

# LT4REC: A Lottery Ticket Hypothesis Based Multi-task Practice for Video Recommendation System

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## ABSTRACT

Click-through rate prediction (CTR) and post-click conversion rate prediction (CVR) play key roles across all industrial ranking systems, such as recommendation systems, online advertising, and search engines. Different from the extensive research on CTR, there is much less research on CVR estimation, whose main challenge is extreme data sparsity with one or two orders of magnitude reduction in the number of samples than CTR. People try to solve this problem with the paradigm of multi-task learning with the sufficient samples of CTR, but the typical hard sharing method can't effectively solve this problem, because it is difficult to analyze which parts of network components can be shared and which parts are in conflict, i.e., there is a large inaccuracy with artificially designed neurons sharing. In this paper, we model CVR in a brand-new method by adopting the lottery-ticket-hypothesis-based sparse sharing multi-task learning, which can automatically and flexibly learn which neuron weights to be shared without artificial experience. Experiments on the dataset gathered from traffic logs of Tencent video's recommendation system demonstrate that sparse sharing in the CVR model significantly outperforms competitive methods. Due to the nature of weight sparsity in sparse sharing, it can also significantly reduce computational complexity and memory usage which are very important in the industrial recommendation system.

## CCS CONCEPTS

• Information systems → Retrieval models and ranking.

## KEYWORDS

post-click conversion rate, multi-task learning, recommendation system, lottery ticket theory, sparse sharing

## 1 INTRODUCTION

Click-through rate prediction (CTR) and post-click conversion rate prediction (CVR) play key roles across industrial ranking systems, such as recommendation system [1, 2], online advertising, and search engine [3]. According to the different item types, the CVR indicator of the e-commerce product expresses whether to buy goods after click whose value is discrete,  $label \in \{0, 1\}$ ; and the CVR of the net media content expresses the degree of consumption whose value is continuous,  $label \in [0, 1]$ , e.g., if someone watched 2 minutes of the video with a length of 5 minutes, the  $CVR = 0.4$ . Most previous works were concentrated on CTR estimation, not only because CTR is an upstream task of CVR, i.e., impression  $\rightarrow$  click  $\rightarrow$  conversion and more widely used, but also because CVR task is more difficult to predict. The main challenge of CVR is extreme data sparsity, with the number of samples is usually one or two orders of magnitude lower than CTR, making the model fitting rather difficult and resulting in poor generalization ability. The more direct way to estimate conversion is to predict post-view click&conversion rate (CTCVR), i.e., impression  $\rightarrow$  conversion. But CTCVR task is more difficult than CVR task for more sparse positive samples, usually one order of magnitude less in sample size. Given impression  $x$ , click  $y$ , conversion  $z$ , the relation of these probabilities follows Eq(1):

$$\underbrace{p(z|x)}_{p_{CTCVR}} = p(z, y = 1|x) = \underbrace{p(y = 1|x)}_{p_{CTR}} \times \underbrace{p(z|y = 1)}_{p_{CVR}} \quad (1)$$

Multi-task learning (MTL) was first proposed to solve STEIN's paradox and improve the performance of a single task by utilizing

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the potential correlation of two similar tasks [4]. The main approaches of MTL in deep learning is hard sharing and soft sharing. Hard sharing assumes representation of specific features or specific neural sub-network is potentially the same in different tasks, and then they can be fully shared across different tasks. Soft sharing relaxes the constraint of hard sharing to a soft one, which holds the hypothesis that the feature embeddings or neural layers are connected but not exactly the same in different tasks such as sharing the same L2 regulation [5]. On the other hand, soft sharing requires more handcrafting network structure design, which is even more challenging and often leads to inaccurate representation. The most classic MTL method is hard sharing which is widely used in many areas, such as natural language processing (NLP), computer vision (CV). In the field of recommendation systems, we currently only see hard sharing practices [1, 2].

The lottery ticket hypothesis (Frankle et al. 2018) [6] has been proposed recently and attracts great attention: dense, randomly initialized, feed-forward networks contain subnetworks (winning tickets) that when trained in isolation, can reach test accuracy comparable to the original network in a similar number of iterations. Although it was initially developed for neural network model compression, Sun et al. (2019) [7] applied the theory in the MTL field and achieved state-of-the-art performance through learning sparse sharing neural network architectures in NLP area for multiple tasks such as Part-of-Speech (POS), Named Entity Recognition (NER), and Chunking task. Sparse sharing holds the hypothesis that some neural node connections should be shared across different tasks while others should not, through which different tasks can have their own specific networks while also sharing certain node connections. The implementation is that each task has a mask network to mark its own node connections in the shared network. Malach et al. (2020) [8] further puts two proofs: 1) For a neural network (ReLU activation function) of any depth  $d$ , one can approximate it by searching for a random network with a depth of  $2 * d$  and a sufficient width and finding a weight-subnetwork which removes specific weights. 2) For a two-layer neural network (a hidden layer), a neuron-subnetwork that removes specific neurons can be found, which has a performance comparable to the original network.

**Representation sharing.** MTL was widely used in NLP and CV field and great efforts have been made on applying it to recommendation systems in recent years [1, 2, 9]. Several studies are trying to optimize CVR model by taking advantage of abundant samples of CTR samples. ESMM [1] builds a post-view click-through rate (CTR) and post-view click-through&conversion rate (CTCVR) joint tasks to tackle the conversion sample sparsity problem. It handles data sparsity (DS) and sample selection bias (SSB) problems by using feature embedding sharing which called hard sharing in MTL. MMOE [2] models multi-task learning with a multi-gate mixture of experts with each expert trying to aggregate different samples, which can be seen as a sample clustering and model ensemble. Wen et al. [9] propose an upgraded version of ESMM that optimizes CVR by utilizing collections, adding to cart and other signals besides clicks in the e-commerce platform.

**Sharing conflict.** The difficulty of applying MTL to a recommendation system is how to resolve the conflicts between tasks that are not closely related or even mutually exclusive to some extent while sharing representation as much as possible. For example, 1)

the positive sample of CTR and the negative sample of CVR exist at the same time for a real event, which have opposite gradients during weights updating. 2) multi-view representation [10]: embedding of entities under different tasks may not be close to each other in vector space, which also exists in CTR and CVR, such as the representation of e-commerce goods, online videos. For example, the user's click signal may be noisy to the purchase, such as a curious browsing scene in which consumers will only scan the goods for interest or curiosity without purchasing. The conflict phenomenon is verified in our theoretical analysis and ESMM, MMOE algorithm experiments whose initial performance is worse than the single task learning if there is no careful tuning.

To improve the performance of multiple tasks in video recommendation, we apply sparse sharing multi-task learning, after careful model design and conflict adjustment, we have achieved good results in CVR and final online performance. Extensive experiments have been done on Tencent Video, a video platform with hundreds of millions of users, to prove the effectiveness of our algorithm. We offer the following contributions:

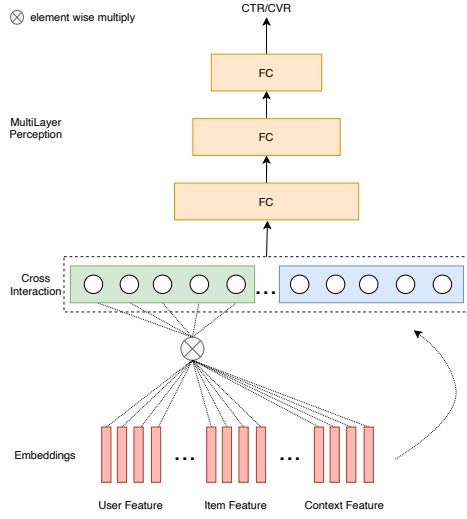
- (1) We apply a lottery ticket hypothesis-based sparse sharing model to solve MTL in recommendation systems. As far as we know, lottery ticket hypothesis-based sparse sharing has not been applied to recommendation systems so far.
- (2) We provide a detailed description of how to tune the performance of sparse sharing CTR/CVR, which is usually the most difficult part of applying MTL in recommendation systems.
- (3) We demonstrate the value of sparse sharing by comparing it with classic models such as single task DNN model, hard sharing, and test it on a large industrial video platform of hundreds of millions of users, achieving a relative reduction of 3.78% in CVR MSE over baseline. We believe that this algorithm can be easily adapted to other recommendation platforms such as e-commerce, news reading, and other related tasks such as like rate, collection rate, adding to cart rate with minor modifications.

## 2 THE PROPOSED APPROACH

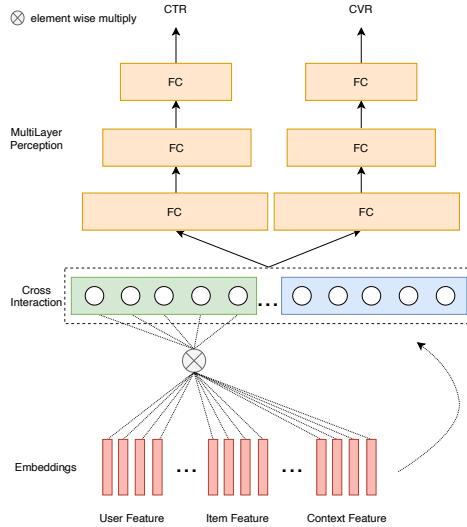
### 2.1 Single Task Model & Hard Sharing MTL

Most CTR/CVR tasks follow a classic deep learning model with similar Embedding&CrossFeature&MLP network architecture, such as DLRM [11], Deep&Wide [11], deepFM [12] etc. Fig 1 illustrates this kind of architecture, which we refer to as BASELINE single task model [11], for simplicity. The first layer is an embedding layer for features; the second layer is a feature-cross layer with an element-wise dot multiplication for each element in the feature vector, which concatenates the original embedding layer; the following are multi-layer perceptrons (MLPs), composed of a sequence of fully connected (FC) layers.

**Hard sharing MTL.** The typical hard sharing model will share the lower layers of the network while keeping its own upper branch layers, i.e., multi-head multi-task. As we can see in Fig 2, the CVR task shares the embedding lookup table with the CTR task, so the fundamental representation of features such as user id, user age, gender, item id, item category learned by CTR can be used to compute the CVR score by feedforward propagation in the network. This approach is reasonable, for example, user A hasn't had a lot of



**Figure 1: Network Architecture of baseline model [9] of a single task.** CTR and CVR use the same network architecture to model their tasks. The embedding layer contains user features (user id, age, gender, user click history, etc. ), item features( item id, item category, tag, etc.), and context features (the day of the week, the hour of the day, source page, etc.), of which we simplified their representation in Fig 1.

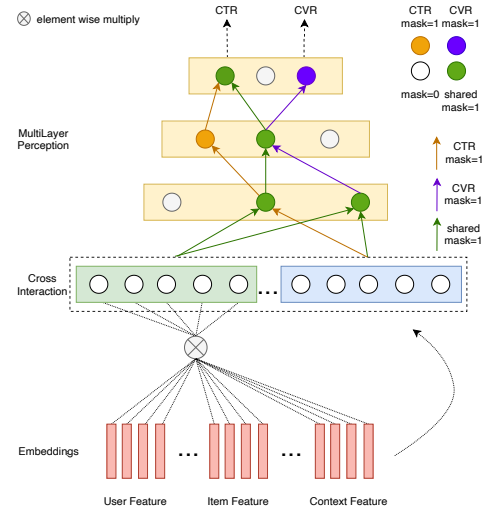


**Figure 2: Network architecture of hard sharing, the left part illustrates the network of the CTR model the same as in Fig 1, while the right part for the CVR model.**

consumption behavior recently, so the representation of the user id can't be well learned only through consumption signals; but if this user has many click behaviors, such signals can be learned by the CTR branch and subsequently assist the CVR prediction.

## 2.2 Sparse Sharing MTL

Unlike hard sharing with the upper layers not shared at all and the lower layers fully shared, we have designed unique mask networks for each task, allowing tasks to flexibly learn which neural connections or neurons should be activated for shared tasks or only for a specific task. Like hard sharing, the interaction layer and embedding layer are fully shared. The proposed method is illustrated in Fig 3.



**Figure 3: Network Architecture of sparse sharing.** Mask=0 means that the neuron or connection is not activated, i.e., never used by any task; CTR mask=1 means it is only used by the CTR task, similar to CVR mask=1; shared mask=1 means it is shared by CTR and CVR. Please note that our masks are only valid for MLPs, and cross interaction layer and embedding layers are fully shared.

**Representation sharing and sharing conflict.** Sparse sharing, as we can see in Fig 3 and Algorithm 1, can automatically design the sharing structure based on characteristics of the tasks. It starts with learning a fully shared network we call sNET. Each task does not learn a network separately, but first learns its own matrix  $mask \in \{0, 1\}$ ; then the sub-network of the current task is obtained through the related effects of the jointly learned network sNET and the task specific mask with  $sNET \odot mask$ , where  $\odot$  denotes element-wise multiplication. As shown in Fig 3, CTR task occupies the yellow part and green part of the shared network while CVR task occupies the purple and green part. The co-occupied green part means CTR and CVR will share the representation of these parameters, while they still can hold their specific representation through yellow and purple part; this sharing representation and task specific representation exactly respond to the typical paradigm of multi-task which tries to maximize sharing while reducing conflict. Because the masks are learned automatically, we avoid analyzing which part of the network should be handled with representation sharing and don't need to design a sophisticated subnet or soft-sharing technique solving conflicts in sharing through manual experience or a large number of hyperparameter experiments which may be

hard to guarantee the benefits. Notice that in addition to masking connection weights we also explored the effect of masking neurons which is different from [7].

**Computation and storage reduction.** Different from [7], the *sNET* is not an over-parameterized network but has the same size as the single task in Fig 1. As model training progresses, the size of the model is greatly reduced, and thus the computation and storage are greatly decreased. Considering the recommendation system is beginning to involve more and more tasks such as conversion rate, adding cart rate, like rate, follow rate in online social media or e-commerce apps, the one shared network will benefit more than multi-models. To simplify, we consider the case of only two tasks, CTR and CVR, the reduced amount of calculation is proportional to the number of remaining weights (in our case, 80% reduction in the calculation), and the reduced size of storage(which typically varies from tens of gigabytes to hundreds of gigabytes) is almost half. If more objects are pursued online, such as like rate and comment rate, the benefits of the sparse sharing model will be greater in engineering architecture. Notice that, although we trained several epochs of samples in the mask generating section in Algorithm 1 as shown below, the conclusion still holds because mask generating process is only executed once while the *sNET* generation is executed incrementally every day.

**Tuning techniques.** We devised some tuning methods to further improve the performance of CVR task in sparse sharing. 1)task imbalance(label-layer-conflict). Because CTR sample size is much larger than CVR, if the model is trained according to the 1:1 sample ratio, then the overall learning will be dominated by the CTR task which goes against our intention of improving the performance of CVR. We adopt Eq(2) as the loss function, where the typical value of *b* will be much larger than *a*. 2)Gradient conflict(sharing-layer-conflict). Consider the situation *sample\_labels* = 1|1|0 or *sample\_labels* = 1|1|0.05, which means the video is impressed and clicked, but not viewed or viewed for a very short time; the gradients of the two tasks is opposite to each other during network back-propagation. In this case, it will be difficult for CVR to learn the correct representation from negative samples because its gradient is offset by the CTR gradient. We increased the weight of CVR loss according to the CVR value dynamically under this circumstance. 3)multi-view representation(lower-layer-conflict). Conventionally, it is believed that the lower-level entity representation in MTL is the same and then can be completely shared. This may be true in some NLP areas, e.g., the word representation in language tasks, but they are quite different in recommendation systems from the perspective of multi-view [10]. For example, people will be attracted by the eye-catching title or the good-looking cover image of a video, but they may not watch the entire video completely, in which case the representation of the video should be different between CTR and CVR. 4)We also tried to increase the size of the sharing network to alleviate conflicts between tasks.

$$loss = a * loss\_CTR + b * loss\_CVR \quad (2)$$

Our proposed algorithms are illustrated in Algorithm 1 [7],

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#### Algorithm 1 CTR/CVR sparse sharing

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**Input:** Shared network *sNET*; masks *masks*[*n\_tasks*], where each mask has the same shape as *sNET*; number of pruning *n\_pruning*; number of batches in an epoch of all task mixed samples *n\_batches*;  $\odot$  means element-wise multiplication.

**Output:** CTR model and CVR model;

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1: for task_id in [CTR,CVR] do
2:   Initialize masks[task_id][0] with all values set to 1.
3:   for i = 1 to n_pruning do
4:     a) Train sNET for an epoch of the task_id task, e.g.,
       CTR, after sNET = sNET  $\odot$  masks[task_id][i - 1];
5:     b) Let x equal to the qth quantile of the absolute value
       of the weights from sNET, where q is a preset parameter. We
       then update the values of masks[task_id][i - 1] by setting all
       the values less than x to be 0 to obtain mask[task_id][i];
6:     c)Reinitialize the network weight of sNET.
7:   end for
8:   Select the best i of masks[task_id][i] according to
       the performance of the model on the validation set as
       masks[task_id][best_i].
9: end for
10: We get masks[CTR][best_i] and masks[CVR][best_i].
11: Reinitialize sNET parameters to be trained in the mixed
    CTR/CVR samples.
12: for batch = 1 to n_batches do
13:   a) Obtain the task_id of the current batch, e.g., CTR;
14:   b) Update sNET weights feeding masks[task_id][best_i];
15:   c) Train sNET to calculate loss and gradient;
16:   d) Gradient update of weights.
17: end for
18: CTR_model = sNET  $\odot$  masks[CTR][best_i].
19: CVR_model = sNET  $\odot$  masks[CVR][best_i].

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## 3 EXPERIMENTS

### 3.1 Experimental Setup

**Datasets.** During our survey, we didn't find a public video recommendation data set containing clicks and other interactive indicators such as conversions; basically, they only include one task. To evaluate the proposed approach, we use the traffic logs from Tencent Video recommendation system. Table 1 summarizes the statistics of the dataset.

**Competitors.** We conduct experiments with several classic methods and effective tuning techniques. 1)**BASELINE** is a single task which models CTR and CVR separately. 2)**Hard sharing** is the classic multi-task paradigm sharing bottom layers while has the task-specific head layers. 3) **S-Weight** is the exact algorithm described in Algorithm 1, with sparse sharing in MLPs and fully sharing in cross interaction layer and embedding layer. 4) **S-Neuron** is a variant of S-Weight, it generates the subnets by removing the entire specific neurons instead of removing the specific weights in S-Weight. 5)**S-Weight-tuning**. We used some techniques to further improve the performance of sparse sharing CVR. These methods include **S-weight-taskbalance** (increasing the weight of the loss of CVR), **S-weight-gradientconflict** (dealing with the

**Table 1: statistics of the experimental dataset**

| dataset       | #user | #video | #impression | #click | #conversion |
|---------------|-------|--------|-------------|--------|-------------|
| Tencent Video | 10M   | 11M    | 297M        | 121M   | 49M         |

**Table 2: offline comparison of different models**

| Model                     | cvr mse                | ctr auc                |
|---------------------------|------------------------|------------------------|
| base_ctr                  | -----                  | 0.78572                |
| base_cvr                  | 0.13688                | -----                  |
| hard_sharing              | 0.13563(-0.9%)         | 0.78808(+0.0024)       |
| s-weight                  | 0.13226(-3.38%)        | <b>0.78874(+0.003)</b> |
| s-neuron                  | 0.13531                | 0.78346                |
| s-weight-taskbalance      | 0.13193(-3.62%)        | 0.78740                |
| s-weight-gradientconflict | 0.13181(-3.7%)         | 0.78801                |
| s-weight-multiview        | 0.13242                | 0.78762                |
| s-weight-biggernet        | 0.13251                | 0.78525                |
| s-weight-tuning           | <b>0.13171(-3.78%)</b> | 0.78689                |

**Table 3: online comparison of different models**

| Model                              | view time      | cvr          | ctr          |
|------------------------------------|----------------|--------------|--------------|
| 1)base_ctr*base_cvr*length         | 491.312        | 54.9%        | 24.7%        |
| 2)base_ctr*hard_cvr*length         | 481.651        | 55.0%        | <b>24.8%</b> |
| 3)base_ctr*s_weight_cvr*length     | <b>498.686</b> | 55.1%        | 24.7%        |
| 4)s_weight_ctr*s_weight_cvr*length | 497.158        | <b>55.3%</b> | <b>24.8%</b> |

<sup>1</sup> view time is measured by seconds.

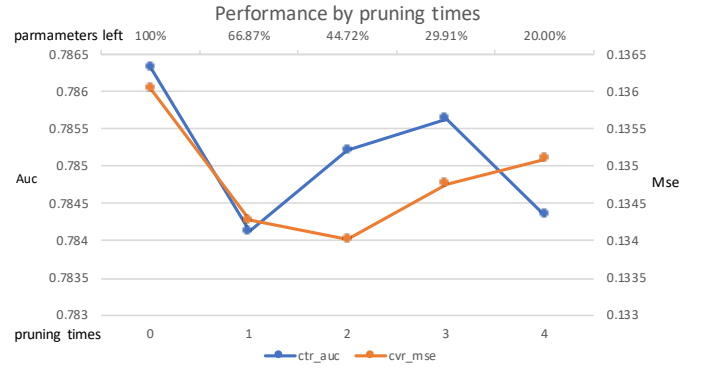
<sup>2</sup> For simplicity,  $a = b = c = 1$  in the rankscore formula.

<sup>3</sup> base\_ctr/cvr denotes single task ctr/cvr; hard\_ctr/cvr denotes hard sharing ctr/cvr; s\_weight\_ctr/cvr denotes sparse sharing ctr/cvr with connection pruning.

problem of opposite gradients between multiple tasks), **S-weight-multiview** (sparse sharing in the embedding layer), **S-weight-biggernet** network size adjustment (a bigger net for sparse sharing). **S-Weight-tuning** experiments combines **S-weight-taskbalance** and **S-weight-gradientconflict** experiment techniques. These methods are described in detail in the tuning techniques part of section 2.2.

**Metric.** The comparisons are made on two tasks, CTR and CVR. The goal of CVR comparison is to verify the improvement of sparse sharing MTL for data-sparse tasks. CTR aims to test and verify whether sparse sharing MTL can improve the performance of auxiliary data-dense tasks. Typical multi-task learning solutions for CVR often sacrifice the performance of CTR. Mean Squared Error (MSE) is adopted as the metric of CVR modeling evaluation, and Area under the ROC curve (AUC) is adopted as the metric of CTR. In the online experiment, we used the view time as the metric, and the online ranking score follows Eq(3), where  $a, b, c$  are hyperparameters:

$$rankscore = pCTR^a * pCVR^b * video\_length^c \quad (3)$$


**Figure 4: the performance with different pruning times in best mask generation stage of algorithm 1**

### 3.2 Results

The offline results are illustrated in Table 2. First, the MSE of **S-Weight** sparse sharing CVR is reduced by 3.38% than the **base\_cvr** single task model and 2.9% less than the **hard sharing** model. This validates the effectiveness of sparse sharing MTL for data sparsity tasks. Second, **S-Weight** sparse sharing CTR achieves an absolute AUC gain of 0.003 over the **base\_ctr** model and a slight gain of 0.0006 over **hard\_sharing** CTR. 1% reduction in MSE and 0.001 gain of AUC are both remarkable in the industrial recommendation systems, which can lead to significant improvement. The improvement of CTR is not as significant as that of CVR. We think this is because CTR samples dominate the whole sample set and CTR is much easier to learn for more sufficient samples. Compared with the single-task model, **S-Neuron** performs well on the CVR index, but not as good as **S-Weight**. This is probably because the pruning of **S-Neuron** is very coarse-grained, using neuron pruning instead of connection weight pruning. The performance of our tuning techniques is shown in **S-weight-\***. Compared to **S-Weight**, **S-Weight-taskbalance** and **S-Weight-gradientconflict** achieve a better result in CVR but worse result in CTR, which is reasonable because both of two models weaken the expression of CTR while strengthening CVR; **S-Weight-taskbalance** reduces the loss weight of CTR and **S-Weight-gradientconflict** reduces the gradient propagation of CTR. We failed to achieve better results in **S-weight-biggernet** and **S-weight-multiview**. That the bigger network don't perform better is probably because we learn the shared network sparsely where the advantage of larger search space brought by a larger network may be offset by our unconscious pruning. **S-weight-multiview** adds 8-dimensional CVR exclusive embedding in addition to the shared 32-dimensional embedding, but because the lower layer representation is more similar, maybe we need more CVR exclusive embedding to be effective. However, due to storage constraints we didn't do larger-embedding experiments. Finally, we combine **S-Weight-taskbalance** and **S-Weight-gradientconflict** and achieve the best result with 3.78% reduction in MSE which is shown in **S-Weight-tuning**.

The online experiment result is illustrated in Table 3. The results of the first three experiments show the sparse sharing CVR outperforms the hard sharing CVR and the BASE model. Experiment

4) tries to explore the online benefit of sparse sharing CTR, but the view time is not better than experiment 3). It can improve the metric of CVR which may be due to the compatibility that sparse CTR model and sparse CVR model are trained together. In the end, we got a 1.5% increase over single task model in online view time.

The detail performance analysis of mask generation in Algorithm 1 is illustrated in Figure 4. With the iterations of pruning, the performance of CVR shows a trend of rising first and then falling (the lower the better). This is because a more sparse network structure is better for sparse tasks like CVR, which is in line with the assumptions of lottery ticket hypothesis; but this sparseness is not unlimited, and too few neurons are not enough to model behaviors in recommendation systems. CTR achieves the best result without pruning (the higher the better), and the trend behind is similar to CVR. This is probably because the samples of the CTR task are relatively dense, but considering the significant reduction of computation and storage, we don't choose the unpruned case.

## 4 CONCLUSIONS AND FUTURE WORK

In this paper, we adopt a lottery ticket hypothesis-based sparse sharing MTL to recommendation systems. The algorithm tackles the difficult problem of sharing conflicts in MTL elegantly with automatically learning which weights to be shared and greatly reduces the computational complexity and memory storage. Experiments on industrial video recommendation systems demonstrate a superior performance and a huge reduction in calculation and storage. This method can be easily generalized to other data tasks in recommendation systems. In the future, we intend to adopt sparse sharing in more tasks such as like rate, comment rate, follow rate besides the two tasks we discussed.

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