Concept Drift Adaptation for CTR Prediction in Online Advertising Systems

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ABSTRACT
Click-through rate (CTR) prediction is a crucial task in web search, recommender systems, and online advertisement displaying. In practical application, CTR models often serve with high-speed user-generated data streams, whose underlying distribution rapidly changing over time. The concept drift problem inevitably exists in those streaming data, which can lead to performance degradation due to the timeliness issue. To ensure model freshness, incremental learning has been widely adopted in real-world production systems. However, it is hard for the incremental update to achieve the balance of the CTR models between the adaptability to capture the fast-changing trends and generalization ability to retain common knowledge. In this paper, we propose adaptive mixture of experts (AdaMoE), a new framework to alleviate the concept drift problem by adaptive filtering in the data stream of CTR prediction. The extensive experiments on the offline industrial dataset and online A/B tests show that our AdaMoE significantly outperforms all incremental learning frameworks considered.

CCS CONCEPTS
• Information systems → Computational advertising; Sponsored search advertising.

KEYWORDS
Concept Drift, CTR Prediction, Incremental Learning

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1 INTRODUCTION
Click-through rate (CTR) prediction has been widely explored in online advertising and recommender systems with deep learning models, mainly focusing on feature interaction [2, 7, 16, 21] and user behavior modeling [9, 24, 26, 27]. These deep CTR models are usually trained with offline batch mode.

However, in real-world production systems such as online advertising platforms, CTR models often serve with high-speed streaming data generated from a huge amount of users. One common challenge is to deal with rapid changes in the distribution of the data stream over time, referred to as the concept drift problem [13, 20]. Figure 1 provides an empirical observation of concept drift with hours-hours similarity and temporal variation of CTR values in a real-world online advertising system.

To guarantee model freshness, incremental learning has been applied to real-world production systems [22]. However, vanilla incremental learning methods are not able to address the stability-plasticity dilemma [5]. Slow updates achieve stability but reduce...
model reactivity. Fast adaptation with large steps can help the model keep up with concept drift, but decreases its robustness.

Many efforts have been devoted to learning and mining of concept drifting stream data [1, 4, 11, 14, 23]. However, these models require an additional buffer to store historical data or need extra drift detection module to work properly. The memory inefficiency and computational complexity of these models can be problematic in the application of online CTR inference [25].

Without extra cache and explicit detection for drifting data, many recent works investigate a more adaptive way to update models according to new patterns [18, 22, 25]. The work in [22] proposed IncCTR which applies incremental learning to CTR prediction task. IncCTR employs knowledge distillation to balance the learned knowledge from the previous model and that from incoming data. However, IncCTR uses a single and fixed-structured model, which limits the adaptation capacity to streaming data with potential concept drift. A more popular way is to leverage ensemble learning paradigm [6, 12, 25]. The work in [25] proposes incremental adaptive deep model (IADM) which starts from a shallow network, evolves to a deep network, and ensemble the outputs from different depth for streaming data. However, when the network evolves sufficiently deep, it is still hard to converge to optimum when training with streaming data.

Mixture of experts (MoE) [10] is a canonical deep ensemble learning structure. In the MoE model, all expert networks share the same backbone network which extracts the representations of input, and a gate network is designed to decide the aggregation weight of the output of each expert. Although the MoE model yields significant performance in various applications, training MoE can be challenging with possible dead gate issues [3, 17].

In this paper, we propose a novel framework of incremental learning, AdaMoE, which decouples the update of aggregation module from regular MoE network training scheme for CTR prediction. To update the aggregation module for fast adaptation, we theoretically derive the optimal updating policy upon the performance measurements of the prediction from experts, rather than inefficient back propagation via iterative gradient descent. This novel statistical update operation with closed-form solution greatly eases the convergence difficulty for MoE based methods.

To validate the effectiveness and efficiency of the proposed method in concept drifting data streams, we conduct extensive experiments against various competing baselines for CTR prediction on real-world production dataset. We further demonstrate the performance of our AdaMoE through a rigorous online A/B test in an online advertising system. An intuitive qualitative analysis of CTR values over time is provided to illustrate the superiority of AdaMoE in handling concept drift.

The contributions of this paper is summarized below:

- We proposed an innovative incremental learning framework, AdaMoE, for serving high-velocity user-generated streaming data. To the best of our knowledge, this is the first attempt to address the concept drift problem in CTR prediction.
- Theoretical derivation has been conducted for incremental update of CTR models in concept drifting streaming data.
- We achieve significant improvements on a real-world industrial dataset over all incremental learning baselines. A rigorous A/B test further demonstrates the excellent performance over a highly optimized baseline models.
- AdaMoE had been deployed in a real-world advertising system, serving hundreds of millions of active users.

2 METHODOLOGY

In this work, we consider the problem of CTR prediction with streaming data. Let \( \mathcal{D}_t = \{x_{t,i}, y_{t,i}\}_{i=1}^{N_t} \) be the stream data at time step \( t \). Here, \( x_{t,i} \in \mathbb{R}^f \) represents the features of the \( i \)-th sample, and \( y_{t,i} \in \{0, 1\} \) is the ground truth label that shows whether the user clicks the advertised product.

As illustrated in Fig. 2, the proposed AdaMoE consists of two modules: the main module that uses the input data feature to predict the CTR, and the weights update module that dynamically updates the aggregation weights of experts’ predictions.

2.1 Main Module

In the main module, the representation \( e_{t,i} \) of the sample \( x_{t,i} \) is first extracted with a backbone model:

\[
e_{t,i} = \text{Backbone}(x_{t,i}).
\]

The backbone model can be deep cross network (DCN) [21] or deep interest network (DIN) [27], etc., depending on the used features. Then, the extracted representation \( e_{t,i} \) is fed into \( m \) experts. Each expert is an MLP network \( \text{Expert}^{(k)} \) with a sigmoid activation function at the end. All experts consume the embedding \( e_{t,i} \) and output their own predicted CTR (pCTR):

\[
y_{t,i}^{(k)} = \text{Expert}^{(k)}(e_{t,i}).
\]

\( y_{t,i} = [y_{t,i}^{(1)}, \ldots, y_{t,i}^{(m)}]^T \) is the concatenation of the experts’ pCTR.

For all data samples \( \mathcal{D}_t \) at time step \( t \), we assume that they use the same aggregation weights, \( \mathbf{w}_t = [\mathbf{w}_t^{(1)}, \ldots, \mathbf{w}_t^{(m)}]^T \in \mathbb{R}^m \), to aggregate the output of each expert. That is, the predicted CTR of
the sample \( x_{t,i} \) is given by

\[
\hat{y}_{t,i} = w_t^r \hat{y}_{t,i} = \sum_{k=1}^{m} w_t^{(k)} y_{t,i}^{(k)}.
\] (3)

In AdaMoE, we separate the training of the main module and the update of experts’ aggregation weights. To train the main module, for the output of expert-\( k \), \( y_{t,i}^{(k)} \), we calculate the cross entropy loss

\[
L_{CE}^{(k)}(t, i) = y_{t,i} \cdot \log(y_{t,i}^{(k)}) + (1 - y_{t,i}) \cdot \log(1 - y_{t,i}^{(k)})
\] (4)

Then, the total training loss for the main module at time \( t \) is

\[
L_{main}(t) = \sum_{i=1}^{N_t} \sum_{k=1}^{m} L_{CE}^{(k)}(t, i).
\] (5)

The main module is optimized with gradient descent, but the data at time \( t \) is used only once as the data is in stream form.

### 2.2 Weight Update Module

In this work, we aim to efficiently update the aggregation weights of experts’ predictions so that AdaMoE can quickly adapt to the concept drift in streaming data. To achieve this, the update of aggregation weights should (1) converge fast to the optimal to ensure the timeliness of the model; and (2) the update should base on not only current data but historical data to ensure stability. The conventional training scheme uses gradient descent method which does not guarantee the convergence speed. Furthermore, in the application of online CTR inference, historical data cannot be cached and reused. To this end, inspired by the adaptive filter theory [8], we design an effective recursive method to update the aggregation weights.

Let \( y_t = [y_{t,1}, \ldots, y_{t,N_t}]^T \in \{0, 1\}^{N_t} \) be the ground truth label of data at time step \( t \). We also denote \( \hat{Y}_t = [\hat{y}_{t,1}, \ldots, \hat{y}_{t,N_t}]^T \in \mathbb{R}^{N_t \times m} \) as the predicted CTR given by \( m \) experts at time step \( t \). Given that the aggregation weights at time step \( t \) are \( w_t \), the squared error between ground truth \( y_t \) and the ensemble predicted CTR at time \( t \) is

\[
\epsilon_t = \|y_t - \hat{y}_t w_t\|^2_2.
\] (6)

Furthermore, inspired by adaptive filter theory [8], we define the decayed historical squared error as

\[
L_w(t) = \sum_{\tau=1}^{t} \lambda^{t-\tau} \epsilon_{\tau},
\] (7)

which records the error between the ground truth and the predicted CTR of the whole history. Here, the decayed factor \( \lambda \) controls how much historical squared error is contributed. The smaller the decayed factor \( \lambda \) is, the less history squared error is considered.

Based on the defined decayed historical squared error \( L_w(t) \), we can update the aggregation weights at the next time step, \( w_{t+1} \), to the one that minimizes \( L_w(t) \), i.e.,

\[
w_{t+1} = \arg \min_w L_w(t).
\] (8)

By setting the partial derivatives of \( L_w(t) \) with respect to \( w_t \) to zero, we can obtain the optimal aggregation weights

\[
w_{t+1} = R_{t}^{-1} d_t,
\] where

\[
R_t = \sum_{\tau=1}^{t} \lambda^{t-\tau} \hat{Y}_t^T \hat{Y}_t,
\] and

\[
d_t = \sum_{\tau=1}^{t} \lambda^{t-\tau} \hat{Y}_t y_t.
\] (9)

**Algorithm 1:** AdaMoE for CTR Prediction.

**Input:** Data \( D_t = [x_t, y_t] \), aggregation weights \( w_t \), and matrix \( R_{t-1} \).

**Output:** Predicted CTR \( \hat{y}_t \), new aggregation weights \( w_{t+1} \).

1. \( \hat{y}_t \leftarrow \text{MainModule}(x_t); \quad // \text{Collect pCTR of experts}; \)
2. \( \hat{y}_t \leftarrow \hat{Y}_t w_t; \quad // \text{Aggregate pCTR}; \)
3. Update MainModule using gradient descent with \( y_t \);
4. \( R_t \leftarrow \lambda R_{t-1} + \hat{Y}_t \hat{Y}_t^T; \quad // \text{Update matrix } R_t \)
5. \( g_t \leftarrow R_t^{-1} \hat{Y}_t^T; \)
6. \( w_{t+1} \leftarrow g_t \cdot (y_t - \hat{Y}_t w_t); \quad // \text{Update aggregation weights}; \)
7. \( w_{t+1} \leftarrow \text{sum}(\text{clip}(w_{t+1}, 0, 1)); \)

Although we have derived the optimal aggregation weights for time \( t + 1 \) as above, this cannot be directly applied in online CTR prediction because the history \( y_t \) and \( \hat{Y}_t \) cannot be cached in memory. To address this issue, we rewrite the optimal aggregation weights \( w_{t+1} \) in recursive form and have the following theorem

**Theorem 2.1.** The aggregation weights \( w_{t+1} \) can be updated recursively as

\[
w_{t+1} = w_t + g_t \cdot (y_t - \hat{Y}_t w_t), \quad \text{where } g_t = R_t^{-1} \hat{Y}_t^T
\] (10)

**Proof.** We first rewrite \( R_t \) and \( d_t \) in recursive form as

\[
R_t = \sum_{\tau=1}^{t} \lambda^{t-\tau} \hat{Y}_t \hat{Y}_t^T = \sum_{\tau=1}^{t-1} \lambda^{t-\tau-1} \hat{Y}_t \hat{Y}_t^T + \lambda \hat{Y}_t \hat{Y}_t^T = \lambda R_{t-1} + \hat{Y}_t \hat{Y}_t^T
\]

\[
d_t = \sum_{\tau=1}^{t} \lambda^{t-\tau} \hat{Y}_t y_t = \sum_{\tau=1}^{t-1} \lambda^{t-\tau-1} \hat{Y}_t y_t + \hat{Y}_t y_t = \lambda d_{t-1} + \hat{Y}_t y_t
\]

With the above derivation, we can rewrite the \( w_{t+1} \) as

\[
w_{t+1} = R_t^{-1} d_t = \left( \lambda R_{t-1} + \hat{Y}_t \hat{Y}_t^T \right)^{-1} \left( \lambda d_{t-1} + \hat{Y}_t y_t \right).
\] (11)

Then with the Woodberry inverse formula [15], we have

\[
R_t^{-1} = \lambda^{-1} R_{t-1}^{-1} - g_t y_t \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T,
\]

and

\[
g_t = \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T \left( I + \hat{Y}_t \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T \right)^{-1}
\] (12)

With (12), \( g_t \) can be further simplified as

\[
g_t \left( I + \hat{Y}_t \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T \right) = \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T
\]

\[
g_t \left( I + \hat{Y}_t \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T \right) = \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T - g_t \hat{Y}_t \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T
\]

\[
g_t = \left( \lambda^{-1} R_{t-1}^{-1} - g_t \hat{Y}_t \lambda^{-1} R_{t-1}^{-1} \hat{Y}_t^T \right) \hat{Y}_t^T = R_t^{-1} \hat{Y}_t^T.
\] (13)

Plugging (12) and (13) into (11), we have

\[
w_{t+1} = R_t^{-1} \left( \lambda d_{t-1} + \hat{Y}_t y_t \right) = R_t^{-1} R_{t-1} d_{t-1} + R_t^{-1} \hat{Y}_t y_t
\]

\[= \lambda R_t^{-1} d_{t-1} + g_t y_t \left( \lambda^{-1} R_{t-1}^{-1} - g_t \hat{Y}_t \lambda^{-1} R_{t-1}^{-1} \right) d_{t-1} + g_t y_t\]

\[= R_t^{-1} d_{t-1} + g_t \cdot (y_t - \hat{Y}_t \hat{Y}_t^T d_{t-1})
\]

\[= w_t + g_t \cdot (y_t - \hat{Y}_t w_t).
\] (14)
The last step of the above uses the fact that \( w_t = R_t^{-1} d_{t-1} \).

From Theorem 2.1, We only need to cache \( w_t \in \mathbb{R}^m \) and the matrix \( R_t \in \mathbb{R}^{m \times m} \) in memory to recursively update the aggregation weights \( w_{t+1} \). Furthermore, we can see that the aggregation weights can be updated based on the current aggregation weights \( w_t \). The change of aggregation weights is decided by \( (y_t - f_{t} w_t) \), which is the difference between the ground truth label and the predicted CTR at time step \( t \). We summarize the updating process of AdaMoE in Algorithm 1. To ensure that the aggregation weights are positive and sum to 1, in the last step of Algorithm 1 (line 7), we further unify \( w_{t+1} \), where clip\( (w_{t+1}, 0, 1) \) constraints each entry of \( w_{t+1} \) in the range\([0, 1]\).

### 3 EXPERIMENTS

In this section, we evaluate the performance of AdaMoE through offline experiments on the industrial dataset and online A/B test.

#### 3.1 Offline Experiments on Industrial Dataset

**Datasets.** The industrial dataset is extracted from the user logs of one of the world’s largest e-commerce companies. The extracted dataset includes about 4.5 billion ad impression records within one day. We first sort the collected data in chronological order. Then, the sorted data are divided into datasets. Each dataset \( D_t \) contains 2048 samples. This constitutes the data stream for offline experiments.

**Settings.** We use DCN [21] and DIN [27] as the backbone, respectively. The output dimension of the backbone is 1024. Each expert is a 2-layer-MLP with \([512, 256]\) hidden units and a ReLU activation function, combining a linear layer with the sigmoid function that maps to the predicted CTR. The decayed factor is set to \( \lambda = 0.4 \).

**Baseline.** We compare AdaMoE with the following baseline models.

- **IncCTR:** which has the same model structure as AdaMoE, but the predicted CTR is simply the average of all experts’ output.
- **MoE:** which has the same model structure as AdaMoE, but the outputs of experts are aggregated by a gate network.
- **IADM:** which stacks “experts” in the depth direction, and the output of experts are also aggregated by a gate network. Note that in IADM, the hidden units of MLP in each expert are set to \([572, 572]\), so that the parameter numbers are the same as AdaMoE and other baselines.

#### Quantitative Results.

As shown in Table 1, AdaMoE outperforms all baseline models with the number of experts varying from three to twelve. When the backbone model is DIN and the number of experts is six, the overall AUC of AdaMoE improves by 0.13% compared to the best baseline method (IADM with 3 experts). The improvement of AUC is significant in CTR prediction [2, 7, 21].

For AdaMoE, we obtain the best result when the number of experts is six. However, for IADM, we can see that too many experts can result in the decrease of overall AUC. This is because IADM ensembles experts vertically which can be problematic when the depth of the network grows larger.

**Evaluation Metrics.** In this work, we adopt AUC (Area Under ROC Curve) as the evaluation metric. In our setting, data is in the stream form and fed for training only once. For dataset \( D_t \) at time step \( t \), we use the first 80% of data as training samples \( D_t^{train} \), and the rest 20% of data as testing samples \( D_t^{test} \). At each time step \( t \), the model is first trained with \( D_t^{train} \). Then, we apply the trained model to \( D_t^{test} \). The output pCTRs and the ground truth click labels of samples in \( D_t^{test} \) are stored. The above training-and-prediction process continues until the whole data stream is consumed.

We use the pCTRs and labels of all test samples to calculate the overall AUC. Furthermore, to better investigate the performance of models with stream data, we collect the stored pCTR and ground truth label of test samples every 10 minutes to calculate AUC per 10 minutes (AUC/10Min).

#### Qualitative Results.

To further study how the models handle the concept drift in streaming data, we plot the AUC/10Min in Fig. 3(a). The number of experts is set to six and the backbone model is DIN. Similar results can be observed with other backbone models and the number of experts, and are omitted here. We marked 18:00 in Fig. 3(a), which corresponds to the occurrence of concept drift in our empirical analysis in introduction. We can see that before 18:00, the AUC/10Min of AdaMoE increases faster than other baseline methods. This shows that AdaMoE can quickly learn with stream data. After 18:00, the AUC/10Min of all methods begins to drop. Among all models, AdaMoE first stops the drop of AUC/10Min, and quickly adapts to the concept drift. This further validates that AdaMoE is more robust and can quickly adapt to the concept drift.

![Figure 3: AUC/10Min of (a) different models and (b) AdaMoE with different \( \lambda \).](image-url)
Influence of Decayed Factor $\lambda$. We investigate the impact of the decayed factor $\lambda$ in Fig. 3(b). When $\lambda$ is small, AdaMoE can quickly adapt to stream data, and AUC/10Min increases before 18:00 and around 24:00. However, when $\lambda$ is large, AUC/10Min fluctuates more and the model is unstable. We empirically find $\lambda = 0.4$ achieves a better tradeoff between the stability and adaptability of AdaMoE, and yields the best overall AUC.

3.2 Online A/B Test
To conduct online A/B test, we deploy the proposed AdaMoE model in the online advertising system of one of the world’s largest E-commerce companies. The online A/B test lasts for a week (from 2022-Jan-7 to 2022-Jan-13). Compared to the highly optimized base model, the proposed AdaMoE model contributes to 1.8% CTR (Click Through rate) and 1.89% eCPM (Effective Cost Per Mille) gain.

4 CONCLUSION
In this paper, we introduce a novel incremental learning framework, AdaMoE, to address the concept drift problem in CTR prediction. The experiments show that our method overcomes all other incremental learning methods considered on a real-world production dataset. The online A/B test results further demonstrate the effectiveness of the proposed method. Qualitative results and theoretical derivation are provided to illustrate the superior performance of AdaMoE on concept drifting data streams. To the best of our knowledge, this is the first work to provide a framework to model and handle concept drift in the CTR prediction task.

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