cross item and user dimensions. Also, different from item-based or user-based method, which uses a predefine static similarity function and calculate the global optimal similarity, we are using a local optimal function, which can dynamic involving similarity using learned parameters, hence can support large scale data in an efficient computation cost.

The main idea of our model is illustrated by Figure 3, where u, v, w are advertisements, and i, j, k are keywords, and the value in each cell is the average daily clicks for the corresponding advertisement from the keyword query. Let's say we want to predict the average daily click value if we want to add keyword k to advertisement v. For keyword pair k and j, we observed ratio $20/12$ in advertisement u and $5/18$ in advertisement w. If we can derive the performance ratio between k and j in advertisement v, then we can make use of j's observed daily average clicks in v to give one estimate of k's daily average clicks in v. To do so, we introduce a set of parameters called *similarity*, one for each pair of advertisements, to capture how similar the performance ratios will be between advertisements. Let S_{uv}, S_{vw} be the similarity between u, v and v, w respectively. The estimate given by keyword pair k, j can be expressed as

$$6 \times \left(\frac{20}{12} \times S_{uv} + \frac{5}{18} \times S_{vw} \right) \div (S_{uv} + S_{vw})$$

Similarly, we can have another estimate by keyword pair k, i, which is

$$9 \times \left(\frac{20}{5} \times S_{uv} + \frac{5}{22} \times S_{vw} \right) \div (S_{uv} + S_{vw})$$

Now how do we combine these estimates? We introduce another set of parameters called *confidence*, one for each pair of keywords. Therefore, the final estimate can be represented as the linear combination of the above two estimates, weighted by the confidences of keyword pairs k, j and k, i. All the parameters are learned from SPAN trainer defined in Section 3. The details of parameters are covered in Section 2.3.

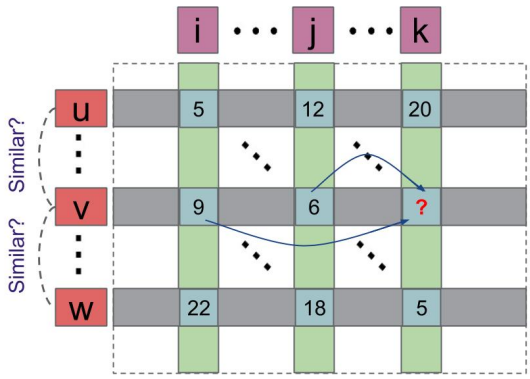

Figure 3. High level idea of SPAN model.

2.3. Model Details

There are two sets of parameters in SPAN model. One set is used to capture the similarity between different advertisement. The other set is used to weigh the importance of different ratios between keywords when calculating estimates. Please refer to the example in Section 2.2. Therefore, use data structure *Similarity Graph* to represent the first set of parameters, and *Pairwise Amplifier Graph* to represent the second set.

Similarity Graph is the graph which describes the similarity between different advertisers. To be more specific, it is a complete undirected graph $G_{\text{sim}} =< V, E >$, where V is the set of all the advertisers. For each edge in E, there is a value which represents how similar the corresponding two advertisers are with each other. Let θ_{uv} denote the similarity between advertiser u and v.

Pairwise Amplifier Graph contains all the ratio information between different pairs of keywords. It is defined as a directed graph $G_{\text{amp}} =< V, E >$, where V contains all the keywords , and E contains all pairs of keywords that have been targeted concurrently in at least one advertisement, $E = \{(i,j) \mid i \in [1, N_k], j \in [1, N_k], \exists u \in [1, N_a] \text{ s.t. } \beta_{ui}, \beta_{uj} \in \Gamma\}$. For each edge $(i,j) \in E$, there are a corresponding confidence value $conf_{ij}$ and an amplifier set $amp_{ij} = \{(a_u, gain^u_{ij}) \mid u \in [1, N_a], \beta_{ui}, \beta_{uj} \in \Gamma\} \cup \{(a_0, c_{ij})\}$, where $gain^u_{ij} = \beta_{uj}/\beta_{ui}$, and (a_0, c_{ij}) are just the bias terms which we will use later in the model.

Should we consider move feedforward estimate here, to show how model produces estimates?

3. Training Algorithm

The mainl workflow of SPAN model is summarized in Figure 4. The training dataset can be regarded as a sparse 2D matrix with known entries shown in Figure 2. Given the training dataset, the training process starts with a set

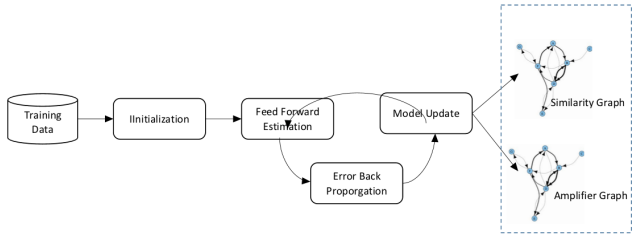

Figure 4. SPAN system overview.

of initial parameters, then there is an update loop between feeding forward estimation and backword propogation, in which *Feed Forward Estimation* uses the given data points to estimate the value of a target entry. *Error Back Propagation* updates current model parameters. The training process is in an incrementally update way, and generate the final model which is composed of similarity graph and pairwise amplifier graph. The learned SPAN model will be directly used to estimate missing values. In the following sections, we will discuss each component in details.

3.1. Feed Forward Estimation

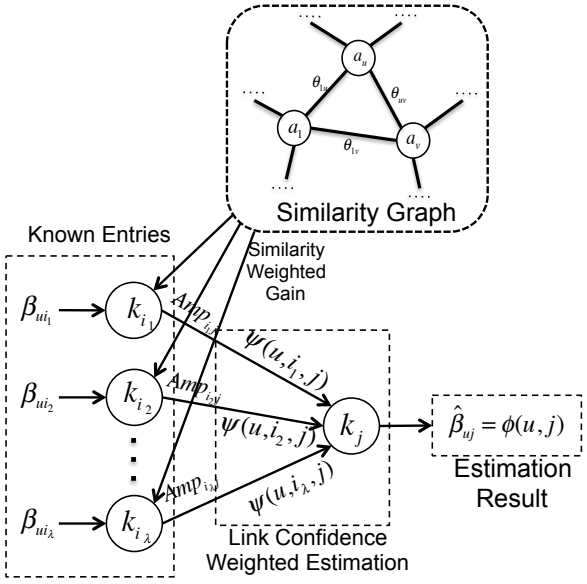

Figure 5. Feed Forward Estimation

Given particular values for initial parameters and the inputs data, to predict parameter settings that minimize the error, our model uses feed-forward network: the inputs feed into a layer of hidden units, which can feed into layers of more hidden units, which eventually feed into the output layer. Each of the hidden units is a squashed linear function of its inputs.

Our SPAN model uses known entry values $\{\beta_{ui_1}, \beta_{ui_2}, \cdots, \beta_{ui_\lambda}\}$ (where λ is the number of known entry values of advertiser u) to estimate the value of target entry β_{uj}. It uses feed forward network to estimate the parameters in a layer-by-layer way: takes known entry values as inputs, it goes through a two layers of calculation units to get the final estimated result. Similarity weighted sum of entry estimation (in Equation 2.) and a link confidence weighted sum of entry estimation (in Equation 1) are used to estimate the value of an unknown entry $\beta_{uj} \in \Lambda$.

As shown in Figure 5, the first layer make estimation of target β_{uj} using $\{\beta_{ui_1}, \beta_{ui_2}, \cdots, \beta_{ui_\lambda}\}$ separately with equation 1, which generates λ output estimated values. The second layer takes all the output estimations from the first layer $\{\psi(u, i_1, j), \psi(u, i_2, j), \cdots \psi(u, i_\lambda, j)\}$ as inputs to calculate the final prediction using equation 2.

$$\begin{cases} \psi(u,i,j) = \frac{\sum\limits_{v \in V} \theta_{uv} \cdot gain_{ij}^{v}}{\sum\limits_{v \in V} \theta_{uv}} \cdot \beta_{ui} \\ V = \{v | (a_v, gain_{ij}^{v}) \in amp_{ij}\} \end{cases} \tag{1}$$

$$\begin{cases} \hat{\beta}_{uj} = \phi(u,j) = \frac{\sum\limits_{i \in I} conf_{ij} \cdot \psi(u,i,j)}{\sum\limits_{i \in I} conf_{ij}} \\ I = \{i | \beta_{ui} \in \Gamma_{(u,*)}\} \end{cases} \tag{2}$$

3.2. Error Back Propagation

In Feed Forward Estimation process , we assume the similarity parameters of advertiser pairs (in Similarity Graph) and the link confidence parameters in the Pairwise Amplifier Graph are given. Indeed the model needs to learn these parameters from the training dataset using error back proprgation. The idea of error back propagation is very similar to artificial neural networks: for an entry in the training dataset, we hide this entry from the rest of the training dataset and use the feed forward estimation algorithm in Section 3.1 to estimate its value with the rest of the training dataset. Then we compare the true value of that entry with current estimation, and back propagate the estimation error (the deviation from estimated value to the true value) to update the parameters. The idea is shown in Figure 6. Gradient descent method [**?**] is used to optimize the model parameters, which calculates the gradient of a loss function with respects to all the weights in the network. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function.

Before developing the parameter update function, we need to calculate the derivative of the squared error function with respect to all the parameters in SPAN model, including both $\{\theta_{uv}\}_{u,v \in [1,N_a]}$ and $\{conf_{ij}\}_{(i,j):(k_i,k_j) \in E(G_{amp})}$.

The objective function of the parameter optimization problem is shown in Equation 3, which is the sum of squared estimation error for all the entries in the training dataset.

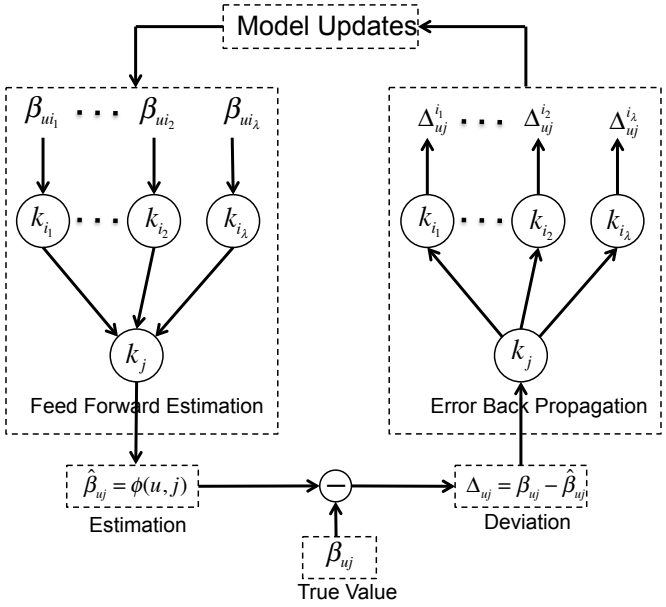

Figure 6. The Loop of the Parameter Update

$$
\begin{aligned}
J &= \frac{1}{2} \sum_{u,i:\beta_{ui} \in \Gamma} \left(\beta_{ui} - \hat{\beta}_{ui}\right)^2 \\
&= \frac{1}{2} \sum_{u,i:\beta_{ui} \in \Gamma} \left(\beta_{ui} - \phi(u,i)\right)^2 \\
&= \frac{1}{2} \sum_{u,i:\beta_{ui} \in \Gamma} \Delta_{ui}^2
\end{aligned} \tag{3}
$$

Where β_{ui} is the true value, and $\hat{\beta}_{ui} = \phi(u,i)$ is the estimated value given by Feed Forward Estimation algorithm we described in Section 3.1. The factor of $\frac{1}{2}$ at the beginning of the objective function is a constant factor which would simplify the expression after the differentiation operation. Noted that an arbitrary learning rate factor will be multiplied with this expression in our later learning process, so that it doesn't make any differences if a constant coefficient is introduced here.

With Equation 1, 2 and 3, the derivatives of our objective function with respect to parameters $\{\theta_{uv}\}_{u,v\in[1,N_a]}$ and $\{conf_{ij}\}_{i,j\in[1,N_k]}$ are

$$
\frac{\partial J}{\partial \theta_{uv}} = \sum_{j:\beta_{uj},\beta_{vj} \in \Gamma} \frac{\partial \left[\frac{1}{2}\left(\beta_{uj} - \hat{\beta}_{uj}\right)^2\right]}{\partial \theta_{uv}}
$$

and

$$
\frac{\partial J}{\partial conf_{ij}} = \sum_{u:(a_u, gain_{ij}^u) \in amp_{ij}} \frac{\partial \left[\frac{1}{2}\left(\beta_{uj} - \hat{\beta}_{uj}\right)^2\right]}{\partial conf_{ij}}
$$

With further formula deductions, we can have Equation 4 as the derivative result of the objective function with respect to $\{\theta_{uv}\}_{u,v\in[1,N_a]}$, and Equation 5 as the derivative result of the objective function with respect to $\{conf_{ij}\}_{i,j\in[1,N_k]}$.

$$
\begin{cases}
\frac{\partial J}{\partial \theta_{uv}} = \sum\limits_{j\in J} \sum\limits_{i\in I} \frac{-\Delta_{uj}^i}{\sum\limits_{v'\in V} \theta_{uv'}} \left(gain_{ij}^v \cdot \beta_{ui} - \psi(u,i,j)\right) \\
J = \{j | \beta_{uj}, \beta_{vj} \in \Gamma\} \\
I = \{i | \beta_{ui} \in \Gamma_{(u,*)}\} \\
V = \{v | (a_v, gain_{ij}^v) \in amp_{ij}\}
\end{cases} \tag{4}
$$

$$
\begin{cases}
\frac{\partial J}{\partial conf_{ij}} = \sum\limits_{u\in U} \left[-\frac{\Delta_{uj}}{\sum\limits_{i'\in I} conf_{i'j}} \left(\psi(u,i,j) - \phi(u,j)\right)\right] \\
U = \{u | (a_u, gain_{ij}^u) \in amp_{ij}\} \\
I = \{i : \beta_{ui} \in \Gamma_{(u,*)}\}
\end{cases} \tag{5}
$$

where Δ_{uj} is the estimation error and Δ_{uj}^i is back propagated error, their expressions are given by Equation 6.

$$
\begin{cases}
\Delta_{uj} = \beta_{uj} - \hat{\beta}_{uj} \\
\Delta_{uj}^i = \frac{conf_{ij}}{\sum\limits_{i':\beta_{ui'} \in \Gamma_{(u,*)}} conf_{i'j}} \cdot \Delta_{uj}
\end{cases} \tag{6}
$$

With the derivatives and back propagated errors given by Equation 4, 5 and 6, we can update the parameter of SPAN model in the Similarity Graph and the Pairwise Amplifier Graph using the gradient descent approach. Given a specific learning rate η, the changes of model parameters are equal to the product of the learning rate and the corresponding gradient value, multiplied by -1. Therefore, the parameter update function for training target β_{uj} can be expressed in Equation 7.

$$
\begin{cases}
conf_{ij} := conf_{ij} - \eta \cdot \frac{\partial J}{\partial conf_{ij}} \\
\theta_{uv} := \theta_{uv} - \eta \cdot \frac{\partial J}{\partial \theta_{uv}}
\end{cases} \tag{7}
$$

where $\frac{\partial J}{\partial conf_{ij}}$ and $\frac{\partial J}{\partial \theta_{uv}}$ are given by Equation 4, 5 and 6. Figure 6 shows the parameter update loop of the Feed Forward Estimation and the Error Back Propagation for a training target entry β_{uj}.

3.3. Training Algorithm for SPAN model

Combining the Feed Forward Estimation and Error Back Propagation, The training algorithm for SPAN model can be summarized in Algorithm 1.

The stop criterion for the training algorithm is a training error threshold: the training will stop if the training error drops to a specific value. Other criterion may also be used, such as maximum iteration number [**?**], error reduction rate threshold [**?**], the convergence of the parameters [**?**] and so on.

The training algorithm generates final SPAN model, which includes the Similarity Graph and Pairwise Amplifier Graph. To estimate unknown entries, we can just follow the Feed Forward Estimation described in Section 3.1, using the well-trained Similarity Graph and Pairwise Amplifier Graph.

Data: The set of given/known entries Γ in matrix M
Learning rate η
Result: $\{\theta_{uv}\}_{u,v\in[1,N_a]}$ in adgroups similarity graph
$\{conf_{ij}\}_{(i,j):(k_i,k_j)\in E(G_{amp})}$ in criteria pairwise amplifier graph
Initialization:

- initialize the pairwise amplifier set $Amp_{ij} = \{(a_u, gain^u_{ij}) \mid u \in [1, N_a], \beta_{ui}, \beta_{uj} \in \Gamma\} \cup \{(a_0, c_{ij})\}$ using $gain^u_{ij} = \beta_{uj}/\beta_{ui}$
- initialize parameters $\{\theta_{uv}\}$ in adgroup similarity graph using small random numbers when encountered.
- initialize parameters $\{conf_{ij}\}$ in criteria pairwise amplifier graph using small random numbers when encountered.

begin
  while *stop criterion not meet* **do**
    for *each* β_{uj} *in* Γ **do**
      /* SPAN Model feed forward estimation of training example β_{uj} */
      /* with Equation 1 and 2 */
      $\hat{\beta}_{uj} = FeedForwardEstimation(\text{SPAN Model}, u, j)$
      /* error back propagation using Equation 6 */
      $(\Delta_{uj}, \{\Delta^i_{uj}\}) = ErrorBackPropagation(\text{SPAN Model}, u, j, \hat{\beta}_{uj})$
      /* update SPAN model using gradient descent Equation 4, 5 and 6 */
      $update(\text{SPAN Model}, \Delta_{uj}, \{\Delta^i_{uj}\})$
    end
  end
  return (SPAN Model)
end

Algorithm 1: Training Algorithm for SPAN Model

3.4. Handling Large Scale Data

Algorithm 1 works well in most cases. However, as the data set become much bigger and less sparse, the iterative process of error back propagation based parameter update for SPAN model often take a great deal of time to completely go through the whole training set. Another advantage of our model is that it can handle large scale sparse data in an effective way. As we can see from Algorithm 1, the SPAN model updates can use different independent training samplesr. Thus, map-reduce techniques can be used to greatly decrease the amount of time that the training algorithm takes to converge.

For each training iteration, the mapping part can takes each training example separately and executes the feed forward and error backward propagation in parallel to generate model updates. Then, the updates for all the parameters of SPAN model are summed up in the reducing units. At the end of each iteration, the SPAN model can be updated using the outputs from the reducing unites. This process continues until the stop criterion is met.

3.5. Handling Extreme Sparse Data

add a section about how to handle extreme sparse data, explain why your model can handle extrem sparse data

4. Experiments

Based on Section 2 and 3, we have implemented the proposed SPAN model in both Python and C++ that can run on a single machine. We also developed an parallel C++ version of SPAN model based on Map-reduce.

In this section, we provide evaluation experiments for the performance of the SPAN model. More specifically, we use the Python version SPAN model, and compared its performance with a baseline method and two Nonnegative Matrix Factorization based methods provided by nimfa Python library [5]:

- *Baseline*: The baseline method is giving prediction simply based on the average value in the training set.
- *LSNMF*: It is based on Alternating nonnegative least squares matrix factorization using projected gradient method for subproblems [6].
- *NMF*: It is based on Standard nonnegative matrix factorization with Euclidean / Kullback-Leibler update equations and Frobenius / divergence / connectivity cost functions [7], [8].

To provide more interpretable experiment results and for data privacy considerations, we show the performance result of NMF, LSNMF and SPAN as their relative performance to the baseline method in all the following subsections. The results of the evaluation experiments show salient advantages of SPAN model compare to those two NMF based methods:

- The matrix factorization based methods LSNMF and NMF are not handling the present extreme sparse CTR data set very well. Their prediction accuracy is even worse than the baseline method.
- In terms of the training and testing error (Root-mean-square deviation), SPAN model performs more than 65% and 40% better than the matrix factorization based methods, and around 60% and 30% better than the baseline method.
- SPAN model has a normal error distribution centered at 0, which means a balanced estimation; while LSNMF and NMF have biased error distributions that are constantly under estimating.

4.1. Data Description

Our evaluation experiments are performed on a click-through rate (CTR) dataset generated from Google Adsense,

which was collected with appropriate end-user license agreement and was fully anonymized without any retrievable personally identifiable information.

The CTR data set can be considered as a 2D matrix shown in Figure 2, where each row represents an advertiser and each column represent a target keyword. The value of each matrix entry in Figure 2 is the weekly average click-through rate (CTR) that we observed for the corresponding advertiser on that specific keyword. The whole dataset is extremely sparse because there are hundreds of thousands of different keywords but advertisers usually only target at several of them. To be more specific, the dataset contains more than 400k different advertisers (number of rows) and 500k keywords (number of columns), but more than 99.98% entries in the dataset matrix are missing.

Because the two Nonnegative Matrix Factorization based methods provided by nimfa cannot handle the entire CTR dataset ($400k \times 500k$ sparse matrix) on a single machine, we also generated a sub-sampled version of data set in addition to the original one. To generate the sub-sampled dataset, we go through each entry in the original dataset and only keep that entry with specified probability. If all the entry for a row (advertiser) or column (keyword) are dropped, we simply remove that row (advertiser) or column (keyword) all together. In Table 2, we summarized the basic information of both the 10% sub-sampled version and original data set, including the number of different advertisers, keywords and known CTR entries. It can be seen that both datasets are extremely sparse with more than 99.98% of the entries missing.

Dataset	whole	10% sub-sampled
Advertisers	$\sim 400K$	$\sim 76K$
Keywords	$\sim 511K$	$\sim 73K$
Known CTR entries	$\sim 21M$	$\sim 2M$

TABLE 2. BASIC INFORMATION

4.2. Evaluation

To compare the estimation performance between LSNMF, NMF and SPAN methods, we separate the sub-sampled CTR dataset described in Section 4.1 into a 95% training set and a 5% testing set through random selecting. The experiment is very straightforward. For each method, we use the 95% training set for model training, and test the model on estimating the entry values in the 5% testing set.

For the Nonnegative Matrix Factorization based method LSNMF and NMF, the Factorization Matrix Rank need to be specified before training the model. Using a higher rank number often means a more complicated matrix model, which is more powerful to represent a dataset but with higher risk of over-fitting. On the other hand, using a lower rank number means a simpler matrix model, which is less possible to be over-fitted but might be too simple to represent the data set. We have tried rank number from 1 to 12 for both LSNMF and NMF methods, their results are very similar. The result training error and testing error versus rank parameter of LSNMF method is shown in Figure 7.

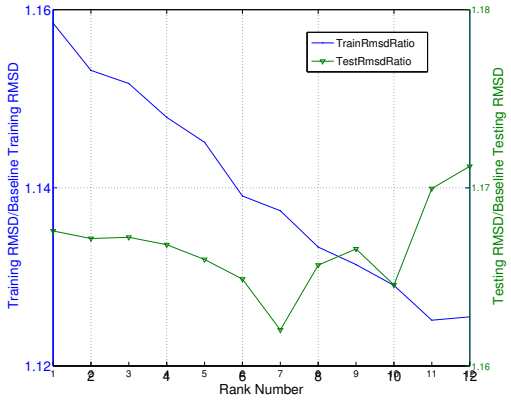

Figure 7. LSNMF: Relative Training/Testing Error Versus Rank Number

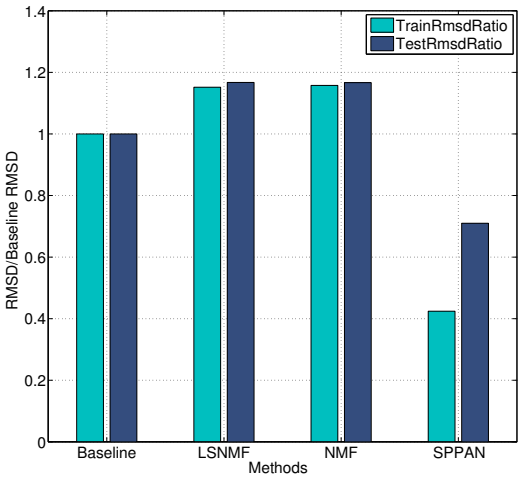

Figure 8. Compare Relative RMSD Between Different Methods

For a fair comparison with proposed SPAN model, we selected the rank numbers with the best test errors for both LSNMF and NMF. The best rank numbers for LSNMF and NMF are 3 and 7 respectively.

Method	TrainRmsdRatio	TestRmsdRatio
Baseline	1	1
LSNMF	1.15	1.17
NMF	1.16	1.17
SPAN	0.42	0.71

TABLE 3. RELATIVE RMSD IN THE BEST TEST ERROR ROUND

Here we list the result relative Root-mean-square deviation(RMSD) of both training set and testing set from Baseline, LSNMF, NMF and SPAN in Table 3 and Figure 8 to compare the estimation performance among these three methods. The root-mean-square deviation (RMSD) is a measure of the differences between the estimated value using a model and the true observed value. It can be expressed using Equation 8, where n is the number of entries that need be

to estimated, and $\hat{\beta}_i$ and β_i are the estimated value and observed value of entry i respectively. The RMSD represents the sample standard deviation of the differences between estimated values and observed values [9].

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(\hat{\beta}_i - \beta_i)^2}{n}} \tag{8}$$

In order to make those results more meaningful, we use the relative criteria TrainRmsdRatio and TestRmsdRatio, that are the Train/Test RMSD of current methods divided by the corresponding RMSD of the baseline method:

$$TrainRmsdRatio = \frac{\textit{Train RMSD}}{BaselineTrainRMSD}$$

$$TestRmsdRatio = \frac{\textit{Test RMSD}}{BaselineTestRMSD}$$

As can be seen from Figure 8, even though we chose the best rank numbers for the Nonnegative Matrix Factorization based methods, they perform even worse than the baseline method in this extreme sparse case. SPAN model, on the other hand, outperforms the Baseline, LSNMF and NMF on both training and testing RMSD. To be more specific, the training and testing RMSD of SPAN are only around 40% and 70% of the training and testing RMSD of Baseline methods, respectively; they are aroung 35% and 60% of the training and testing RMSD of the Matrix Factorization based methods LSNMF and NMF; which shows a great improvement.

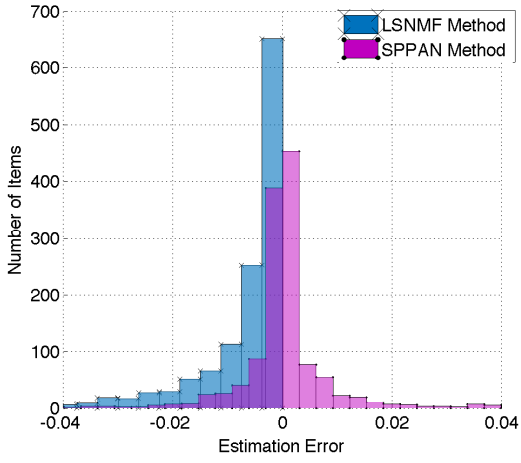

Figure 9. Histogram of Estimated Error

We also draw the histogram of estimated error generated using SPAN and LSNMF on the testing set as in Figure 9. The estimated error is defined in Equation 9. For data privacy considerations, we multiply an constant k in Equation 9, which doesn't not affect the interpretation of the following analysis at all. Note that the testing error distribution of LSNMF and NMF are very similar. Thus we regard the LSNMF result in Figure 9 as the representative result of Nonnegative Matrix Factorization based method.

$$Estimated\ Error = k \cdot (Estimated\ CTR - True\ CTR) \tag{9}$$

It can be noticed that the distribution of estimation error of SPAN model is centered on 0 with a normal distribution shape, while LSNMF's estimation errors are distributed on the left side of 0. It means the estimations given by LSNMF always have a negative bias which leads to a constant underestimation. Therefore, the estimations from the SPAN model is more accurate and reasonable.

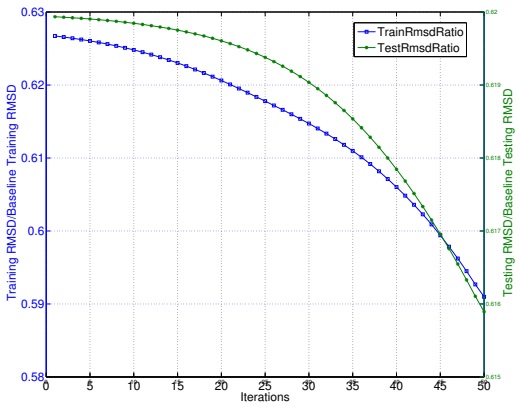

Figure 10. SPAN Learning Curve on Whole Dataset

Besides the experiments on 10% sub sampled data set, it is worth mentioning that the proposed SPAN model can also handle the whole CTR data set on a single computer. Similar to the model evaluation experiment on the sub-sampled data set, we separate the whole CTR data set described in Section 4.1 into a 95% training set and a 5% testing set through random selection. Then, we use the 95% training set to train the SPAN model, and test the model on the 5% testing set. The output training RMSD ratio and testing RMSD ratio are 0.59 and 0.62 respectively, which shows a great improvement from the baseline method.

We also show the learning curves of SPAN model in Figure 10. It can be seen that both the training error and testing error were decreasing are decreasing during each training iterations until the training stop criterion was met, which is a strong indicator that the SPAN model is not overfitted on the whole CTR data set.

5. Related Work

Among the prevalence in online advertisements system, e-commerce platform and social networks, there has been an increasing interest in developing recommendation systems [2], [10] that can automatically predict the "preference", "rating", "performance" or "interest" of a item for a end user or a client based the history data, such as the task

we introduces in Section 1. One popular technique that has been used in many recommendation systems is called collaborative filtering, which is based on the intuition that if two users(or clients) have a similar opinion on an item(or issue), they are more likely to have similar opinions on other items(or issues) [2], [3], [10], [11]. Generally, collaborative filtering is an approach that make use of the preference information from many users to give prediction of the interest of one user. There are many forms of collaborative filtering systems. For examples, Linden et al. uses the item-to-item collaborative filtering to offer personalized recommendations for each customer in the online store [12]; Cai et al. captures the interaction between users within a social network and formulates a collaborative filtering approach to allow high quality people to people recommendations in social networks [13]; Hu et al. implements a large scale TV recommender system with a collaborative filtering based on prior implicit feedback that can recommend new TV programs to their users with high accuracy [14].

As a special type of collaborative filtering, various forms of matrix factorization based recommendation system were used by researchers for different recommendation tasks [5], [6], [7], [8], [10], [15]. For instance, to help Flickr users more easily engage in group activities, Zhang et al. proposes a tensor decomposition-based Flickr group recommendation model, which is based on CANDECOMP/PARAFAC tensor decomposition method to capture the underlying patterns in the user-tag-group relations [16]. Gu et al. introcudes a graph regularized nonnegative matrix factorization model for general collaborative filtering tasks, which outperform many state of the art collaborative filtering methods on benchmark data sets [17]. Other work by Baltrunas et al. presents an context-aware matrix factorization (CAMF) method which extends the classical Matrix Factorization approach by taking contextual information into consideration [18]. By applying their method on MovieAT data set and Yahoo Webscope movie data to do movie rating prediction, Baltrunas et al . have shown that the CAMF method can substantially improve the rating prediction accuracy comparing to the the classical Matrix Factorization approaches in certain circumstances in which the relevant context information is available.

Despite there being a lot of researches of matrix factorization based collaborative filtering methods, many algorithms still have salient weaknesses under sparsity conditions [19]. Even though there are approaches like multi-Domain collaborative filtering by Zhang et al. and adapting neighborhood and matrix factorization model by Liu et al. trying to improve the model's performance by integrating other available context information [20], [21], an extreme sparse data set would easily make most of the matrix factorization based models over-fitting. The SPAN model in this present paper, however, adjust the complexity of the model automatically according to the sparsity of the data set, which makes it more accustomed to extreme sparse data set.

6. Conclusions

In summary, the Similarity Powered Pairwise Amplifier Network (SPAN) model we proposed in this article shows promising results in predicting click-through rate (CTR) in a very sparse CTR data set. It utilizes the pairwise ratio similarity information that embedded in the data set, and its model complexity is automatically adjusted according to the sparsity of the data set. Comparing with several matrix factorization based recommendation methods, our evaluation experiment results show that this model can substantially improving the performance of the recommendation system in extreme sparse situations. It has also been shown that the training process of the SPAN model can be easily implemented in a paralleled version through map-reduce, which makes the model can handle even bigger data set efficiently.

Since all evaluation experiments in this paper were performed on a click-through rate data set, we must observe that more experimental evaluations of the proposed SPAN model should be performed in the future in order to make a more comprehensive conclusion of the performance of the model. In fact, out next plan is to apply the SPAN model on other sparse data sets from different domains so that we could confirm if the *Homogeneous Amplifying Effect* described in Section **??** is valid only in online advertisement traffic data or can be generalized in other areas. Moreover, the experiment result in the present paper only shows the advantages of the SPAN model in a situation with a certain sparsity level. A sensitivity analysis about the effect of the sparsity on the model's performance would help us to decide when to use SPAN model instead of other approaches.

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