Unstructured Semantic Model supported Deep Neural Network for Click-Through Rate Prediction

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ABSTRACT
With the rapid development of online advertising and recommendation systems, click-through rate prediction is expected to play an increasingly important role. Recently many DNN-based models which follow a similar Embedding&MLP paradigm have been proposed, and have achieved good result in image/voice and nlp fields. In these methods the Wide&Deep model announced by Google plays a key role. Most models first map large scale sparse input features into low-dimensional vectors which are transformed to fixed-length vectors, then concatenated together before being fed into a multilayer perceptron (MLP) to learn non-linear relations among input features. The number of trainable variables normally grow dramatically the number of feature fields and the embedding dimension grow. It is a big challenge to get state-of-the-art result through training deep neural network and embedding together, which falls into local optimal or overfitting easily. In this paper, we propose an Unstructured Semantic Model (USM) to tackles this challenge by designing a orthogonal base convolution and pooling model which adaptively learn the multi-scale base semantic representation between features supervised by the click label. The output of USM are then used in the Wide&Deep for CTR prediction. Experiments on two public datasets as well as real Weibo production dataset with over 1 billion samples have demonstrated the effectiveness of our proposed approach with superior performance comparing to state-of-the-art methods.

CCS CONCEPTS
• Information systems → Display advertising; Recommender systems;

KEYWORDS
Click-Through Rate Prediction, Display Advertising, Recommender System

1 INTRODUCTION
Click-through rate (CTR) is widely used in advertising and recommender systems to describe users’ preferences on items. For cost-per-click(CPC) advertising system, the revenue is determined by bid price and CTR, so it’s important to improve the performance of CTR prediction. For recommender system, CTR is used to improve user experience. CTR prediction has received much attention from both academia and industry communities.

In recent years, DNN has been gradually researched and applied with unstructured data for CTR prediction after gaining popularity of deep learning in image, voice, NLP, etc. fields.

Unstructured data is particularly abundant(such as user behavior data, blog segmentation, user interest, etc.) for CTR prediction, which requires a lot feature engineering work with traditional methods. DNN-based models can take advantages of those unstructured data and deep feature representation could be learned through embedding and multi-layer perceptrons. But its relying large number of variables and train epochs which aggravate the risk of overfit and dramatically enlarge the computation and storage, and not be tolerated for an industrial online system.

The principle of most methods is Embedding&MLP, research of DNN-based CTR prediction mainly focuses on the design of the embedding layer [Edizel et al., 2017], such models solve traditional features added to DNN training issues, such as FNN, PNN, etc. There are many researches based on CNN, but due to the particularity of advertising/recommended data, there are no context data like images and voices. Therefore, the convolution and pooling over advertisement/recommended data usually unexplainable.

In the field of search, Microsoft’s proposed DSSM[1] model establish supervised semantic model for doc and query, which mining the non-linear relations of word granularity well. Inspired by this, we propose an unstructured semantic model (USM) to learn embeddings and then perform fine tune together with the rest of DNN variables. Additionally, the USM we propose use a series of base convolutions instead of traditional trainable convolutions, and then follows a hidden layer to train convolution variables and poolings together, we named this “delay convolution”. This method effectively learn the multi-scale base semantic representation of the user-item and perform complex interact in later DNN training.

The contributions of this paper are summarized as follows:

- We propose a novel approach to train the embedding of sparse feature which effective improve the convergence of DNN-based models than initialize the embedding randomly. The semantic relations between user and item features can be figured out with the unstructured semantic model.
- We introduce series base convolutions to USM to learn multi-scale base semantic representation, and follow a hidden layer to perform complex interactions we called “delay convolution”, which perform better than traditional CNN paradigms.
- The model we proposed make unstructured feature(i.e., word of feed/item and history browser behavior or social network of user) widely and easily use in CTR prediction, which evolve the DNN more compatible for CTR prediction.
- We conduct extensive experiments on both public and Weibo datasets. Results verify the effectiveness of our proposed USM. Our code\(^1\) is publicly available.

\(^1\)Experiment code on two public datasets is available on GitHub: https://github.com/niuchenglei/usm-dnn
2 RELATED WORK

Predicting user responses (such as clicks and conversions, etc.), based on historical behavioral data is critical in industrial applications and is one of the mainly machine learning task in online advertising. Recommending suitable ads for users not only improve the user experience in real online advertising scenarios, but also significantly increases the company’s revenue.

For handle the obstacles of dimensional disasters in the language model, NNLM[2] proposed using the embedding method to learn the distributed representation of each word, and then using the neural network model to learn the probability function which has a profound impact on the subsequent researches. Based on the former research, the Word2Vec method[3] was proposed to learn the distributed representation of words and phrases and their combinations continuously. Meanwhile, RNNLM[4] was proposed to improve existing speech recognition and machine translation systems, and used as a baseline for future research of advanced language modeling techniques. These methods laid a solid foundation for later language models, especially CTR predictions with unstructured data.

To capture the high-dimensional feature interactions, LS-PLM[5] and FM[6] use embedding techniques to process high-dimensional sparse inputs and also design the transformation function for target fitting. To further improve the performance of the LS-PLM and FM models, Deep Crossing[7], Wide&Deep Learning[8] and YouTube Recommendation CTR model[9] propose a new approach, which uses a complex MLP network instead of the original transformation function. Moreover, PNN[11] adds a product layer after the embedding layer to capture high-level feature interaction information and improve the prediction ability of the PNN model. Based on the design of the Wide&Deep framework, DeepFM[12] tried to introduce the FM model as a wide module, aiming to avoid feature engineering. However, these methods will convert the embedding vector into a fixed-length vector, which will result in the loss of the user’s original preference information. DIN[13] adaptively learns user interests from the advertisement historical behavior data by designing a local activation unit. The representation vector varies with different advertisements, which significantly improves the expressive ability of the model. Considering the influence of the ordering of embedding vectors on the prediction results of the model, CNN[14] proposed the greedy algorithm and random generation method to generate multi-feature sequences in the embedding layer which greatly improved the prediction ability of the model, but the calculation time complexity is extremely high with high-dimensional sparse inputs. In summary, these researches are mainly accomplished by the techniques of the combination of embedding layer and exploring high-order feature interaction, mainly to reduce the heavy and cumbersome feature engineering work.

In this paper, we also follow these structures and techniques to improve the performance of advertising CTR prediction which have ability to take advantages of unstructured data.

3 UNSTRUCTURED SEMANTIC MODEL SUPPORTED DNN

Different from sponsored search(or image,voice and nlp), there are no explicit intentions in advertising and recommender system which make DNN-based model overfitting or fall into local optimal easily. Hence, it is critical to improve the performance of embedding by introducing effective approaches for DNN-based models.

[10] aims to solve this by imposes factorization machines as embedding initializer, and [11] introduce out-product to perform more cross interaction. Our method follow the same principle by replace factorization machines with an unstructured semantic model. We introduce series base convolutions and poolings to USM to learn the multi-scale base semantic representation, which perform better than traditional CNN-based model.

3.1 Feature Representation and Word Hashing

Original features of CTR prediction model often come as two types, one is categorical form such as age=25, gender=male, and another is continuous form such as history_ctr=0.005. Categorical features are normally transformed into high dimensional sparse features via so called one-hot encoding procedure. Arbitrary x having m unique ids, there is a trivial embedding mapping x → Rm. Specially, for multi-value features like words and tags, usually represented as [13, 26, 98, 201], one-hot encoding creates a mapping of a vector rather than a single value. That is to say, X → T ∈ Rm. m denotes the dimensionality of vector X, and T[j] denotes the j-th element of X and T[j] ∈ (0, 1). mT[j] = n, apparently for single value n = 1, and for vector n > 1. For example, we have feature set of history_ctr, age, gender, tags from 78 tag set encoding as:

\[
\begin{bmatrix}
0.052 \\
0,0,1,\ldots,0 \\
0,1 \\
1,0,\ldots,0,1,\ldots,1,0
\end{bmatrix}
\]

history_ctr=0.052 age=20 gender=Female tags={Food,MakeUp,Tourist}

Continuous features usually remain unchanged.

Different from english text, text segmentation is a tough task in NLP for chinese text, and a bad word segmentation may lead bad performance in the later experiment. Inspired by DSSM[1], we directly treat individual character as origin feature inplace of word segmentation. For chinese or some other languages not like latin, we break the word into single characters(e.g. p,h,o,t,o) with a given segmentation. For chinese or some other languages not like latin, we break the word into single characters(e.g. p,h,o,t,o) with a given segmentation. For example, we have feature set of history_ctr, age, gender, tags from 78 tag set encoding as:

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Continuous features usually remain unchanged.
Deep Component. The deep component is a feed-forward neural network consists of four layers of units [100, 75, 50, 25] using categorical features. After one-hot encoding, categorical features are sparse and high dimensional. In this part, these features are transformed into dense and low dimensional real valued vectors, normally called embedding vectors. To do so, we need an embedding layer and a pooling layer for multi-value features.

First, initialize embedding matrix randomly and then train the variables to minimize the final loss function via feed-forward procedure. For single-valued features, these low dimensional dense embedding vectors are directly fed into the hidden layers of a neural network. Specifically, each hidden layer performs the following computation in Eq(1), which \( f \) is the activation function usually chosen as linear units (ReLU).

\[
d(1^{l+1}) = f(W(l)\hat{a}(l) + b(l))
\]

For multi-value features, a pooling operator usually performed to get fixed length vector for fully connected networks. The most popular pooling layers are sum pooling and average pooling, which apply element-wise sum/average operations to the embedding vectors. All the word type features have both embedding layer and pooling layer.

Loss. The objective function of base model is the cross-entropy loss function defined as Eq(2), which \( i \) denotes the \( i \)-th sample, \( y_i \in \{0, 1\} \) denotes the true label, \( \hat{y}_i \) is the output of the network after sigmoid layer representing the probability of the \( i \)-th sample being clicked or not.

\[
loss = \sum_{i=0}^{N}y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)
\]

3.3 The structure of Unstructured Semantic Model

Among all those features of Table 1, there are much user behavior and item features to use in modeling CTR. The relation representations between those high level implicit features are too difficult and computation complex in feature engineering way. Hence, it is critical to improve the performance of CTR by finding a good representation of high level features. Base model initialize the embedding randomly and optimize it along the DNN variables while training. Due to the vanishing gradient problem, it is difficult to get a high quality embedding by training the model with end-to-end method.

DSSM[1] was designed to modeling the semantic relation between query and doc, inspired by this, we introduce an unstructured convolution pooling network to modeling the unstructured semantic relationship between those features. The dot-product of two embedding vector commonly used to represent the similarity of two item, which can be treat as a special convolution and pooling over two vector Eq(3).

\[
\text{pooling(Conv}(e_1, e_2)) = e_1^T e_2
\]

Therefore, we introduce a convolution and pooling layer to simulate the relations between embedding vectors, and optimize a logistic loss over the prediction \( \hat{y} \) which is sigmoid of trainable variables \( W \) and flatten vector \( U \) as show in Eq(4).

\[
\hat{y} = \text{sigmoid}(W^T U + \text{bias})
\]

Why convolution and pooling DNN can learn unstructured semantic relations from the user and item features? Our unstructured semantic model mainly contains three aspects:

- i) We introduce an embedding permutation over user and item embedding vectors, and the rank of permutation to characterize which of those features interact each other. The output of permutation can be describe as:

\[
C^m_n = \frac{n!}{m!(n-m)!}
\]

In generally, the number of features greater than 5 may leds permutation expansion. It can be solve by permute user-item combinations instead of all permutations, normally rank less than 4 could get enough better result. The number of permutation over features shows in Eq(7) while \( n_1 \) denotes the number of user features and \( n_2 \) denotes the number of item features. We defined \( R \) as a function of \( n_1 \) and \( n_2 \) to produce the combination of feature number, and defined \( P \) as a cumulative of \( R \).

\[
P_{n_1, n_2}^m = \sum_{j=1}^{m-j} C^j_i C^m_j\quad m = 2, 3, \ldots n
\]

\[
P_{n_1, n_2}^r = \sum_{l=2}^{r} P_{n_1, n_2}^l\quad r = 2, 3, \ldots n
\]

- ii) Let \( e \) be the embedding vector, we declare the 1-d convolution as Eq(8) which \( K \) denotes a convolution kernel. We use many kinds of 1-d linear convolution operators to simulate how embeddings interact each other, and introduce dot-product as a special convolution operator as same as some linear kernel functionsie. [1,1], [1,1]. Normally, the size of convolution set from [1,2] to [1,4] corespond to the rank of permutation.

\[
\text{Conv}_1d([k_1, k_2], e_1, e_2) = k_1e_1 + k_2e_2
\]

The 1-d convolution kernel shows as matrices3.3 was used in our practice (permutation rank 3 was used), which describes

| Table 1: Statistics of feature sets used in the display advertising system in Weibo. |
|---------------------------------------------------------------|
| Category       | Feature Group | Dimensionality | Type   |
|----------------|---------------|----------------|--------|
| Continuous     | history_ctr   | 1              | float  |
|                | hierarchy_ctr | 1              | float  |
|                | ...           | ...            | ...    |
| Categorical    | gender        | 2              | one-hot|
|                | age           | ~ 80           | one-hot|
|                | location      | ~ 300          | one-hot|
|                | ...           | ...            | ...    |
| Item           | user_tag      | ~ 10^3         | multi-hot|
|                | cust_tag      | ~ 10^3         | multi-hot|
|                | user_interest | ~ 10^3         | multi-hot|
|                | ad_word       | ~ 10^3         | multi-hot|
|                | ...           | ...            | ...    |
8 linear and 1 special convolution kernels, and they all orthogonal each other. In addition, traditional CNN-based models train multi trainable convolution kernels (like $w_1, w_2$) could get good enough result too by enlarge training epochs, but orthogonal linear fixed convolution kernels follow a hidden layer benefits much better performance, and we will explain it in later chapters.

Figure 1: Network Architecture. Above show the structure of USM we proposed, it introduces kinds of convolution and pooling operators on embedding, which have ability to find unstructured relationship between features.

CNN[14] pointed out that using convolutional networks with multiple feature sequences benefit much non-linear and deep representations, but it also brings more variables to train which may led not convergent or fall into local optimized point. As show in our practice, pre-train the embedding with USM get better convergent result.

\[
\text{dot product} = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} -1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & -1 \\ -1 & 1 & -1 \end{bmatrix}
\]

Put It All Together. the flatten layer of USM can be denote as:

\[
P = \text{Perm}(r, (\text{Emb}(\theta_1, f_1), \text{Emb}(\theta_2, f_2), \ldots, \text{Emb}(\theta_n, f_n)))
\]

\[
U = \text{Flatten}(\text{Pooling}(s, \text{Conv}(k, P)))
\]

As show in above, $\theta_1$ and $\theta_2$ denote the embedding matrix of user and item feature, $f_1/f_2$ denotes the input features, and $r$ is the rank of permutation which correspond to the shape of convolution kernel $k$. The convolution kernels are matrices3.3, $s$ is the parameter of pooling operator, $3/11$ and 19 was set in our practice. We can find that USM perform semantic mining by convolution and pooling on embedding combinations, which pass the gradient of trainable variables in very short way.

In our practice, we embedding 3 user features and 2 item features with the shape of embedding $e$ was set to $[5K, 100]$, and then with a permutation of rank 2 and 3 produce 20 matrices $P$ with shape $[100, 2]$ and $[100, 3]$. Convolute 20 matrices with 10 kernels which shape are $[1, 2]$ and $[1, 3]$ produce 80 vectors. And then, take pooling over 80 vectors with 3 kinds of pooling operators which shape are $3/11$ and 19 to get 3 matrices $p_1, p_2, p_3$ to a flattened vector $Flt_{[1,11600]}$ as the input of LR.

With the approach above, the USM learns feature embeddings and its multi-scale base semantic representation for DNN which improve the performance a lot. The embedding learned by USM can
describe the semantic information over features efficiently and will be fine tune in the rest of training process, also the last flatten layer of USM describe multi-scale base semantic information of features.

3.4 Multi-Scale Base Semantic Representation

As we can see from the architecture of USM in Fig1, we named the last flatten layer of USM as multi-scale base semantic representation, and it will concat as partial input of DNN in our whole architecture.

Base Semantic and Multi-Scale. For signal processing, wavelet and fourier transformation play a critical roles to transform signal from time domain to frequency domain, and the base functions of wavelet are sine and cosine function. We promote the base function to CTR prediction, which contains kinds of \([1,2]/[1,3]\) shape linear convolution kernels and dot-product as a special convolution kernel. In \([14]\) and other convolution related approaches, the convolution kernels are usually trainable variables that result in overfitting and computational consumption. In this paper, we introduce several linear convolution kernels as base function to demonstrate the linear relations between embedding vectors, and follows a hidden layer to dig out non-linear and complex representations.

Our approach decomposes the complex relations between embedding vectors into two parts:

- i) Firstly, using click or not as label to supervise learn with 9 kinds of orthogonal convolution kernels get variety simple linear function response. We call that the base semantic representation.
- ii) Secondly, by follow a hidden layer after USM, we generate various non-linear or complex interactions which is a linear combination of base semantic representations.

As we mentioned above\((3.3)\), 8 kinds of linear and a dot-product as special convolution kernels are used in our practice. The output of USM contains different base function response which learned by supervise on click label, and it reveals different reaction over base functions in semantic domain.

In traditional CNN-based approaches, a convolution kernel \([w_1, w_2]\) can be describe as a hidden layer node over USM output which weight is \([\theta_1, \theta_2]\) as the red lines shown in Fig2 and Eq(10), obvious we deduced that \(w_1 = \theta_1 + \theta_2\) and \(w_2 = \theta_1 - \theta_2\). Additionally, the nodes of hidden layer in Fig2 can also describe different combination across \([1,2]\) and \([1,3]\) shape base functions and different scale of them which brings more non-linear relations, the multi-scale can be demonstrated by kinds of pooling operators with various size.

\[
\text{Conv}_{1d}(w_1, w_2, [e_1, e_2]) = \theta_1 \cdot \text{Conv}_{1d}([1, 1], [e_1, e_2]) + \theta_2 \cdot \text{Conv}_{1d}([1, -1], [e_1, e_2]) \quad (10)
\]

Delay Convolution. Aside base functions mentioned above, there exists lots of interaction affections between multi-scale embeddings in CTR prediction, such as interactions between word and word vectors, word and classification vectors, classification and classification vectors. We define this as multi-scale interaction modeling.

In traditional CNN-based models, the convolution and pooling operators are independent. Pooling operator always follows convolution operators which means the model determines the convolutions over embedding vectors firstly, and then follow many kinds of pooling over the convolution result. That process produce \(\text{sum}(\text{conv})\) multiply \(\text{num(pooling)}\) number of parameters need to train. For NLP or CTR prediction, interaction affections exist between multi-scale embeddings and the number of parameters with traditional CNN-based models will be extremely huge to get a good result.

The USM we proposed in this paper can solve the above problems efficiently. First of all, we produce series of base semantic representation using base functions (the matrices\(3.3\) we mentioned above), and then use hidden layer to learn what relations as convolution and what scale as pooling at the same time, we named it delay convolution, and a node of hidden layer can be define as Eq(11).

To do so, USM follows a hidden layer get better performance than traditional CNN-based models which training convolution kernels and multi-scales together to reduce computation load and improve the convergence efficiently.

\[
N_k = \text{Relu} \left( \sum_{i=0}^{N} \theta_i \text{Pooling}(S, \text{Conv}(K, P)) \right) \quad (11)
\]
For instance, the modeling between words and classifications can be expressed as a linear combination of two pooling layers with different scales. Weights of base functions as well as scales can be learned by the following hidden layer at the same time which take advantages of base semantic and multi-scale.

3.5 USM supported Wide&Deep
The embedding learned by USM can describe the unstructured relations between features which used as the initialization of embedding in DNN and iteratively optimized in the rest training epochs. The multi-scale base semantic representation learned by USM could be concat to the flatten input of DNN. In Eq(12), $\bar{y}$ denotes the prediction value of CTR which is the output of sigmoid function $\sigma$ and $W_{\text{wide}}$ denotes the weights of origin features $X$ and feature engineering features $\phi(X)$, $W_{\text{deep}}$ denotes the weights of the output of DNN, and the red arrowhead denotes the multi-scale base semantic representation concat to the input of DNN. In Eq(13), $a^{(l)}$ denotes the input of DNN which is a concat of embeddings $e_i$ and USM output $U$, and then $a^{(l)}$ follow a standard MLP transform in Eq(1). The whole architecture of Wide&Deep-USM show as Fig3.

$$\bar{y} = \sigma \left( W_{\text{wide}}^T [X, \phi(X)] + W_{\text{deep}}^T a^{(l)} \right)$$ (12)

$$a^{(l)} = \text{concat}_\text{flatten}(e_1, e_2, \ldots, e_n, U)$$ (13)

4 EXPERIMENTS
In this section, our experiments are introduced in detail including the datasets, experimental setting, model comparison and the corresponding analysis.

Both the public datasets and experiment codes are made available1.

4.1 Datasets and Settings
We conduct experiments on Weibo dataset and two opensource datasets.

Avazu Dataset2. In Avazu dataset, which is provided in the competition of Kaggle in 2014. The dataset contains 40 million samples with 22 fields for ten consecutive days, and all fields are used in the experiments. We use the samples of first nine days as training set and the samples of the tenth day for evaluation.

MovieLens Dataset3. MovieLens data[15] contains 138,493 users, 27,278 movies, 21 categories and 20,000,263 samples. To make it suitable for CTR prediction task, we transform it into a binary classification data. Original user rating of the movies is continuous value ranging from 0 to 5. We label the samples with rating of above 3(e.g. 3.5, 4.0, 4.5, 5.0) to be positive and the rest to be negative. We segment the data into training and testing dataset. Among all 20,000,264 samples(movie.csv), of which 80% samples are randomly selected into training set (about 16,197,321 samples) and the rest 20% into the test set (about 3,802,943 samples). The task is to predict whether user will rate a given movie to be above 3(positive label) based on historical behaviors. Features include movie_id, movie_cate_id and user rated history movie_id_list, history movie_cate_id_list.

Weibo Dataset. In Weibo dataset, we collected impression logs from the online display advertising system in Weibo, of which two weeks' samples are used for training and samples of the following day for testing. The size of training and testing set is about 1 billions and 0.1 billion respectively. 31 fields of features are separated into three categories (user profile, ad information and context information) for each sample.

Due to the huge size of weibo dataset, we set the batch size to be 10000 and use Adam as the optimizer and set learning rate at 0.0001.

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1https://www.kaggle.com/c/avazu-ctr-prediction
2https://grouplens.org/datasets/movielens/20m/
Figure 4: Performances of different model on Weibo Dataset. Wide&Deep-USM shows the improvement over test logloss and AUC.

Table 2: Model Comparison on Avazu, MovieLens and Weibo Datasets. All the lines calculate RelaImpr by comparing with BaseModel on each dataset respectively.

| Model               | Avazu (Electro) | MovieLens | Weibo |
|---------------------|-----------------|-----------|-------|
|                     | AUC             | RelaImpr  | AUC   | RelaImpr |
| LR                  | 0.6525          | -24.0%    | 0.6984| -25.2%   |
| Deep                | 0.6963          | -2.19%    | 0.7576| -2.87%   |
| BaseModel (Wide&Deep)| 0.7007          |           | 0.8371| -12.58%  |
| Wide&Deep-USM       | 0.7011          | 0.2%      | 0.7754| 3.9%     |

4.2 Model Comparison

**LR** [16]. Logistic regression (LR) is a widely used in CTR prediction task because of strong explanation and efficiency. We treat it as a weak baseline.

**BaseModel (Wide&Deep Model)** [8]. The google’s wide&deep model has been widely used in real industrial applications. We treat it as the benchmark model. It consists of two parts: wide model, which handles the manually designed cross product features and deep model, which automatically extracts non-linear relations among features and equals to the BaseModel. Wide&Deep needs expertise feature engineering on the input of the “wide” module. We follow the practice in to take cross-product of user behaviors and ad information as wide inputs.

**Wide&Deep-USM**. Different from Wide&Deep, the embeddings of Wide&Deep-USM are initialized by USM and the result of USM also concatenated to the input of DNN, and then fine tune the embeddings with Wide&Deep.

4.3 Performance of the Experiment

AUC is a most popular evaluation metrics for CTR prediction which measures the goodness of order by ranking all the ads with predicted CTR, including intra-user and inter-user orders. To make the experiment more convincing, we adapt RelaImpr introduced in [17] to measure relative improvement over models. For a random guesser, the value of AUC is 0.5. It is defined as follows:

\[
\text{RelaImpr} = \left( \frac{\text{AUC(measured model)} - 0.5}{\text{AUC(base model)} - 0.5} - 1 \right) \times 100\%.
\]

Figure 5: Visualization of flatten layer of samples in USM. Shape of points represents a single sample. Color of points corresponds to CTR prediction value.
From Table 2, we can see that, in terms of RelaImpr all deep networks perform well than LR significantly, and Wide&Deep-USM has the best performance. The result shows that using pre-trained embedding layer for initializing yields a better result, cause embedding layer can get better generalization during pre-training. When using pre-trained embedding for initializing and the USM as partial input of DNN, its not only speeds up training process but also learns much complex interactions for trainset.

4.4 Visualization of USM

We take samples with different tags to visualize the learned multi-scale base semantic representation by two-dimensional scatter plot using t-SNE[18]. The close points represent the same type of item/ad text. That means words from similar item/ad are almost aggregated together, which demonstrates the aggregation ability of USM flatten vector. Besides, it’s also a Heat Map that different colors indicate the prediction values. Fig5 shows the distribution of users’ inclination to click advertisements in semantic space. As we can see, USM can express a preference distribution in semantic space efficiently.

5 CONCLUSIONS

In this paper, we focus on the task of CTR prediction in the scenario of online advertising with rich unstructured data. The performance of the embeddings of those unstructured data learned by DNN-based model is a bottleneck for the performance of the CTR prediction. To improve the performance of the embeddings, a novel approach named USM is designed to pre-train the embeddings by unstructured semantic model to get semantic relations between features, and fine tune it with DNN variables. Additionally, we introduce series base convolution instead kinds of trainable convolutions to learn the multi-scale base semantic representation, and follow a hidden layer for complex interactions which we called “delay convolution”. USM get good performance both in opensource dataset or Weibo dataset, and can be extend to other DNN-based models easily.

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