SHORT VIDEO-BASED ADVERTISEMENTS EVALUATION SYSTEM:
SELF-ORGANIZING LEARNING APPROACH

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ABSTRACT

With the rising of short video apps, such as TikTok, Snapchat and Kwai, advertisement in short-term user-generated videos (UGVs) has become a trending form of advertising. Prediction of user behavior without specific user profile is required by advertisers, as they expect to acquire advertisement performance in advance in the scenario of cold start. Current recommender system do not take raw videos as input; additionally, most previous work of Multi-Modal Machine Learning may not deal with unconstrained videos like UGVs. In this paper, we proposed a novel end-to-end self-organizing framework for user behavior prediction. Our model is able to learn the optimal topology of neural network architecture, as well as optimal weights, through training data. We evaluate our proposed method on our in-house dataset. The experimental results reveal that our model achieves the best performance in all our experiments.

Index Terms—CTR prediction, 3-second play rate, user generated videos, multi-modal signal processing, deep learning

1. INTRODUCTION

As daily active users (DAU) of video sharing apps, e.g., Youtube, Snapchat and Kwai, have rocketed in recent years, advertisers take advantage of this trend to promote their products or services through user-generated videos (UGVs)-based advertisements. Generally, user behavior-related metrics, e.g., click-through rate (CTR)\textsuperscript{1}, 3-second play rate\textsuperscript{2} are employed to assess advertisement quality and performance. These two metrics can be calculated as follows: \( CTR = \frac{\text{number of clicks}}{\text{impressions}} \); and \( 3\text{-second play rate} = \frac{\text{number of plays (more than 3s)}}{\text{impressions}} \). Recent researches\textsuperscript{1,2} on recommender system require user profiles, which are extracted from user browsing history and user basic information, as essential model input to make precise prediction on video CTR within each user account. However, in some application scenarios, such as cold start and automatic generation of advertisements, where user-related information cannot be obtained, advertisement publishers have to rely on video content to estimate advertisement performance. Accordingly, methods for making precise prediction on UGV-based advertisement performance without user profile are of great value. Multi-Modal Machine Learning (MMML), which exploits signals of different modalities jointly, is able to help in mentioned video-related tasks.

Application of MMML tasks has been widely studied, including emotion recognition\textsuperscript{3,4}, object localization\textsuperscript{5,6}, speech recognition\textsuperscript{7,8,9}, speech separation\textsuperscript{10}, voice activity detection\textsuperscript{11,12} and etc. We notice that multi-modal fusion strategy plays a decisive role in multi-modal tasks. Previous works have proposed sophisticated fusion methods and achieved remarkable success. However, in our case, previous solutions have two limitations: 1) they mainly focus on signal perception-related tasks, rather than user behaviors; 2) it is unclear how modalities interact with each other. For example, in ASR task\textsuperscript{7}, visual content is taken as auxiliary information for audio content and therefore, audio modality is taken as query information in attention model. However, in our case, we have no prior knowledge about the relationship between input modalities and user behaviors. These shortages may lead to difficulties of applying existing methods in computational advertising.

Our study focus on building an end-to-end system for predicting CTR and 3-second play rate of UGV-based advertisement...
ments. The contribution of our work can be summarized as follows: 1) To the best of our knowledge, our proposed system is the first work of predicting CTR and 3-second play rate directly from video content (combining audio and visual modalities), which is equivalent to predicting user behavior directly from raw signals. 2) We propose a self-organizing system that is able to learn the optimal topology of neural network architecture. More specifically, it is a data-driven framework which can adjust information flow by changing model architecture.

We evaluated our proposed method on a video dataset which consists of 9841 advertisements videos collected from Kwai, a trending short video app worldwide. All videos are uploaded by advertisers and contain unconstrained information. The experimental results of CTR and 3-second play rate prediction reveal that the proposed method outperforms all models for comparison.

2. RELATED WORK

To build the first framework for predicting user behavior from videos, we borrowed ideas from recommender system and MMML studies. Recommender system relied on designated data pre-processing to collect descriptive features. Google’s Wide-&-Deep model [13], which has been widely deployed in industry, combined these features at different levels within one neural network. Recently proposed AutoCTR framework [14] explored the optimal model structure in a data-driven way. These ideas inspired us to design a model that is able to process features collected from different levels. However, AutoCTR and Wide-&-Deep model may not be applicable in our task, as they could not handle raw signal inputs. Densenet [15] essentially had similar strategy to Wide-&-Deep model that it used cross-layer connection in image classification task. It merged information from different levels in dense block, where one layer was directly connected to all its subsequent layers.

In MMML research, one straight-forward fusion method was to combine weighted prediction results across all modalities, where the weight of each modality was determined by its own performance on validation set. This method may fail in handling UGVs, whose modalities had different significance across UGV topics. Another widely applied fusion method was to concatenate the features extracted from different modalities into a joint representation [16, 8, 10] and then the concatenated feature vectors could be processed by a classification/regression model. Such simple method has shown its effectiveness in many video-related tasks introduced in previous section. However, merging features into one vector did not provide enough flexibility in dealing with unconstrained videos. In many other works, attention model [17] has been considered [18] to assign weights dynamically, where the strategy could be learned through end-to-end training. Also signal from one modality could be utilized as auxiliary information on other modalities [9, 19]. These methods made prior assumptions on relationship among all available modalities and set constrains on the architectures of fusion models, which was not the case in our study. To tackle the shortages mentioned above, we develop a self-organizing framework, which is able to explore the optimal topology of neural network architecture through training data. Our proposed method bridges these two research domains so that it is able to make prediction on user behavior with original video input.

3. DATASET

In our study, we use our in-house dataset, containing advertisement play history within one week. The advertisements have been grouped into 19 pre-defined categories by advertisers. This video setting is same as KWAI-AD [20] dataset. All audio tracks are sampled 44.1kHz sampling rate and each audio track has two channels. We mix each track into mono-channel in this study. The visual tracks have the resolution of 720 × 1280, a typical vertical setup for mobile devices. All advertisements have the same frame per second (FPS) of 25. Also, we summarize one-week performance for each advertisement, including impression, CTR and 3-second play rate. However, CTR and 3-second play rate are lack of statistical significance without enough impressions. Therefore, based on our experience, we set 70,000 as impression threshold, under which advertisement samples have been discarded. After this step of filtering, a total of 9841 advertisements are collected. The total length of these advertisements is about 82 hours.

4. PROPOSED APPROACHES

The overview architecture of our system is shown in Figure 1. It consists of two parts: single modality sub-networks (visual and audio) and fusion sub-network. In this study, we train all these sub-networks jointly.

4.1. Feature extraction

In our study, CTR is related to the entire video, while 3-second play rate only corresponds to the content in the beginning three seconds (based on the definition introduced in
Section 1. Therefore, we prepare the feature extraction separately for these two tasks. For CTR prediction, we utilize our in-house key-extractor to extract 8 visual frames from each video and keep entire audio track. For 3-second play rate prediction, we extract 3 visual frames only from the first three seconds, one frame per second and only keep audio track of the first three seconds. Extracted visual frames and audio tracks are then processed through Mobiilenetv2 [21] and VGGish [22] respectively to generate visual and audio inputs. Our primary research showed that advertisement category also had impact on CTR prediction result and thus, we introduce category into our case as an extra modality. Category information (we have 19 advertisement categories) are processed by an one-hot encoder to generate category embedding.

4.2. Single Modality Sub-networks
Inputs of visual and audio modalities are processed by two sub-networks respectively. The visual sub-network has a fully-connected (FC) layer, whose parameters are shared across all frames. The output of visual sub-network is a sequence of 128-D embeddings. The audio sub-network consists of a FC layer, an uni-directional LSTM layer and a self-attention layer. The output of audio sub-network is a 128-D embeddings. Numbers of neurons in each layer are shown in Figure 1. For each video, we have several frames for visual input, while we have only one embedding for audio input and one embedding for category. Therefore, audio embedding and category embedding are repeated to match the frame count in each video. These collected embeddings are then sent to our proposed fusion model.

4.3. Fusion Sub-network
In our study, we have two fusion approaches: baseline and self-organizing. For the baseline approach, we adopt fusion model sub-network proposed in Ti-AV network [23] (Figure 2(a)). It has two 1-D convolutional neural networks (CNN), one max-pooling layer and one FC layer to predict targets. For our proposed approach, which we name as “self-organizing” approach, we follow the following steps to learn fusion strategy from data: (1) Modify the fusion sub-network in the baseline approach. We connect input embeddings to the second CNN layer and the max-pooling layer, in addition to the first CNN layer. The output of the first CNN layer is also connected to the max-pooling layer, as shown in dashed border of Figure 2(b). It is equivalent to connecting the output of each layer to all of its following layers in the dashed boundary. Therefore, we name it as “all-connected” fusion sub-network. (2) Optimize all-connected fusion sub-network until there is no more improvement in performance on validation set (shown in Figure 3(a)). (3) Select the 5% of connections with the lowest absolute values (shown in Figure 3(b)). (4) Remove connections selected in step (3) and fine-tune the sub-network (shown in Figure 3(c)). (5) Repeat step (3) and step (4) until parameters number reaches a pre-defined threshold. We employ the parameter number of fusion model in baseline approach as our threshold in the experiments.

The logic behind removing connections is that connections with low absolute values indicate that they play less important role in forward propagation than others. With these connection removed, our model re-organizes information flow and learns the optimal topology. Therefore, we name our fusion model as self-organizing model. The entire procedure is data-driven and does not require manually defined rules. Our self-organizing framework is flexible and sophisticated.

5. EXPERIMENT AND ANALYSIS
5.1. Experiment Setup
We evaluated our proposed method on CTR prediction and 3-second play rate tasks. For each task, two types of experiments were conducted: regression and classification. For the classification experiment, we uniformly binned the data into five groups (every bin had same count of sample in training set), based on the distribution of data on training set (shown in Figure 4(a) and 4(b)). Here, the 1-D output layer in regression model was replaced by a 5-D softmax output layer.

Two models, which have been introduced in Section 4, were built for comparison with our proposed work. The first one was the fusion model in the baseline approach (named as “Baseline”). The other model for comparison was the fusion model in all-connected approach (named as...
5.2. Experiment Results and Analysis

The results of all regression experiments are listed in Table 1 and 2. In CTR regression experiment, our proposed Self-Organizing model beats Baseline model and All-Connected model by 0.9% and 6.0% respectively (absolute difference). In 3-second play rate regression experiment, our proposed Self-Organizing model outperforms Baseline model and All-Connected model by 0.5% and 0.3% respectively (absolute difference). We notice that MAE of Self-Organizing model is 2.5% lower than Baseline model and 1.8% lower than All-Connected model. As shown in Figure 4(a) and 4(b), the CTR distribution follows an heavy-tail distribution, while 3-second play rate follows a normal distribution. In both types of distribution, our proposed model achieves the best performance, indicating that it has strong flexibility and generalization ability.

Table 3 summarizes classification experiment results. In CTR classification experiment, our proposed model outperforms Baseline model and All-Connected model by 5.0% and 2.8% respectively (absolute difference). In 3-second play rate classification experiment, our proposed model outperforms Baseline model and All-Connected model by 1.4% and 1.3% respectively (absolute difference). We note that classification is a task with courser granularity compared with regression. It shows that our proposed Self-Organizing model outperforms other baseline models in all granularities.

6. CONCLUSION

In this study, we propose a self-organizing approach, which can learn the optimal topology of neural network architecture in a data-driven way. Unlike previous approaches, our proposed method does not require prior knowledge or assumption about relationships among modalities. It provides more flexibility in handling tasks related to UGVs, which contain complex and complicated information. Also, our proposed

![CTR distribution](image1.png)

(a) CTR distribution.

![3-second play rate distribution](image2.png)

(b) 3-second play rate distribution.

Fig. 4. Training data distribution in regression tasks.
method is able to predict CTR and 3-second play rate directly from video inputs. Our experimental results reveal that our proposed method successfully predict user behaviors and outperforms all other models for comparison.

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