User Response Prediction in Online Advertising

ZHABIZ GHARIBSHAH and XINGQUAN ZHU, Dept. of Computer & Elect. Eng. and Computer Science, Florida Atlantic University

64

Online advertising, as a vast market, has gained significant attention in various platforms ranging from search engines, third-party websites, social media, and mobile apps. The prosperity of online campaigns is a challenge in online marketing and is usually evaluated by user response through different metrics, such as clicks on advertisement (ad) creatives, subscriptions to products, purchases of items, or explicit user feedback through online surveys. Recent years have witnessed a significant increase in the number of studies using computational approaches, including machine learning methods, for user response prediction. However, existing literature mainly focuses on algorithmic-driven designs to solve specific challenges, and no comprehensive review exists to answer many important questions. What are the parties involved in the online digital advertising eco-systems? What type of data are available for user response prediction? How do we predict user response in a reliable and/or transparent way? In this survey, we provide a comprehensive review of user response prediction in online advertising and related recommender applications. Our essential goal is to provide a thorough understanding of online advertising platforms, stakeholders, data availability, and typical ways of user response prediction. We propose a taxonomy to categorize state-of-the-art user response prediction methods, primarily focusing on the current progress of machine learning methods used in different online platforms. In addition, we also review applications of user response prediction, benchmark datasets, and open source codes in the field.

CCS Concepts: • **Information systems** → *World Wide Web*; *Online advertising*; *Information retrieval*; *Users and interactive retrieval*; *Information systems applications*; *Computational advertising*; *Data mining*; *Multimedia information systems*; • **Computing methodologies** → *Machine learning*;

Additional Key Words and Phrases: Click, conversion, impression, landing page, demand side platform, supplier side platform, data management platform, dwell time, bounce rate, user engagement, factorization machines, deep learning, knowledge graph, graph neural network, convolutional neural network, recurrent neural network

ACM Reference format:
Zhabiz Gharibshah and Xingquan Zhu. 2021. User Response Prediction in Online Advertising. *ACM Comput. Surv.* 54, 3, Article 64 (May 2021), 43 pages.
https://doi.org/10.1145/3446662

This work is partially sponsored by the U.S. National Science Foundation through Grant Nos. IIS-1763452 and CNS-1828181 and by the Bidtellect Inc. through a sponsorship agreement.
Authors' addresses: Z. Gharibshah and X. Zhu, Department of Computer & Electrical Engineering and Computer Science, Florida Atlantic University, 777 Glades Road, Boca Raton, FL 33431; emails: {zgharibshah2017, xzhu3}@fau.edu.

0360-0300/2021/05-ART64 $15.00
https://doi.org/10.1145/3446662

1 INTRODUCTION

Online advertising [195], as a multi-billion dollars business, provides a common marketing experience when people are accessing to online services using electronic devices, such as desktop computers, tablets, smartphones, and so on. Using the Internet as a means of advertising, different stakeholders act in the background to provide and deliver advertisements to users through numerous platforms, such as search engines, news sites, and social networks, where dedicated spots of areas are used to display advertisement (ad) along with search results, posts, or page content.

Similarly to traditional media, such as print magazines and newspapers, where specific spaces are assigned to be sold for ads, a portion of online services and websites are filled with clickable components to display marketing messages. Under such circumstances, the ads to be displayed to audience (i.e., users) are either pre-sold (i.e., negotiated) by sellers (publishers) to buyers (advertisers) or they are dynamically selected through a real-time bidding (or auction) [151, 173]. In online advertising, advertisers are bidding an ad opportunity, but only the winner has the chance to serve their ads to users (so only the winner needs to pay to the publisher for the purchase of the auctioned ad opportunity). During the whole process, the effectiveness of the online advertising is typically evaluated through signals made by users toward the displayed ads. These signals are typically considered as user responses starting with a click on ads in web-pages or a tap on screen in mobile apps. Once displayed ads are clicked by users, the payment/revenue is generated between advertisers and publishers. As a result, for both advertisers and publishers, it is crucial to design a user response-based pricing model.

Predicting a click, as the first measurable user response, is an important step for many digital advertising and recommendation systems to capture the user propensity to following up actions, such as purchasing a product or subscribing a service. Based on this observed feedback, these systems are tailored for user preferences to decide about the order that ads should be served to them. In the era of search engines and social websites, companies like Google introduce paid search advertising [128] via user intents recognized through the query keywords. In social media marketing, platforms like Facebook provide advertisers with user demographic information from user-generated content for viral marketing [24]. In conventional advertising in TV or printed newspapers, monitoring the effectiveness of ads is difficult. However, online advertising leverage performance metrics for targeting ad audience, so stakeholders can immediately obtain ad advertising feedback, through clicks, conversions, and other types of user response, to adjust their budget, price for bidding, and so on [151].

The essential goal of different types of advertising systems, either traditional media based or modern online advertising based, is to find the best matching between audience (users) and ads, given contextual features in each platform. From computational perspective, this is equivalent to finding a way to accurately predict positive or negative user responses to an ad, given observed user data. It is shown that the accurate prediction of user response metrics can directly determine the revenue for both publishers and advertisers [1, 17]. The variation of the problem is defined by the availability of context in different platforms. The context in search engines are query generated by users. In display advertising, the context is considered as websites visited by users, and in-app advertising the context is the specific logical stage in mobile apps for marketing.

For years, industry and academia have developed numerous approaches to use holistic data to predict positive response of users where the positive response is typically defined in the form of the estimation of click-through rate on ads or user interactions for purchasing a product, i.e., a conversion. Such approaches vary from data hierarchy [1, 2, 68, 99], clustering [47, 119, 124, 158], collaborative filtering [82, 95], classification [13, 26, 53, 122, 164], to graph- and network-based analysis [146, 149].

As data are becoming rapidly available, machine learning-based approaches have been used in nearly all domains to solve different types of challenges for knowledge discovery [194]. For online advertising, this is especially true. Since the very beginning, industry has been actively seeking effective and efficient computational methods to tackle the data volumes and real-time decision challenges. Many approaches, such as deep learning and factorization machine-based methods, demonstrate a great potential to accurately estimate user responses [44, 57], but the data intensive nature and the real-time requirement have made the accurate user response prediction for online advertising extremely challenging. Here, we briefly summarize the major challenges as the following fourfold:

- **Scalability:** In real-world advertising eco-system, the number of visited web-pages is extremely large. Combining with factors like the number of unique visiting users and the amount of ads, it results in a giant dataset for analysing. In many studies [19] machine learning has been applied to predict user response and boost the personalizing of digital advertising. It is important to design solutions for large scale advertising data [17, 38, 110, 150].
- **Response rarity:** Statistics shows that the rate of click and conversion of all types of ads is not more than 2% over all displaying ads. Therefore, finding a way to overcome class imbalance issue and mitigate the adverse effects on prediction results is a challenge for the prediction algorithms.
- **Data sparsity:** This issue in online advertising and recommender systems stems from two factors. First, the majority of input data consists of categorical features that need to use binary representation, resulting in high-dimensional vectors with very few non-zero values. Additionally, interactions between users and items follow the power law distribution, meaning majority users are interacting with a small number of items and products.
- **Cold start:** This is the common challenge for new new ads, products, and services, because no historical user information available is available to be used for estimation.

Indeed, many solutions have been proposed but primarily focus on new methods for user response prediction. Several works propose to study current business model and technologies evolved from traditional media buying [18, 173], or review display advertising literature and new directions [23]. In Reference [173], the authors go over the business model of real-time bidding by introducing keys actors in the market for ad delivery. From economic perspective, Reference [23] outlines the eco-system of display ad market and non-guaranteed selling channels provided to buy and sell ads in real time. It reviews the disciplines regarding the ad pricing decision made by different actors like advertisers and publishers and other intermediary nodes. The study in Reference [18] reviews the technologies provided for online and mobile advertising, including pricing models implemented between advertisers and publishers, inherent networking schemes by addressing the user privacy and malicious ad related activities.

Unfortunately, all existing works, including the literature review, do not provide a complete overview about types of user response and underlying technical solutions in online advertising. Answers to many key questions remain unclear for both industry and academia, especially for someone who just steps into the online advertising field. What are the main advertising platforms? What type of user response can be modeled/predicted using computational approaches? What are the features and the source of features useful for use response prediction? How to utilize features for use response prediction? What are the main types of technical solutions for user response prediction? Are there any benchmark and online resources (datasets/software) available for evaluation purposes?

In this article, we provide a comprehensive literature review of the latest computational methods for user response prediction in online advertising, with a focus on machine learning-based

approaches. To the best of knowledge this is the first survey study that is focusing on computational approaches for user response prediction. Our review covers different types of user response prediction tasks ranging from click-through rate prediction to user post-click experience evaluation. Our survey includes the description of the online advertising eco-system, platforms, data sources, and early studies for user response prediction. We also consider the most recent work in this context that propose more advanced algorithmic designs and feature extraction methods.

2 ADVERTISING ECO-SYSTEM AND USER RESPONSE

In this section, we introduce key components and important concepts of online advertising eco-system. For ease of understanding, we summarize key concepts and their descriptions in Table **??**.

2.1 Online Advertising Eco-System

Online digital adverting heavily relies on real-time bidding (auction) [173] for advertisers to make decisions to display ads in online portals. In this architecture, an ad exchange network connects sellers (publishers) and buyers (advertisers), so they can negotiate to respond to ad requests in real time. To participate in the ad bidding, publishers and advertisers connect to the ad exchange network through **Supply-Side Platforms (SSP)** and **Demand-Side Platforms (DSP)**, respectively, to cast auctions (for SSP) and manage bids (for DSP), therefore ads are eventually delivered to different media platforms, e.g., a third-party website, search engine result page, or the web-page of social networks.

In Figure 1, we illustrate an online advertising eco-system. The workflow starts with an event when a user, i.e., an audience, launches an URL request from a publisher's web-page. The ad request for ad placements is sent to SSP to trigger an ad auction call (i.e., an opportunity). If the requested web-page contains available ad placement, then the ad call will be submitted to Ad Exchange Network, leading to negotiations with advertisers through DSP based on bidding mechanism. The winning advertiser will insert ad script in the user requested page, so the ad is eventually delivered to the user. In the case that the displayed advertisement matches to the user preference, user response in the form of click or further user engagements, like purchasing or subscription, is generated.

The revenue of advertisers and publishers, in the online advertising, is based on the user response such as clicks or conversions. Therefore, serving users with ads best matching to their preference is of interests to both advertisers and publishers. Under such circumstances, using context to find users' preference plays an essential role for user response prediction. The information from publisher websites is usually obtained from crawling the web-pages to summarize the context. It is then complimented by online analysis of cookie data and browsing history made by users. Such information allows system to identify user interest and response regarding ad impression.

2.2 User Response Types

In web applications like web search engines, display advertising, recommendation systems, or e-commerce platforms, a user response to advertisements starts with a simple click on the ad or a touch on the screen in mobile app. This action is considered as an implicit positive user response that will direct users to a landing web-page. If ad content matches user preferences, then it encourages users to follow up promoted messages by generating the next clicks that can end up with desired activity such as a purchase. In online advertising the initial click or final purchase actions over displayed advertisements are considered as the critical measures to evaluate the performance of user response predictive models. Online advertising systems are generally integrated with recommendation systems in e-commerce platforms to provide users with ranked items based on explicit user's rating and implicit feedback. These feedback can be measured using different

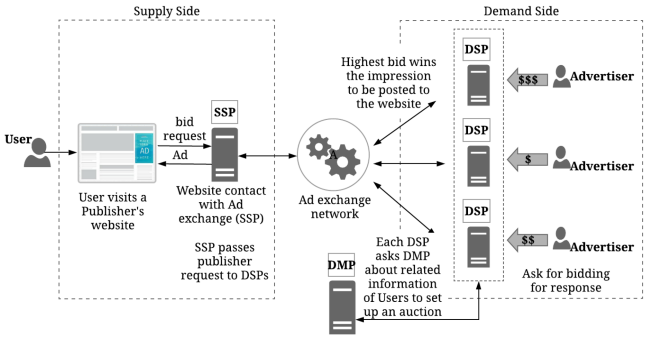


Fig. 1. Advertising Eco-system. From left to right, a process is triggered when users start to interact with online services through either visiting a web-page, searching an item, or checking the social media in publisher website. In the case that the web-page has web placement available, the publisher sends ad request through SSP node to the Ad Exchange. The bid request related to requested ads are forwarded from Ad Exchange to DSP nodes that represent advertisers. After getting relevant user information, such as user profile and their previous interaction, through DMPs, the auction is set up to gather bid among DSPs. The bidder with the highest bid wins and its ad script is forwarded to the publisher to be embedded in the page requested by users.

metrics to show the performance of the advertising systems. In the following subsections, we define prevalent metrics in this domain.

2.2.1 Click-Through Rate. **Click-through rate (CTR)** value is one of the most important metrics to evaluate the quality of ads and the performance of campaign ads. Two elements to calculate the click-through rate values are clicks and impressions. The click-through rate is typically defined as the number of click events over impressions or the percentage of served advertisement ending up with user click events,

$$CTR = \frac{\#\ of\ Clicks}{\#\ of\ Impressions}. \tag{1}$$

The number of impressions are perceived as the number of times an ad or a promoted product is served to the users' device that is engaged to an active online platform, where the publisher can be the website of search engine, a social media, or a third-party website. A click event is an indicator of user engagement, which can be a mouse click on ad creatives on a desktop system or touching them on mobile devices. The definition of click event is extended in different applications like the number of downloads [79] or in the social media context as positive and negative actions like reply, commenting, sharing, dismiss, and so on [70]. A common issue that frequently exists regarding this metric is the data class imbalance problem where the number of clicks compared to the number of impressions is very few. Some studies [66, 187] suggest that relying on this metric to evaluate the performance of e-commerce search results can be noisy and generate misleading outcomes.

2.2.2 Conversion Rate. To evaluate user experience and activities after the click, metrics are introduced to evaluate ad campaigns following cost-per-conversion business model. The desired actions for advertisers like purchases, subscription of service, registrations, and installation of a software, are considered examples of conversion events.

Conversion rate is simply defined as the proportion of users who visited ad creative in online portal and chose to take any above-mentioned actions after opening the landing website,

$$CVR = \frac{\#\ of\ Conversions}{\#\ of\ Impressions}. \tag{2}$$

A conversion is generally considered as a user response following a temporal order of events starting with the page visit, ad display, click, to the conversion. In the case where the sequence of conversion, click, and visit of ads are all available, the prediction of conversion rate is defined as a post-click conversion prediction. The essential goal of the problem is to estimate the probability of a conversion event given clicks and the context [88, 160].

2.2.3 User Engagement. Recommender systems have been commonly used in different application platforms range from social networks and news feed services to e-commerce portal and entertainment data stream services. The common problem in these system is the overload of information that users are confronted with the high volume of items being overwhelming to browse. The priority of these systems is to attract more users by replying their requests with a relevant list of items matched with their preferences. So, the common objective is to recommend a small set of items that includes promoted ones to get immediate implicit user feedback (e.g., CTR) while keeps users activating. User engagement objectives have been studies differently in prior research. There are some studies that model active users by following churn-rate and dwell time analysis. Recent studies have modeled user engagement using multi-objective optimizations. So two recommending and online advertising are optimized together to satisfy user experience in the long-term [185, 186].

With the advent of smartphones and the increase in their popularity among users, there is a surge of interest in developing softwares operating on this platform. As a result, a new online advertising, called in-app advertising, emerges where specific spots on screen before completing a transition in the app are designed for commercial ads. In this context, some studies proposed to provide personalized ads [66, 163] that are evaluated by studying different users' activity patterns to model users' engagement. Because smartphone platforms are personalized with respect to individual users, user response can be extended to the user engagement concept with the general questions to learn the factors that can (1) retain user being active to use an online service, like streaming providers and (2) also help gain revenue through directing people to take a desirable action with regard to ads. Therefore, several researches [85, 127] investigate features leading to user engagement with regard to mobile apps, and a recent work [8] proposes to study factors that are resulting in users being disengaged from mobile apps through hierarchical clustering models.

In video streaming platformss like YouTube, video ads have become a modern effective way of conveying commercial messages via telling a story to users. In this context, video completion rate value is a metric designed to evaluate the effectiveness of video advertisements and user engagements.[1] As shown in Reference [63] the content, position, and length of video ad along with the length and the provider of host videos in addition to user connection information (geography and connection devices) are key factors to impact video completion rates and evaluating the effectiveness of video ads.

In the context of e-commerce system, use engagement is generally evaluated by ranking metrics used in information retrieval systems. The performance of ranking in the produced ordered lists is established by considering a samples of users who have positive interaction with items. Generally, there is a chance that items preferred by users are missing in the list. **Mean average precision at rank K (MAP@K)**, **mean average recall at rank K (MAR@K)** and **Normalized Discounted Cumulative Gain (NDCG)** at rank K, are the frequent metrics that give more details about the ranking performance. The MAP@K assesses how much system can incorporate relevant items in the list. The second one MAR@K checks how well model can create a list from all available items being relevant to user preferences. Due to the fact that the relevancy of items to user preferences

[1]It is defined as the percentage that videos are watched to the end. The more time the video ad is watched by users, the higher the chance it may influence users to take follow-up actions.

Table 1. The characteristics of different user response types

Metric	Abundance	Accuracy	User feedback		Illustration of user preferences	Description
			Implicit	Explicit		
Click-Through Rate	High	Low	✓		Positive	Often not the final goal
Conversion Rate	Low	High	✓		Positive	Needs a domain specific definition
User Engagement	High	High	✓		Positive	Assumes a direct trend between retention & engagement Takes short-term or sequential user behavior and intents
User rating scores	Low	High		✓	Pos. and Neg.	Sparse data

are not the same, NDCG@K consider the performance to put the more relevant items before the others in the recommended list S. It gives more significance to hit rates happened at higher ranks of the recommended list. According to Equation (4), for each item in the recommended list, $rel_{s,r} = 1$ represents a case that the item s ranked at r is matched with the ground truth; otherwise, it would be $rel_{s,r} = 0$. A log factor is used to assign a penalty with regard to position of items in the list,

$$MAP@K = \frac{\#\ of\ recommended\ items\ being\ relevant}{\#\ of\ recommended\ items} \quad MAR@K = \frac{\#\ of\ recommended\ items\ being\ relevant}{\#\ of\ relevant\ items}, \tag{3}$$

$$NDCG@K = \frac{\sum_{s \in S} \sum_{r=1}^{K} \frac{rel_{s,r}}{\log_2(r+1)}}{\#\ of\ recommended\ items}. \tag{4}$$

2.2.4 Explicit User Feedback. In contrast to implicit user feedback, explicit rating score information allows users to express their interests or opinions through online methods like surveys. Compared to implicit user feedback, this information are scarce, since they require users to provide additional input with regard to items via surveys and online forms. In addition, they may come with bias in user's opinions. Implicit feedback are frequently analyzed through models for classification tasks where explicit user responses are adopted for regression tasks such as rating prediction so that user rating score with regard to new items are estimated by the system.

Table ?? summarizes characteristics and challenges of different user response types.

3 FEATURES FOR USER RESPONSE PREDICTION

User response prediction plays an essential role for online advertising and recommender systems [68], where the prediction is typically defined as the probability of users making a positive response on promoted item in a marketplace, ad, or news article in online platforms [95, 135, 151]. The performance-based advertising is the paradigm mainly followed in online advertising systems, where the predicted probability is not only used as an indicator to present user preferences, it is also involved in bidding strategies to determine the revenue of advertiser and publishers [125].

Figure 2 shows the workflow of typical user response prediction models consisting of two main stages. The first stage is related to data collected from different data sources (Users, Advertisers and Publishers) in online advertising systems. After the pre-processing and labeling steps, data samples are described with series of features (fields) along with label (class) values that are normally specified as binary user response value such as 1 for click, conversion, purchasing, and so on, and 0 otherwise. For recommendation systems, the output in Figure 2 is an ordered list of promoted/recommended products. For the prediction task, it will output probability of users making an interaction (e.g., a click) on items in the list. Like typical machine learning problems, the input data should be described through feature vectors to capture the class correlation, meaning that features need to be discriminative for the prediction task. Therefore, during the second (learning) phase, features are extracted using different approaches, such as (1) using data fields to represent

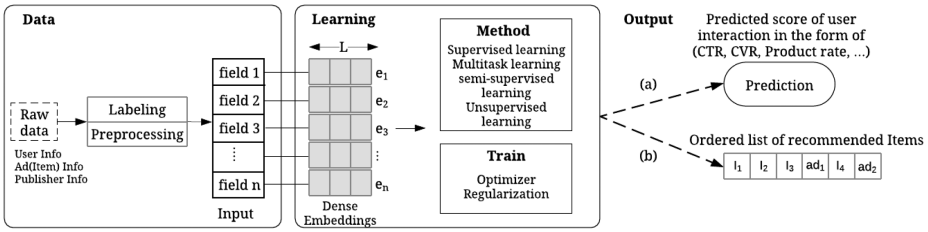


Fig. 2. The schema of user response prediction workflow. Embedding layer is the common paradigm to deal with high-dimensional binary representation in user response prediction. They can either be set by predefined values or be trained as internal parameters in end-to-end models like deep learning methods. The output can be considered as two types of user responses (a) a scalar value of predicted score for an interaction between given user u_i and item I_j (b) a ranked list of regular and promoted items ordered by predicted user response scores.

users, pages, and so on, and create sparse features or (2) using embedding-based approaches to create dense features.

3.1 Type of Features

To accurately predict user response, it is important to train models using discriminative features. In the following subsection, we will discuss features studied by various methods.

3.1.1 Multi-field Categorical Features. The typical input data fed into online advertising systems are generally formed as multi-field categorical values. Contrary to continuous features that are generally found when dealing with images or audios, the input data contains an array of categorical fields including Gender, City, Age, Id, . . . and device type and ad category, . . ., to describe users and ads or the other related objects in the system. An event representing the user interaction with online advertising includes features from different actors like users, publishers, advertisers and the context in online advertising systems. A representative list of categorical features corresponding to user profile and behavior, advertisement and publisher's web-page is provided in Table **??**. The one-hot encoding is the conventional approach to deal with this type of data [48]. As shown in Figure 3, each field is shown as a binary vector. The dimension of vector is determined by the number of unique values that are taken in the field in which one entry is set as one while the remaining as zero. In this example, fields like gender has the length of 2 and the length of weekday is 7. The simple way to represent features is the concatenation of these vectors that typically creates a high-dimensional sparse binary vector. In the mathematical way, considering the input data with n feature fields and x_i is the hot-encoded vector of the field feature i with dimension of K_i where $\sum_{j=1}^{n} |x_i| = k$. In the case $k = 1$, we have one-hot-encoded vectors while $k > 1$ refers to multi-hot-encoding [39, 97, 190] that feature field is represented by more than one value entries. To handle the high-dimensionality issue, the common approach for many classification-based methods is employing the embedding step to generate condensed embedding vectors. These vectors can be concatenated like $x = [x_1, \ldots, x_i, \ldots, x_n]$ to create input layer of different user response predicting models.

3.1.2 Textual Features. In search advertising, ads are displayed in the search result pages, incorporating textual data such as headline, relevant keywords and the body to highlight the details of promoted products. Many research proposes to treat click-through rate prediction task as the similarity learning between users' query keywords and keywords of ads using their proposed text-based similarity. For example, keywords in the title and body of advertisements [6, 33] and

Table 2. Representative categorical features corresponding to the main online advertising objects

Object Code	Features
User	Id, location(Area, city, country), IP, Network Spec, Browser cookie, Gender, Age , Date
Advertiser	Ad id, Ad group Id, Campaign Id, Ad Category, Bid, Ad Size, Creative, Creative Type, Advertiser Network
Publisher	Publisher(Id), Site, Section, Ad Placement, Content Category, Publisher Network, Device type, Page Referrer
Context	Serve time, Response Time

field 1=Mobile	field 2=Tuesday	field 3=Male	field 4=Berlin
user_device_type	weekday	gender	city
[1,0,0,0]	[0,1,0,0,0,0,0]	[1,0]	[0,0,1,0,...,0]

Fig. 3. The characteristics of multi-field categorical features as the input to user response prediction models. The binary representation of multi-categorical features is created using one-hot-encoding.

keywords in user queries are considered as two sources of data to extract textual features in many designed models [32, 41, 147]. Relying only on ad textual content and user query at character- and word-level, a deep CTR prediction model [32] collects data from textual letters of query along with the title, the description, and the ad URL. They are organized to feed into system as a one-hot-encoded matrix.

3.1.3 Visual Features. E-commerce platforms, which are available through web portals and mobile apps, are hosts of many categorical ads and items. Each item is generally described by texts and images, acting as visual features to attract users' attention. Categorical features are generally used for model user behavior history. However, the data sparsity issue in categorical data encourages to consider intrinsic visual information in images for the development of further methods [19, 38]. There is also an increasing interest to develop video ads for digital streaming platforms in which user responses generally happen by clicking on the image section [134]. Very recently, user facial information along with user behavior history is proposed to use for modeling user purchase interest. Analyzing this type data can provide an estimation of some user profile information such as gender, age and ethnicity, which in turn draw inferences about user background and status and their manner for purchasing [86].

3.2 Organization of Features

Earlier studies to analyze user responses in online advertising mainly use one type of multi-field, visual or textual features for model designing, mainly because of their transparency and easy to interpret. Advanced models are later studied to extract complex features for better prediction accuracy. In the following section, we will go over a couple of models that take advantage of two important layout of features such as sequential and hybrid features to improve the performance of predictive models.

3.2.1 Temporal and Sequential (User Behavior) Features. Users activities are commonly recorded as data logs available in many online data provider services. Considering the sequence of user actions *w.r.t.* different types of ads are valuable features for analyzing user response prediction [115, 170, 189]. The majority of proposed methods are categorized into recurrent neural network-based and network-based models (detailed in Sections 4.3 and 4.4.2). Some studies in the literature showed that the history of previous visited pages, clicked ads [163], and not-clicked ads [100] sorted by time in system can be leveraged to model sequential dependency between input features. Several studies have shown the importance of these features to enhance the performance of various user response prediction tasks [36, 40, 189, 190].

In Reference [190], user behavior features are represented as a list of visiting events of ads, each of which are described by categorical features about goods, shop, and page categories of past user-defined time points. Each time point is described using multi-hot-encoding.

Sessions are also used to represent user's behavior history [36]. Separated by occurring time, user activities are considered homogeneous in very short time slots within sessions but different with regard to other sessions. User interaction patterns over time are evolving in short-term and long-term trends. A common scenario is to deal with virtually short-term sequences of user behaviors when user profile (e.g., ID) of active users is not accessible via log-in to system. So, the task of predicting user responses is defined to extract relevant patterns based on limited actions of anonymous users. In this case, the complete user interaction histories are also organized into sessions [115, 183]. The long-term user interaction can also be studied to create user profile behavior. It can not only provide indication of user intent change over time that can be used to improve the predication user responses, but also the popularity pattern regarding products can be identified to remind users about a product according their previous interactions. In Reference [40], the authors consider a sequence of user activity events before and after the ad click and corresponding passed time-slot to investigate the potential user conversion intents. They analyzed the effect of elapsed time as a feature for conversion rate prediction and using targeting and retargeting[2] paradigm for different users in online advertising systems.

3.2.2 Hybrid Features. Combining different types of features are also studied to enhance user response prediction. Some studies use textual features along with multi-field categorical features to improve the performance of recommendation systems in e-commerce platforms [97] and the sponsored search marketing [25]. Some research consider the compounds of categorical features and image data [19, 38] and the combination of categorical features with video data [134] to improve predictions. The combination of different features in modeling lead to various compound embedding layer for input data to generate a condensed feature representation, with pooling being employed to reduce parameters and cope with over-fitting. Max and sum pooling are also studied as the aggregation mechanism in some studies [25, 38]. The concatenation of feature embedding vectors is a straightforward approach commonly used in many studies [78, 117, 130, 179]. Recently, an adaptive approach to combine most relevant features from different feature types is employed based on attentive mechanism [38, 190].

4 USER RESPONSE PREDICTION FRAMEWORKS

For years, user response prediction, in online advertising, has been continuously evolving. Early approaches usually reply on hand crafted features to dissect data into different segments, where each segment contains users with similar response. Therefore, the click-through rate values or conversion rate values estimated on each segment can be used to estimate future (new) users' CTR values. Following similar approaches, clustering or collaborative filter-based approaches are also proposed to recommend ads to users. In the context of recommendation systems, the ordered list of items including promoted products are proposed to users by predicting how likely the list contains items matching to user preferences. The evaluation of these systems are examined with different ranking and regression metrics (detailed in Section 2.2). Typical types of recommender systems have analyzed past user interactions to detect a connection between users and products either through studying users with same tastes or similar items visited by different users. Recently, machine learning-based, especially deep learning-based, approaches have become increasingly pop-

[2]A cookie-based advertising that tracks users clicking or visiting ad in a website who have not taken further actions against promoted products. Using this paradigm advertising systems remind users their previous interest about a promoted product.

Table 3. A Taxonomy of User Response Prediction in Online Advertising, along with Representative Publications

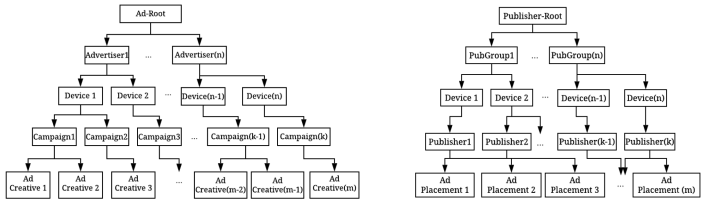
Category			Publication
Data Hierarchy Based			[1, 2, 15, 62, 68, 99]
Collaborative-Filtering Based	Hierarchy Based		[82, 95]
	Network Based		[50, 61, 146, 149, 156]
	Hybrid Methods		[20, 51, 161]
Supervised Learning	Predictive Models	Logistic Regression	[5, 17, 27, 48, 65, 68, 121, 145, 180, 193]
		Factorization Machines	[21, 53, 57, 84, 99, 99, 106, 107, 112, 118, 122, 177, 179]
		Deep Learning Methods	[12, 15, 15, 19, 25, 32, 36, 38, 41, 51, 78, 83, 97, 100, 110, 130, 137, 163, 166, 189–191]
		Hybrid Methods	[22, 44, 117]
	Ensemble Methods	Cascading	[179]
		Stacking	[5]
		Boosting	[87]
		Mixed	[159]
Un-supervised & Semi-supervised Learning	Network Based	Network Embedding: *(Node Embedding, GNN-based methods, User Intention Network Modeling)*	[71, 74, 115, 150, 169, 170]
		Knowledge Network Based: *(Node Embedding, Meta-path-based methods, GNN-based methods)*	[35, 50, 116, 147, 148, 156, 157, 174]
	Clustering Based		[47, 119]
Stream-Based Data			[9, 29, 64, 67, 70, 126, 192]

ular for user response prediction, mainly because these approaches can simultaneously accommodate a large number of features, and learn to create new features, for accurate user response prediction.

In Table 3, we propose a taxonomy of user response prediction, which includes hierarchical-based methods, collaborative filtering-based approaches, supervised, semi-supervised, and unsupervised learning studies. In the case where labeled data are available, supervised learning algorithms leverage the label in the definition of the loss function in their learning procedure. Unsupervised learning rely on unlabeled data for the loss function optimization. Semi-supervised models are between supervised and unsupervised models where their objective functions are optimized considering both data with and without labels. The supervised methods can be further categorized into basic predictive models and ensembles ones whereas semi-supervised and unsupervised category consists of network-based and clustering-based methods. The last category in the taxonomy includes stream-based methods. Following subsections will discuss and review representative methods in each category.

4.1 Data Hierarchy-based Approaches

Using unstructured input features, data sparsity and cold start are common issues in online advertising and recommender systems. Data hierarchy-based methods refer to approaches that organize data in a hierarchical format [81]. The motivation is to build a tree structured hierarchy, using some selected features, such that each leaf nodes represents a user groups sharing similar response. This hierarchy provides valuable information to show correlation between user responses at different level of granularity, which alleviates the adverse effect of limited historical information about users.



(a) Advertiser hierarchy (b) Publisher hierarchy

Fig. 4. The sample taxonomy representing a hierarchical structure for Advertiser and Publisher data where (a) demonstrates grouping ad creatives through multi-level joint points when they are of same campaigns and are designed for the same devices by an individual advertiser; (b) the publisher hierarchy from ad placement in web-pages, the running devices, and grouping of publishers.

4.1.1 Data Hierarchy. As the first attempt to cope with data sparsity and limited historical data in online advertising, hierarchical structures of publisher web-pages, ads and end-users are commonly used to address correlation between input features [1, 2, 68, 81, 99]. In this case, users, web-pages, and ads are grouped based on different factors, such as demographic or geographic information about users, domain and content of web-pages, and the context and campaign of ads. An example of the data hierarchy is shown in Figure 4. From an advertiser perspective, the hierarchy can be created by classifying ads based on campaign, content type, and advertisers. For publishers, web-pages can be grouped using simply URL path or the content category. Users can also be organized as hierarchical data using third-party information like user geographic, ad and web-page visit history, and so on. Studies show that data hierarchy for ads, pages, and users provides useful knowledge to handle data rarity in click-through prediction [68]. Partitioning input space using tree structure represents similarity between connected nodes with respect to user responses in local areas [2, 99]. In industry, these data hierarchies are created and maintained by domain experts.

4.1.2 Representative Hierarchy-based CTR Prediction Frameworks. Input features of online advertising systems consist of various sparse categorical features, which contribute to generate rare user responses such as clicks or conversions. To address these issues, many methods propose to create a hierarchical structure from input features to estimate user response from previous similar available samples [2, 68].

Problem Definition. For ads being served to users multiple times, the baseline problem to predict user response is defined as: given a pair of web-page j and ad k, the probability of response, like a mouse click, is calculated through the probability formula $P_{jk} = Pr(Click|Impression; j, k)$. This probability, i.e., CTR, can be computed via binomial **maximum likelihood estimation (MLE)** where V_{jk} indicates the number of times ad k is displayed on the web-page j, and C_{jk} is the indicator of click number, respectively [125, 158]. For the case $V_{jk} = 0$ or equals to a small value, the value of MLE estimate for CTR values becomes unreliable. Therefore, in literature, different methods are proposed to exploit hierarchical information for smoothing out the MLE predictions.

For instance, authors in Reference [2] proposed to utilize two hierarchical structures between input features related to web-pages and ads to improve the prediction of user click responses in online advertising. In this study, they tackled a form of sparsity issue in the input data with a few number of available clicks and impressions. To reduce the variance made by the sparse clicks and/or impressions, a sampling approach is used to alleviate the rarity issue via negative sampling of majority class, i.e., web-pages without a click response. To control the effect of the bias made by sampling, a two-step method is used to predict the click-through rate. In the first step, a maximum

entropy model is optimized based on an iterative proportional fitting method to estimate the actual number of impressions at all defined levels in the hierarchical structure. A tree-shaped Markov model is then used to predict the click-through rate value in the whole levels of the hierarchy using correlations between sibling nodes.

Further, a statistical solution for high-dimensional hierarchical categorical data named as log-linear model for multiple hierarchies(LMMH) [1] is introduced for online advertising systems. It improves user response prediction by exploiting correlations between sibling nodes at different data hierarchy levels. To increase the scalability of model to large dataset, a spike and slab variable selection method is proposed to control number of parameters in the regression model. This method deals with rare response rates by pooling data along a directed acyclic graph obtained through a cross-product of multiple hierarchies.

Another study [62] advances the LMMH method using higher-order feature interactions by fitting local LMMH models to relatively homogeneous subsets of the data. Given a relatively homogeneous partitioning of the feature space, several local LMMH models are fitted to data subsets on different nodes of a decision tree. To address over-fitting issue in the model, models are coupled with a temporal smoothing procedure designed based on a fast Kalman filter style algorithm.

Last, the study in Reference [68] investigates the data hierarchy for three objects of users, advertisers, and publishers to deal with the data sparsity and class imbalance problem for conversion prediction. Taking conversion event as Bernoulli random variable with two possible values of conversion and no conversion, a binomial distribution is used to model the conversion given a triple of user u_i and ad a_k and web-page p_j. To address the data sparsity, they propose to capture the correlation in the conversion output using clustering of similar users with regard to conversion rate values, grouping advertisements from the same campaigns and web-pages with same category types. The conversion estimation is calculated at different levels of the hierarchy made from the cross product of levels in three hierarchical structures of users, publishers and advertisers via the maximum likelihood estimation as follows:

$$P(Y = 1 | u \in C_{u_i}, p \in C_{p_j}, a \in C_{a_k}) = \begin{cases} \frac{C_{ijk}}{I_{ijk}} & \text{if } I_{ijk} > 0 \\ unknown & \text{otherwise} \end{cases}, \tag{5}$$

where C_{u_i} is the cluster to which u_i belongs; C_{p_j} and C_{a_k} indicate the cluster of web-page p_j and ad a_k, respectively. The final estimation of the conversion rate value is then modelled using logistic regression from the linear combination of MLE estimators at different hierarchical levels.

4.2 Collaborative Filtering-based Approaches

Collaborative filtering is an effective approach to predict online user interests. The general idea is to analyze previous behaviors of users to predict possible future user interests or to generate suggestions that may match to the preferences of the new similar users.

Problem Definition. For collaborative filtering methods, the input is an incomplete sparse matrix $X \in R^{m \times n}$ of user-item preferences, which suffers from the data sparsity, i.e., some X_{ij} entries are missing. The goal is to fill in missing entries with predicted scores. The state of the art in collaborative filtering is matrix factorization [52, 95], which is based on an idea that the matrix of users' preferences *w.r.t* items X can be factorized into two low-rank matrices of Users α and Items β. It is modelled as $X \simeq \alpha^T \beta$, where $\alpha \in R^{k \times m}$ and $\beta \in R^{k \times n}$ and k is the dimension of latent features. Conceptually, each α_i represents a user, and each β_j represents an item. The simplest factorization model is to solve the following optimization where latent feature vector of users and

items are controlled with user-defined regularization function σ in different studies to prevent the model from the over-fitting issue [61, 95],

$$\min_{\alpha,\beta} \frac{1}{|O|} \sum_{(i,j)\in O} (X_{ij} - \alpha_i^T \beta_j)^2 + \sigma(\alpha, \beta). \tag{6}$$

In general, collaborative filtering is based on the past interactions between users and products. It can be seen as the implicit feedback like click or conversion event on products or explicit feedback like product ratings. Interactions between web-pages and ad banners can be shown as a matrix of web-page-by-ad feedback score (click-through or conversion rate rate or product rate values). The correlation between web-pages and ads is captured to calculate predicted scores for missing entries that can be intuitively related to the user response prediction task. The major studies in this category take advantage of collaborative filtering methods along with side information such as the user and item neighborhood models [61], the data hierarchies [82, 95], and knowledge graph data [146, 149]. Hybrid models are used to tackle scenarios with data sparsity and cold start problems to improve the prediction performance. It is conventional that initial models resorted to apply matrix factorization and inner-product operator on latent factor vectors to establish connection between users and items. Recently, neural architecture [51, 161] and attention mechanism [20] are proposed as the alternative to learn higher-order interactions on data. The user responses analyzed to evaluate the performance of models in the studied papers range from explicit product rate scores [61, 161] to implicit user feedback like CVR scores in References [95, 146, 149] and recommended ordered list [20, 51].

One of initial works in the collaborative filtering domains, developed based on latent factor models like singular value decomposition, is known as SVD++[61]. For a personalized recommendation system task, the authors improve the accuracy of system by addressing both explicit and implicit user feedback in a hybrid model. To do so, additional terms are added to optimize the loss function (6), which is organized in three levels. In the first level, bias terms, in form of the addition of average of rating value of all items, the bias in average rating made by user α_i, and the corresponding bias for item β_i to control the discrepancy between actual values and predicted values in the loss function, are added. In the second level, a loss function is defined by adding a term to include implicit available feedback. They refer to all items that user had an interaction before. The implicit feedback here are considered from a series of browsing, purchasing, and search user histories in e-commerce systems. In the last level, a neighborhood model that addresses the effect of bias in average rating value made by neighbor users and items is added. Combining these terms together, the parameters of proposed model are updated using gradient descent optimization. It led to an improvement calculated for product rating prediction and providing top-k personalized recommendation tasks.

In an extended matrix factorization design [95], hierarchical information of web-page and ads are integrated as additional side information into latent features of collaborative filtering to tackle data sparsity and cold start problem. Explicit features from ads and web-pages in side information are linearly augmented to implicit features using a log-linear latent features model and a suggested user friendship-interest propagation framework to enrich input features. As a hybrid method, it includes hierarchical structural information into their factorization model using three learning ideas such as hierarchical regularization, agglomerate fitting and residual fitting.

In online advertising, interactions are generally made between multiple entities including users, items, and ads. Tensor factorization, as an extended version of matrix factorization, can use the similarity between different types to predict potential interaction between pair of instances. To address the compound similarity of entities with regard to a possible interaction, a Hierarchical

Interaction Representation model [82] is proposed to provide a joint representation to model mutual actions between different entities. Three-dimensional tensor multiplication is used for modeling characteristics of pair of entities.

Recently, some studies [146, 149] propose to organize user and ad as heterogeneous information graph to improve collaborative filtering. The authors of Reference [146] suggests an end-to-end learning method to incorporate side information from knowledge graph into an item-based collaborative filtering approach for click-through rate prediction. They propose an extended knowledge graph embedding method that starts building an initial user preference sets in the knowledge graph that are originally set up from previous user click activities. An iterative propagation of user preferences along edges over the knowledge graph is used to create k Ripple sets to model potential user liking versus items. Learning an embedding vector for each ripple set, the embedding vector of user response versus items is calculated from the sum of corresponding embedding vector of ripple sets. The click-through rate score of user u versus item v is modeled using dot product embedding vectors of u and v each of which are trained based on a Bayesian framework and gradient descent learning.

4.3 Supervised Learning-based Approaches

In this section, we review supervised learning-based methods that formulate the prediction of user response rates as binary or multi-class classification task in online advertising platforms. These methods can be categorized into two categories including the basic and ensemble predictive methods. Following the structure in Figure 2, input features are generally considered as multiple feature fields gathered from different sources like user, advertiser and publisher. The input layer in classification methods are considered as a numeric vector from concatenation of all fields,

$$x = [x_1||x_2||\dots||x_n], \tag{7}$$

where n is the number of features and x_i is the representation of field i. For categorical data, feature value is encoded into a numeric vector through directly one-hot-encoding. Fields with continuous values are first discretized to be encoded to binary vectors by one-hot encoding.

Logistic Regression-based methods. Logistic Regression (LR) is one of the first attempts to train models to predict user response from input categorical features. As it is shown in Figure 6(a), this method uses linear combination of coefficient values and input sparse binary feature vector to predict the binary output value. Given the input dataset with m instances of (x_i,y_i) where $x_i \in \{0,1\}^n$ is an n-dimensional feature vector and y_i is the label to represent the user response as (click:1, no-click:0). The predicted probability of x_i belonging to class 1 is modeled by Sigmoid function as

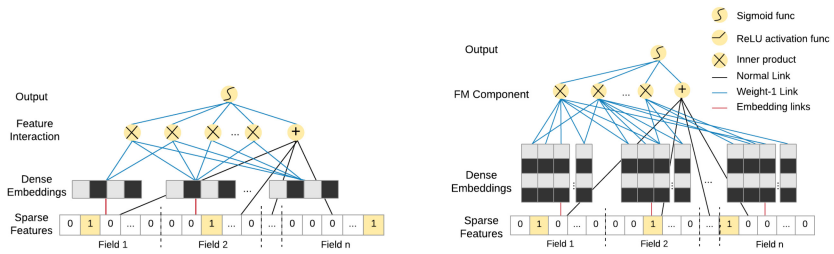
$$Pr(y = 1|x_i, w) = \frac{1}{1 + \exp(-w^T x_i)}. \tag{8}$$

The model coefficient $w \in \mathbb{R}^d$ is achieved by minimizing the negative log likelihood as follows:

$$\min_w \frac{\lambda}{2} \|w\|^2 + \sum_{j=1}^{m} \log(1 + \exp(-y_i \phi_{LR}(w, x_i))), \tag{9}$$

where $\phi_{LR}(w,x) = w_0 + w^T x = w_0 + \sum_{j=1}^{n} w_i x_i$ is the linear combination of coefficients along with bias value w_0 and features that $w_0 \in \mathbb{R}$ and $w \in \mathbb{R}^n$. As it is shown in the literature, Equation (9) is convex and differentiable, so gradient-based optimization techniques can be applied.

Challenges and extended methods. Some studies [17] indicate that the implementation of logistic regression methods is possible with high scalability through Maximum Entropy approach and a generalized mutual information and feature hashing as the regularization. However, modeling



(a) FM (b) FFM

Fig. 5. (a) FM Model: The architecture of Factorization Machines method as the extension of logistic regression by using dot-product $\otimes$ operators fed by dense embedding vectors of input sparse features. (b) Field-aware factorization machines (FFM) model: The structure is similar to FM model. The difference is that the sparse interaction between each feature value in the current field i with another one in the other field (ex. $i+1$) is modeled by a separated embedding vector. Each feature field i is represented by an embedding matrix.

linear interaction between feature values only address the effect of features with class label separately. Therefore, it cannot always generate an acceptable performance in user response prediction task that gets impacted by some issues such as class imbalance originated from low click and conversion rates, the cold start issue for new instances, long cycle of user purchase responses, and non-linear interaction between input features. The authors in Reference [27] use historical information of brand website visit as the proxy to model predictor using logistic regression model. A study [68] suggests to create hierarchy structure from previous user performances that is captured from grouping ad campaigns and publisher pages and users. A logistic regression model is used for linear combination of local MLE estimators.

Employing the side information using transfer learning has also been studied in some work [26, 165]. In Reference [26] a transfer learning method is developed to combine data from a model on small set of conversion data to improve post-view conversion rate for large number of ad campaigns where click event is not necessarily required. In Reference [165] a transfer learning approach was developed to design a natural learning processing method to capture transferable information of related campaigns. It is motivated by the fact that the similar searched content and visited web-pages by users can be indicators of their future purchase interest. In another work, a practical result from applying logistic regression for big data in social media platform demonstrated that the weakness of linear modeling could be reduced by cascading with decision tree models to implement non-linearity of input categorical data [48].

Factorization-based Methods. To consider non-linear interaction between features values, **factorization machines (FM)** combine support vector machine method with factorization models [122]. This allows the method to carry out parameter estimation under the data sparsity using linear complexity. This can be done by modeling the feature value interactions through a product of two latent vectors $v_i, v_j \in \mathbb{R}^k$. The dimensionality of latent vectors is the hyper-parameter that defines the number of latent factors,

$$\phi_{FM} = w_0 + w^T x + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle v_i, v_j \rangle x_i x_j. \tag{10}$$

Figure 5(a) shows the architecture of factorization machines as the combination of two terms including the feature interaction $\langle v_i, v_j \rangle$ and linear information $w_0 + w^T x$ to model click responses. The idea is that embedding vectors of features can be trained well to preserve feature interaction

through dot product operation if there are enough occurrences that the features appear in the dataset.

Extended Factorization Machines models. Since factorization machines have a closed form equation that can be calculated in linear time, it is shown that the parameters of models can be trained using gradient-based methods like **stochastic gradient descend optimization (SGD)** [122]. Some studies showed that FTRL-Proximal algorithm with L_1 regularization and per-coordinate learning rate, which was successfully used for logistic regression-based models [92], can also outperform SGD algorithm for extended factorization machine models [139]. However, this method suffers from some limitations.

One of the downsides of factorization machines modeling is that for multi-field categorical data, feature values may come from different field feature that may change the interaction between feature values. But most methods deal with feature values uniformly. Therefore, **Field-aware Factorization Machine (FFM)** [57] is proposed to discriminate the interaction between various feature values of different fields. To this end, it suggests to add one dimension to model parameters to allocate more than one embedding vector to features, since pairs of features incorporate different feature types information. This changes the modelling of feature interaction as the following equation:

$$\phi_{FFM} = w_0 + w^T x + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle v_{i,F(j)}, v_{j,F(i)} \rangle x_i x_j, \tag{11}$$

where $F(i)$ is an indicator of field name that feature corresponding to the first entry of feature interaction while $F(j)$ is an indicator of field name that feature is related to the second entry of interaction. Lack of consideration into the importance of features and the limitation of inner-product to model feature interaction are two issues in baseline methods of factorization methods have been studied in many other works as follows.

The baseline factorization machine methods usually consider all combinations of feature values in different fields with the same weight. But interactions between features often vary and do not have equal values. So there is a chance that using less important features in the training set, the noise is actually learnt by the model that can have the adverse effect on the performance. This motivates studies to impose weights on the interactions [53, 106, 162] To this end, the authors of Reference [106] proposed a weighted version of field-aware factorization machine that can use the memory efficiently for model parameters. It adds more information through a weight matrix to consider the difference in the strength of interaction between feature values originating from different pair of fields. In Reference [162] follows a deep learning study in which the importance of feature interaction were studied using an attention network through a layer to learn corresponding weights. The study in Reference [99] centered the work on a different aspect to use a cost sensitive approach to address the cold-start issue and using the data hierarchy for the data sparsity. They designed an importance-aware loss function to assign the more importance weights and penalty values for ad samples that are shown more to users but their user response predicted wrongly. The authors of Reference [112] also proposed a robust factorization machines method considering user response prediction as a classification problem under the noise. The uncertainty within input samples is modeled by an optimization through an uncertainty vector with each dimension corresponding to independent noise value.

Aside from the above-mentioned points, the capability of factorization machines to address data sparsity issue using inner-product operation can be limited when confronting high-dimensional data. Modeling only second-order feature interactions is not expressive enough for implicit higher-order feature conjunctions. This stimulated motivations to propose high-order variants of factorization machines method [13, 53, 164]. In Reference [53] authors extended the feature interaction

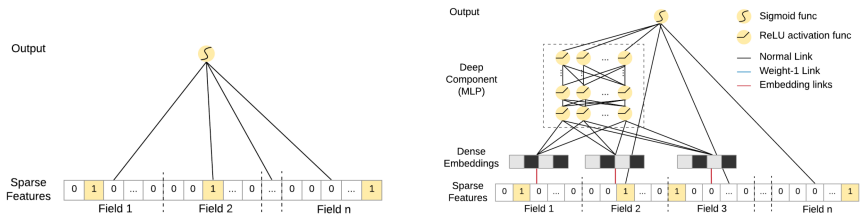
modeling in factorization machines using a bilinear interaction method that combines inner product and Hadamard product together to generate a fine-grained feature interactions. Very recently, Reference [164] proposed a score function to replace inner-product operation between embedding vectors of input features. They discussed that using Lorentz distance, the triangle inequality principle between two points with regard to the origin point is not always consistent. They suggested to use the sign of triangle inequality to learn feature interactions through a proposed Lorentz embedding layer. To this end, a novel triangle pooling layer is proposed to substitute for the typical factorization machines structure.

Hybrid Approaches. Hybrid methods follow a classification technique that involves a number of heterogeneous methods each of which acts complementary to each other. Each method solves a different task and the classification decision is reached by the one method at the end. The distinction between ensemble methods and hybrid methods is that the former models are trained separately to generate the predictions at the inference time. On the contrary, hybrid models follow a joint training that optimizes all parameters simultaneously. This idea makes a motivation for attempts at developing more complex machine learning methods that are able to model a nonlinear user interaction in online advertising systems. Regarding the user response prediction, the primitive predictors based on the logistic regression or factorization machines have weakness to capture limited range of feature interaction by addressing linear relations or dot product interactions between input features. Their performance is suffered from the data sparsity, class imbalance problem and cold-start problems. To address these issues,hybrid architecture of classifiers has been proposed in many studies. The categorization of hybrid models are presented as follows:

Logistic regression-based methods. One of the first studies to improve logistic regression performance was the addition of decision trees to the structure of model [48]. To address the data sparsity in input data consisting of multi-field categorical data, they use a cascade of decision trees structured by boosting ensemble paradigm to provide a non-linear transformation of categorical features. Following a gradient boosting machine, the boosted decision trees generate a feature vector with the user-defined dimension k that is passed to logistic regression classifier for prediction.

The success of deep learning methods in capturing higher-order interactions motivates research to include deep neural networks to improve the Logistic Regression in different studies [22, 130].

Although the logistic regression models have shown a good scalability and interpretability to handle the massive data in the online advertising industry [17], the generalization of model for predicting new samples is limited and highly dependant to whether high quality features can be obtained through feature engineering. Using the polynomial regression applied, the logistic regression model can only capture low-order feature interactions. This drives the authors of Reference [22] to approach a hybrid structure of logistic regression and deep neural networks that are trained jointly to consider low and high-order feature interactions when there is the data sparsity issue and dealing with massive data. As shown in Figure 6(b), the framework includes two components, i.e., wide and deep. Wide linear component is modeled by the logistic regression classifier. It analyzes two sets of input features including raw categorical features and transformed features that are designed to memorize sparse feature interactions using a cross-product feature transformation. Following the feature engineering approach on the training data, the transformation function is designed to represent the frequent co-occurrence of features to explore the possible correlation with user responses. The deep neural network component is trained to generalize the prediction for unseen inputs through low-dimensional embeddings. In this model, the final output is calculated from the combination of wide and deep components using the logistic loss function. In initial studies, the embedding vectors are generated from a embedding dictionary by feature



(a) LR (b) Wide&Deep

Fig. 6. (a) Logistic Regression (LR) model: linear modeling of sparse feature values. (b) Hybrid model (Wide & Deep model) as the alternative to Factorization Machines to use a deep component to capture higher- (≥two) order feature interactions combined with the Logistic Regression addressing low-order feature interactions.

hashing method [17] where most frequent categorical values are transformed by projecting into pre-defined fixed-size numerical vectors [22, 25, 130]. The other models covered in the next section fix this issue using trainable embedding vectors.

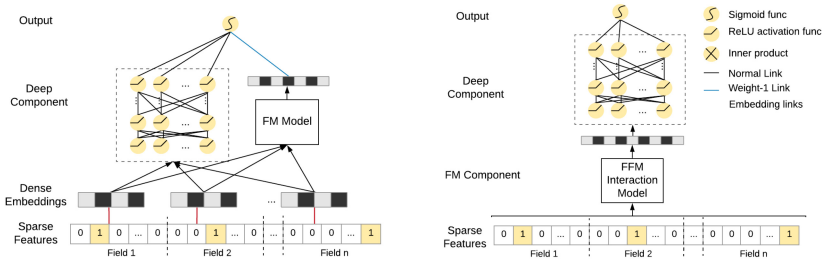
Some recent studies in this category extend different elements in the hybrid design like embedding vectors [49, 97, 191] and neural network architectures [130, 189, 190] to improve prediction performance. Although it is typically expected that stacking of multi-layer fully connected neural networks can capture arbitrary non-linear relations between input features, dealing with a lot of parameters can cause different issues such as the degradation and over-fitting. A study [130] proposes to use a residual neural network for a deep component, where five hidden layers of residual units combined with original input features are added to the result of two layers of ReLU transformations. The effect of aggregation of embedding vectors on the prediction performance is also studied in Reference [49]. The baseline methods [22, 130] follow a simple concatenation of embedding vectors in Figure 6(b) to be fed in a deep component to capture feature conjunctions. They demonstrate that it may carry less non-linear information in the low-level. Therefore, they suggest a Bi-Interaction pooling encoder to capture more informative feature interactions. Considering an embedding vector for each feature value, the Bi-Interaction pooling operation is designed to generate the aggregated vector as follows:

$$f_{BI}(V_x) = \sum_{i=1}^{n} \sum_{j=i+1}^{n} x_i \mathbf{v}_i \odot x_j \mathbf{v}_j, \tag{12}$$

where $V_x = \{x_1\mathbf{v_1}, \ldots, x_n\mathbf{v_n}\}$ is the set of embedding vectors, x_i is binary feature value in sparse input vector, $\mathbf{v_i}$ is embedding vector and $\odot$ operator makes element-wise product of two vectors.

Further, the authors of Reference [97] pinpointed that the semantic intrinsic relations between embedding vectors of user and ads can be captured through their proposed structured semantic models. They propose a series of orthogonal convolution and pooling operators rather than trainable convolutional operators that can be applied as embedding vectors to address semantic relations in input features. Experiments reported in the above studies show that applying hybrid methods can improve logistic regression, which highly depends on the quality of features prepared by using feature engineering. This encourages further studies to develop extensions of factorization machines with better generalization ability.

Factorization-based hybrid methods. In Reference [44], the authors provided a successful version of hybrid methods as the stack of factorization machines and fully-connected neural networks. The success of this design later led to employ this structure as a base for developing many extensions [152, 176]. The study pinpointed that Wide & Deep method [22] has some challenges in modeling of feature interactions, since the wide component includes the logistic regression model



(a) DeepFM (b) DeepFFM

Fig. 7. (a) Hybrid model (DeepFM): It is combined by a deep component (fully connected neural network) with a Factorization Machines method (Figure 5(a)) using a shared embedding layer to feed dense embedding vectors as the input to the structure. (b) Hybrid model (DeepFFM): It cascades the FFM interaction model in Figure 5(b) to a MLP network as the deep component.

trained using a feature engineering. It can cause a poor generalization. They investigated to use a factorization machine to automatically capture feature interactions from one-hot-encoded features. Following the structure shown in Figure 7(a), the proposed model, DeepFM, combines the power of factorization machines and deep learning for the feature learning in a recommendation application. The new neural network architecture models linear and second-order feature interactions through FM and models high-order feature interactions by fully connected neural network. Replacing the logistic regression with factorization machines and using a shared embedding layer between these two components, they build a model in an end-to-end manner without a feature engineering.

Figure 8 shows the embedding layer structure, which is designed to project discrete feature values to a dense numerical vector space. This projection is modelled by a layer of linear neurons defined on the top of one-hot-encoded input vectors [43]. It includes an embedding matrix of parameters learned for each feature field. Embedding vector representing each categorical field can be shown as follows:

$$e_i = W_i x_i, \tag{13}$$

where e_i is the dense embedding vector and x_i is the sparse binary representation. W_i is the embedding matrix for the i field with the dimension of $m_i \times d_i$. m_i denotes the number of discrete values for categorical field i and d_i is the user-defined dimension of dense embeddings. In practice, the functionality of embedding layer is identical to one layer of densely connected neurons without considering bias links and activation functions. It is shown that the embedding matrix W_i can be considered a lookup table for each field. This is because in the case of one-hot-encoded input, the multiplication of input with embedding vectors in Equation (13) can be replaced by corresponding embedding vectors at referred indices in the embedding matrix. Randomly initialized, the weights w_{ij} in the embedding matrix are trained during the optimization of the target value in different models.

In Reference [117] a new hybrid is proposed through combining embedding vectors and a cascade of factorization machines and a MLP network. This method takes advantage of learning ability of neural networks and discriminative power of latent patterns in a more effective way than MLPs, through adding a product layer between the embedding layer and the first layer of the fully connected neural network. The model is examined with inner and outer product operations in the product layer, to examine different methods to model the feature interactions, combined with Stochastic Gradient Descent training (using L2 regularization) and a dropout mechanism to address the over-fitting issue.

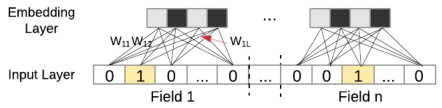


Fig. 8. The structure of embedding layer to generate dense embedding vectors. It includes a linear mapping from discrete categorical features represented by one-hot-embedded vectors to dense numerical embedding vectors. It equals to a layer of linear neurons above input layer whose weights are getting trained using gradient descent optimization. The weights are formed in a embedding matrix(lookup table) to accomplish the linear transformation. The rows in the matrix represent embedding vectors for discrete values in the categorical fields.

As introduced in Section 4.3, in the FFM [57] method as the field-aware factorization machines, each feature value is represented by more than one embedding vectors to model combinatorial features in input space. It addresses different weights for interactions occurring between different feature types.

The large number of features in latent vectors generally cause space complexity problem and memory bottleneck [57]. In addition, DNN-based models may run into insensitive gradient issue when dealing with multi-field categorical data that deter the progress of gradient-based optimization. To tackle these challenges, a net-in-net architecture is proposed as the generalization of kernel product [118] to model feature interactions. So a micro network including one layer of the fully connected neural network cascaded by dot-product feature latent features is used as the special kernel function to alternate a simple inner-product function in factorization machines.

Following the success of field-aware factorization machines [57] in capturing feature interaction with regard to feature fields information, a study [168] extends this idea to provide a hybrid model of FFM and a fully connected deep neural network to learn feature conjunctions in the input data, as shown in Figure 7(b). In this case, each sparse input feature is represented by multiple embedding vectors to address the effect of feature with regard to the feature field in inner (dot-product) feature interactions. The embedding vector are organized as a two-dimensional matrix with size of $k \times n$ where k is the dimension of embedding and n is the number of feature fields. Applying $n(n-1)/2$ inner-product calculations between pair of embedding vectors to generate intermediary input vectors, the predicted click-through rate value is generated from the output of Deep component. Field-aware Neural Factorization Machines [177] further extends this method, by introducing a Bi-Interaction operator with a wide concatenation based on Hadmard product operator as the alternative to the inner product layer in Figure 7(b). Using Bi-interaction operator to calculate feature interaction, the dimension of input vector of deep component is changed to $n(n-1)/2 \times k$. The increase of parameters in the embedding vectors of field-aware-based factorization machines methods can decrease the prediction performance because of the over-fitting issue. Therefore, it demands to select features before the feature interaction procedure in factorization machines. Compared to the Attentional Factorization Machines method [162], which captures the important cross features interaction step in the FM model, a recent study [176] evaluates the importance of features before applying feature interaction step using Squeeze-Excitation network [53, 176]. The authors of Reference [176] introduced an attention-based method to selectively use more informative features in embedding vectors. They propose to apply Compose-Excitation network as the extension of Squeeze-Excitation Networks to select important feature representations.

Generic hybrid methods. Some studies [75, 154] develop a hybrid method to generalize the idea of factorization machines method. The authors of Reference [154] extended the second-order feature interaction in factorization machines to higher-order levels through a multi-layer network structure where the maximum level of interaction order is determined by the number of layers.

Considering the structure of DeepFM method in Figure 7(a), a cross network is employed for feature crossing operation using Equation (14) through weighted dot product of current output vectors at subsequent layers,

$$\mathbf{x}_{l+1} = \mathbf{x}_0 \cdot \mathbf{x}_l^{\mathsf{T}} \cdot w_l + b_l + \mathbf{x}_l, \tag{14}$$

where $\mathbf{x}_l \in \mathbb{R}^d$ denotes the output vector calculated at level l and $w_l \in \mathbb{R}^d$ and $b_l \in \mathbb{R}^d$ constitute system parameters in this structure. In the first layer, the dot-product of concatenated embedding vectors $\mathbf{x_0}$ are used to generate the first output. For input data as a multi-field categorical data, the proposed component explains the main difference between this model and factorization machines methods in which dot product interaction here is applied on the concatenation of feature fields rather than between pair of feature fields. The study [75] is the other extended work to create a new cross network in which feature interaction is modeled at a vectorwise level through outer product instead. This leads to generating an embedding matrix in which the operation in each layer has intuitively connection to convolution neural networks by considering the weights as filters.

Deep learning-based methods. In literature, various deep learning techniques have been studied for the user response prediction. The majority of previous work following a deep network structure are typically based on two components of embedding and interaction basically designed through deep neural networks to capture non-linear feature interaction in sparse input data. Figure 9 demonstrates the structure of this paradigm. Embedding component is designed to transform the sparse input data into a low-dimensional dense latent space. The embedding vectors are then processed by applying an aggregation mechanism to produce a fixed length vector for the deep component. The high-order interactions between features are addressed through feeding a fixed-length vector into the deep neural network component generally implemented by the multi-layer perceptron [25, 130]. Gradient-based training is adopted to learn the non-linear correlation between user features and user responses. In this regard, there are lots of studies conducted to improve the performance of each component. Table 4 demonstrates a summary of representative methods mainly developed based on multi-layer perceptron, recurrent neural networks and convolutional neural networks some of which are combined with attention mechanism design their proposed models.

In online advertising, input features can be gathered from different sources. In Figure 9, sparse binary features representing the input data can be grouped into multiple categories like Table **??** regarding users, advertisers and context. Deep neural network can process input data vectors with a fixed length dimension. However, using a fixed-length vector for users with diverse interests against advertisements can be bottlenecks for prediction, since each user and web-page can have different labels and diversities at the same time. Addressing the variety of user interest generally needs the expansion in the dimension of embedding vector for user features in the aggregation step that increase the risk of over-fitting and the cost of computation.

Dealing with this issue, two sub-categories of features such as user profiles and user behaviors [190] are proposed for click-through rate prediction, where an array of user behavior in a period of time attributed by categorical data [100, 190] like visited good, shop and web-page category ids, are used to describe users and their interests. The idea is further followed in Reference [38] to model user behaviors from the continuous image data. In the case of categorical features, since the category of a shop and web-page visited by users may be shown with multiple values, the binary representations are modeled by multi-hot-encoding. They also address the importance of feature interaction in modeling of user behaviors. To this end, they design a local activation unit to provide an adaptive feature representation with regard to different ads, and assign weights to the relevant pair of a visited page and advertisement in the user behavior sequence with regard

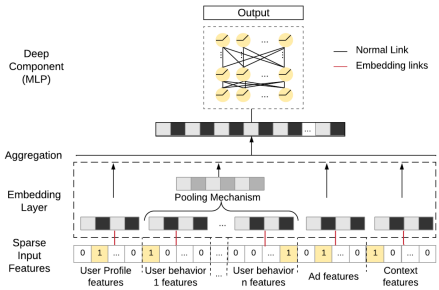


Fig. 9. DNN-based architecture (Embedding and MLP) including two main steps embedding layer followed by the aggregation operation to generate a merged vector. The vector is used as the input for second step using MLP to generate predicted user response value (CTR, CVR, etc.) developed in different studies. The selected input features are chosen from user profile and online user behaviour sequence in addition to those selected for Ads and context.

to the targeted ad. The output vectors are later passed to a weighted sum pooling to generate a fixed length user behavior embedding vector, and then passed into deep component to generate the predicted output value.

pt The application of attention units to model user behavior history has also been studied for click-through rate and conversion rate prediction [37, 38, 73, 100, 137, 147, 163]. A multi-head self-attentive networks [137] is proposed where features are mapped to multiple subspaces through multi-head mechanism. This would help the model to consider different orders of feature interaction with adaptive weights. In addition, this method proposes a residual neural network rather than the conventional MLP network to model high-order combinatorial feature interactions. The study [100] extends the analysis of user behavior from two temporal and spatial aspects. Because a webpage can be filled with more than one ad, they model user behavior history not only by ads clicked by users but also those not clicked by users. They consider ads shown in the same page above or below the targeted in both spatial and temporal order. Their interactions to targeted ads are modeled by adding an attention-based factorization machines layer followed by a fully connected neural network. In Reference [163], the multi-head attention mechanism is adopted to model the user behavior history from a sequence of clicked/purchased advertisement information by adding discriminative features likes dwell time on landing page for a conversion rate prediction task.

Some studies also extend the deep component using different structures of MLP-based networks [88, 101, 102, 160]. To tackle the data sparsity, researchers [102] propose to consider input features to be fed into a couple of subnets built based on MLP network for a feature interaction modeling, using features of users, query and ads entities. The subnets are created to model the interactions between user-ad, the correlation between ads. These models are then combined with the third one designed for the prediction in a joint optimization. For conversion events followed after clicking on ads, a deep learning-based model is developed [88, 160] to consider not only all clicked ad impressions, but also include all impressions and further user actions like “add to card” (DAction) and “add to wish list” (OAction) taking place before conversion events. Following a multi-task framework, multiple deep components are trained for each event to generate the prediction of conversion post-click rates.

For the embedding, some studies propose to handle categorical and continuous input features at the same time [38, 191]. For images, convolutional neural network have been developed in several studies [19, 38, 166]. In the scale of industrial applications, the authors of Reference [38] suggest to generate embedding vectors of images using a pre-trained very deep convolutional neural network

Table 4. Summary of Selected DNN-based User Response Prediction Methods with a Hybrid Structure

Main DNN Structure	System Framework: Embedding Component	Deep Component	Aggregation	Method	Features	Application Domain	Predict. Task
MLP	**All features**:RE[a]	MLP	FM/Pooling Layer	DSTN [100]	User, Query, Ad, Context, User clicked ad history	E-commerce[b]	CTR
	All features: RE[a]	MLP	Concatenation	MA-DNN [101]	User, Query, Ad, Memorized user interest (memory link)	E-commerce[b]	CTR
	All features: RE[a] cascaded by FM	MLP	Concatenation	PNN [117]	User behavior, item, context information	Display advertising	CTR
	All features: RE[a]	MLP alongside FM	Concatenation	DeepFM [44]	User behavior, item, context information	Display advertising	CTR
	All features: RE[a]	Multiple MLP Stacking	Concatenation	$ESMM$ (ESM^2) [88, 160]	User, Item, users' historical preference scores	E-commerce[b]	CVR
	All features: RE[a]	Multiple MLP Stacking	Concatenation	DeepMCP [102]	User, Query, Ad, Context, negative ad sample features	E-commerce[b]	CTR
	All features: RE[a]	MLP alongside Hadamard product layer	Concatenation	NCF [51]	The identity of Users and Items	Movie/Image recommendation	Ranking
	All features: via Auto-feature grouping and high-order feature interaction selection	MLP alongside FM	Concatenation	AutoGroup [79]	User behavior, item, context information	Display advertising	CTR
CNN	CNN(Pre-trained CNN model using orthogonal base convolutions)	W&D [22]	Concatenation	W&D SSM [97]	User behavior, item, context information	Display Advertising	CTR
	Image ad features: CNN subnet **Other Ad features**: fully connected subnet	MLP	Batch Normalization	DeepCTR [19]	Image, categorical (Impression)	Display Advertising	CTR
	All features:RE[a] augmented to CNN subnet	MLP	Concatenation	FGCNN [78]	Categorical+ continuous features in display advertising	Display Advertising	CTR
	Ad,Query features (under character-level): 1d CNN subnet, Ad,Query features (word-level)	MLP	Cross-convolutional pooling	DCP/DWP [32]	Ad, Query	Sponsored search	CTR
RNN	**Ad, context features:**RE[a] **User behavior features:** Hierarchical GRU-based memory network	MLP	Concatenation	HPMN [120]	User behavior sequence, item context info	E-commerce[b]	CTR
	All features: RE[a]	MLP LSTM	Concatenation	NTF [161]	User behavior sequence, item, time	Recommendation	Product rate
	Ad, context features:RE[a] **User behavior features:** Memory induction GRU-based unit	MLP	Concatenation	MIMN [110]	User behavior sequence,item context info	Display advertising	CTR

(Continued)

Table 4. Continued

Main DNN Structure	System Framework: Embedding Component	Deep Component	Aggregation	Method	Features	Application Domain	Predict. Task
Neural Attention	RE[a]	Multi-head ResNet	Concatenation	AutoInt [137]	User profile, item attributes	Display advertising	CTR
	user profile, Ad features: RE[a] **User behavior features:** Self Attentive Bi-LSTM	MLP	Concatenation	DSIN [36]	User profile, User behavior sequence, item,	Display advertising	CTR
	User behavior (event) sequence: RE[a] **User behavior (timestep) sequence:** Attentive embeddings followed Bi-GRU	MLP	Attention Mechanism	DTAIN [40]	Event, Timestep information	E-commerce[b]	CTR
	user profile, Ad, context features:RE[a] **User behavior features:** self Attentive GRU relative to target ad	MLP	Concatenation	DIEN [189]	User profile, User behavior sequence, item,	E-commerce[b] Display advertising	CTR
	User behavior sequence features: RE[a] controlled by multi-head self-attention structure **Other features**: RE[a]	Jointly training two MLP stacks for CTR and CVR	Concatenation	PFD+MD [163]	User, Item, Post-click info, User Clicked/Purchased sequence, User-item interaction statistical info	Display Advertising	CVR, CTR
	User profile features: RE[a] User behavior sequence features based on Ad image: Pre-trained embeddings	MLP	Concatenation, Sum/Max/ Pooling	DICM	User, Ad (image), user behavior sequence(image) [38]	E-commerce[b]	CTR
	Pre-trained knowledge graph Word embeddings combined with, entity and context embeddings via CNN	MLP	Attentive pooling, Concatenation	DKN [147]	User (clicked news item), News item	News recommendation	CTR
	Query & ad under word-level: 1)Pre-trained word embedding, 2) regular embedding[a] Followed by bi-LSTM and MLP	CNN MLP	Pooling, Query-Ad tensor matching	DSM [41]	Ad(title, URL, description), query words	Sponsored search	CTR

[a]Regular Embedding using trainable look-up table parameters (matrix embedding per feature) following the structure shown in Figure 8.
[b]In the e-commerce scenarios, the prediction task is defined as the the probability that user clicks or makes an conversion on the recommended items(ads).

rather than employing an end-2-end training model. The convolutional networks are also adopted in Reference [78] to extract implicit features from the sparse input data and deal with the overfitting issue in fully connected-based networks [25]. In the proposed model, the convolutional neural network structure designed based on shared weights followed by pooling module can considerably reduce the number of parameters. Considering these embedding vectors along with raw features result aggregated vector to be processed by a deep multi layer perceptron component.

Recurrent neural network-based methods. Deep neural networks is typically made of multi layer fully connected neurons. Following a stateless structure for neurons, the independent features incorporate the data that flow through multi-layer perceptrons to generate the output without backward links. Considering independently visited or clicked advertisements to model the user

behavior history fail to extract efficient useful user interests with regard to user response prediction. Therefore, recurrent neural networks are developed to process the sequence of input data sorted by time to improve user response prediction performance [15, 36, 74, 110, 181, 189].

In online advertising or e-commerce platforms, user intention is often not explicitly expressed through their behavior history. Therefore, it is hard to identify real interested users only based on captured online user behaviors. In addition, living in a dynamic life environment, people's knowledge increase and their latent interest and behavior may change over time [105], indicating that temporal correlation in online user behaviors can show the evolution in the user interest to have more tendency to advanced items compared to previous converted ones. It leads to studies of developing LSTM models based on user behavior sequence from previous bought and clicked items to predict conversion rates [105]. Following Figure 9, to aggregate embedding vectors, two categories of aggregation modules are generally discussed in different recurrent neural network-based studies. The approaches like min-max or sum pooling-based aggregation are generally applied to model user behavior from independent input features. In the body of neural network structure, GRU/LSTM neural units were commonly used in many studies to model latent user interests [36, 74, 110, 189].

Comparing to deep neural network-based methods, recurrent neural networks suffer from computational and storage overheads. They include hidden states in the structure to capture user interests from sequence of user behavior data. Therefore, it makes it difficult to use these network for industrial applications visiting numerous users and ads everyday. It causes limitations to apply these methods to model long term user interests based on long sequential user history records. To tackle these challenges, some studies introduced memory-based architectures [15, 101, 110].

Convolutional neural network-based methods. Studying to design deep learning network structures are not limited to the above-discussed ones, since the input space suffer from the data sparsity that makes it hard to learn directly using simple gradient descent methods. Although the deep neural network including multi-layer perceptrons in theory is known as a universal approximator that has a capacity to capture almost all non-linear feature interaction in input space, but the order of magnitude of parameters used a fully connected neural network deters to capture feature interaction in a sparse feature space and leads to over-fitting issue. This encourages to apply **convolutional neural networks (CNN),** which benefits from parameter sharing and pooling mechanism to work with a feasible number of parameters [14, 32, 37, 78, 83]. Dealing with image data along with multi field categorical data, CNN networks are used to extract non-linear latent features in the form of embedding vectors for raw pixel image data [19, 38, 41, 97]. As one of the primitive studies, the authors of Reference [83] conducted experiments to apply convolution filters followed by a flexible max pooling in a CNN network on two datasets including multi-field categorical data and a series of impressions in an e-commerce platform to capture neighbor patterns in input data. The downside of this method was that they applied the convolution for neighbors field feature while the feature interaction between non-neighbor fields is neglected. However, for user response prediction tasks, any order of feature fields are possible. The order of feature fields in the certain alignment in input data does not have meaningful inference like images or texts. Therefore, the other studies developed methods to take advantage of both CNN and deep multi layer perceptron to address high-order and low-order feature interactions.

For news recommendation, a knowledge-aware model [147] proposes to use knowledge graph to represent news items, with each news article being attributed by word, contexts, and entity embeddings. For user response prediction, CNN network, previously proposed for sentence representation learning, is used to generate the final embedding vector of user and ad features. Attentive neural network is applied to address user interest diversity to estimate click-through rate values.

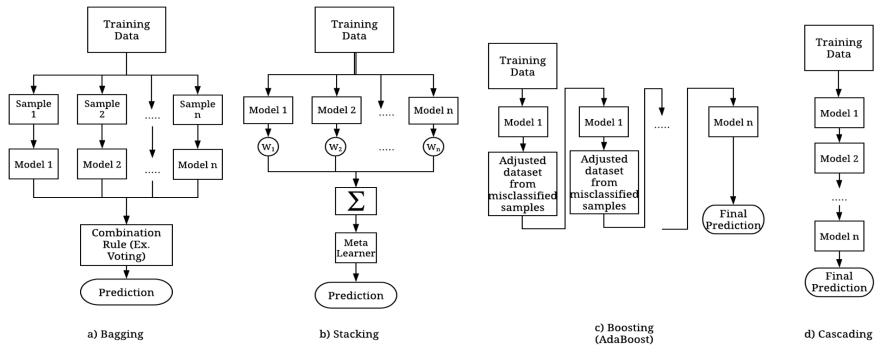


Fig. 10. Ensemble structure types: (a) Bagging randomly samples training data, with replacement, to generate N subset data and train N predictor models. The final result is the combination of N classifier outputs. (b) Stacking: N models are trained in parallel based on the same training data. The final output is combined through a meta-classifier. This classifier is fitted on the output of base classifiers. (c) Boosting(AdaBoost): A series of predictor models are trained using a subset of training data sequentially. The subsets of data are created adaptively using misclassified samples in previous model. (d) Cascading: This is based on concatenation of multiple classifiers.

Other methods. In the previous section, we have provided an review on classification methods ranging from linear logistic regression-based methods to advanced deep learning-based methods. A few other classification-based methods that may gain attention are **generative adversarial network– (GAN)** based models [28, 72], transfer learning [138, 178], fuzzy design [56], decision trees [46, 159], and multi task learning [104, 149] approaches.

4.3.1 Ensemble-based Approaches. While early proposals for user response prediction mainly use linear logistic regression classifiers, which provide the simplicity along with the scalability, modern approaches are developed to address non-linear interactions in data using methods likes factorization machines, generalized version of decision trees, and neural networks. Some studies show that using a single machine learning method may lead to non-optimal results, and propose a new aspect of development to design a model structured from an ensemble of machine learning models. These models can bring more improvement in the level of accuracy for the prediction task. Generally, the design of ensemble models are mainly categorized into four sections like Bagging and Boosting, Stacked Generalization, and Cascading shown in Figure 10 [4].

The combination of different classification methods in the form of ensemble structures are utilized in different studies. The study in Reference [179] followed a cascading version of an ensemble model that includes two learners. They investigated the performance of combining factorization machines with a fully connected neural network to predict CTR values for the digital advertising. Because of the data sparsity in the categorical input data, the feature interaction cannot be easily detected directly using deep neural networks that generally lead to the overfitting issue. They propose to cascade factorization machines to a deep neural network to address this issue.

In the context of e-commerce websites, Reference [5] suggested multi-modal ensemble learning to consider texts and images of posts as different modalities. They separately built a logistic regression model for historical CTR values and another model for embedding vectors of images and textual information. Following the multi-modal learning approach, the stacking ensemble model is used to combine linearly their results by passing to the final logistic regression classifier.

In another study, authors in Reference [159] propose to develop an ensemble model for conversion rate prediction that is mainly based on gradient boosting decision trees (GBDT) learners.

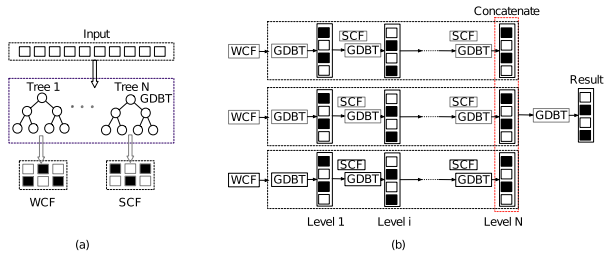


Fig. 11. Ensemble GBDT model: (a) Input features randomly selected from the feature pool fed into GBDT model. Their importance for prediction is evaluated based on their correlation to class labels by traversing from the root node into leaf in a tree. They are sorted into two categories according to the explanatory power into WCF and SCF. (b) The structure of proposed multi-level deep cascade trees including stacking multiple sequence of GBDTs.

These learners basically follow a boosting method to create sequential decision trees. The authors in this study used GBDT as a building block to create a more complex model. Following the Cascading and stacking techniques, they used multi-level cascade of **gradient boosting decision trees (GBDT)** models to extract features that are coming for values received from the previous model. To improve the diversity of extracted features, multiple cascade of decision trees are aggregated like Figure 11 through the concatenation to be passed to the conclusive GBDT to generate the final features for the classification. As a part of the contribution of this work, to improve the prediction performance, the importance of input features is also considered. They use a separate GBDT model to pre-process the input raw features and generate two class of features that have weak and strong correlations (**weak correlation features (WCF)** and **strong correlation features) (SCF)**) with regard to the prediction result. These class of features are used relatively as the input to train the model.

In literature, some works also comparatively study the effect of ensemble techniques [60, 77]. Following the ensemble techniques introduced in the beginning part and the goal to improve click-through rate values, the study in Reference [77] examined two ensemble techniques Boosting and Cascading with GBDT, **Logistic Regression (LR)** and a fully connected deep neural network classifiers. They compared the performance of corresponding single learners with the cascaded and boosted version of pair of models in the click-through rate prediction for the sponsored search advertising. For the sponsored search advertising application again, the study in Reference [60] made a comparison between the effect of four different structures of ensemble learning such as the majority voting, bagging, boosting and stacking for pay-per-click classification. The features are selected from different information sources like the attributes describing ad impression, click-through rate value, conversion rate value, and the position of ads in addition to the textual features captured from the title and the body of ads and campaign categories. They are joined together to train ensemble learners such as Naive Bayes, Logistic Regression, Decision tree, and SVM to estimate the pay-per-click value of campaigns.

4.4 Unsupervised and Semi-supervised Approaches

In this section, we review two categories of methods in the literature that do not fully rely on labeled data. In this case, the predictive models are designed based on the implicit and explicit pattern in data. Semi-supervised models refers to approaches like graph neural network-based models that involve designing a user feedback estimation model using both labeled and un-labeled sampled data. Two categories of these methods are represented in the following subsections.

4.4.1 Clustering-based Approaches. Clustering methods have also been investigated in the literature for online advertising. As an unsupervised approach, clustering involves grouping sample data into related clusters based on similarity among data points.

Some studies develop statistical clustering methods for categorical data in different contexts, such as k-modes [131] as an alternative to the popular k-means method that uses hamming distance as the distance metric, COOLCAT made in Reference [7] uses the notion of entropy for the similarity metric, or CLOPE clustering approach in Reference [167] research that develops a scalable method to leverage the trend of a height-width ratio of the cluster histogram as the similarity criterion. But these categorical clustering methods are not well studied in the online advertising with the multi-field categorical data.

However, some clustering-based studies are proposed to improve classification-based methods. As the initial study in this category, to supplement the logistic regression [17] and GBDT [47] methods for user response prediction task, the authors of Reference [119] propose to use feedback features that are prepared from historical user behaviors. Considering advertiser and publisher that come from with different hierarchical granularity, they incorporated the combination of publisher page and advertisement along with user-publisher-creative that are created based on the hierarchical structure of user as the new features. The extra features are quantized using the k-means clustering to be added to input features for training.

Some methods [119, 124, 158] organize the user input, such as keywords used in search engine or pages visited by users, by using clustering to reduce the severity of the above-mentioned issues and improve the correlation with user responses. In Reference [119], the authors suggest that since a different click response probability can be assumed for different query keywords, the topic of ads and query keywords can be used to organize data into clusters where more closely related terms have more similar click-through rate values. They propose to generate groups of terms using hierarchical clustering and keyword-advertiser matrix. The similarity of samples intra and between clusters are evaluated by the textual similarity of terms in ads. Therefore, assuming the fixed CTR value for clusters, the estimated value of click-through rate for new samples is determined by the nearest neighbor clusters.

4.4.2 Network-based Framework. With development on the Internet, information networks are the common element of online businesses. In this subsection, we will go over approaches addressing the network structure in the input data to develop predicting models for the user response prediction.

Graph embedding-based methods. Recent years have seen a lot of studies that focused on the application of network representation learning methods for recommender systems and the user response prediction. Motivated by the success of CNN and RNN, there has been an interest in developing neural network-based models for the graph structured data. Considering three major challenges in recommender systems, scalability, data sparsity, and cold start, many methods have been proposed in the literature using graph embedding [150, 197] and graph neural network [35, 59, 74].

The authors of Reference [150] designed a recommender model based on the graph embedding that takes advantage of side information to cope with the three challenges. The model includes two sections such as matching and ranking. Focusing on the first section with the network of users interacting with items in an e-commerce website, they applied DeepWalk [109] to generate embedding vectors of items in the directed graph of items formed using user online behavioral history. Because of the data sparsity, there is a lack in the number of interaction in the graph. Therefore, as the part of the contribution, side information such as the price value, shop, category and brand, are included as the one-hot encoded vectors in network representation learning procedure.

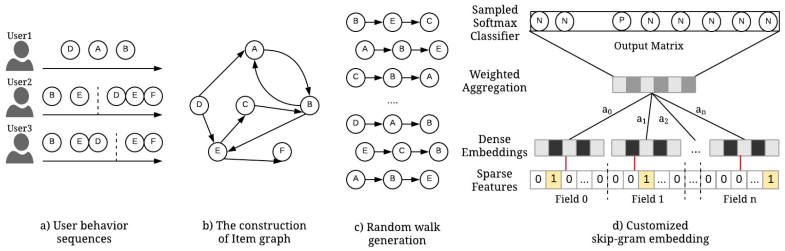


Fig. 12. The billion-scale commodity embedding proposed in Reference [150] for E-commerce recommendation in Alibaba: (a) user behavior sequences including items(Ads) visited in one or more session specified by dash lines. (b) Item(ad) graph generated user behavior sequences that a direct edge representing two subsequent items(ad) in user history. (c) Generating sequence of nodes using random walk in graph following Deepwalk method. (d) Proposed graph embedding algorithm to use side information to reduce data sparsity. Field 0 specifies a node in random walk and field 1 to field *n* are the one-hot-encoded vectors for side information corresponding to the ad node in the graph. Hidden layer is a weighted average aggregation of dense embedding vectors.

Graph Neural Networks (GNN) are known as one the most effective solutions to develop predictive models for network-based data. Extended from recurrent neural networks and convolutional neural networks, GNNs have a unique capability to generalize neural networks to cope with directed and un-directed input graphs, by using an iterative process to propagate node status over their neighborhoods. After optimization, it can provide an embedding output of nodes in the graph in which the feature information are aggregated using their neighbor nodes. Recently, GNN-based methods have received more attention for online advertising and recommendation systems applications [35, 59, 74, 156, 157, 174]. Like deep learning-based models in Table 4, Embedding and Interaction components are two major components in the design of these predictive models in the literature. The embedding component is dedicated to map information associated to node and edges in the graph-structured data into numeric vectors. However, the interaction component tries to make the reconstruction of user feedback in the system. This part can be designed by different ways through a MLP component in deep learning-based models [157] or inner-product between embedding vectors [156] or element-wise multiplication of embeddings [174] to represent collaboration between users and items to rank and predict user preferences in recommendation and online advertising systems. The embedding component is developed using recent advance in graph neural networks. The authors of References [50, 156] propose an propagation layer in their embedding component to refine embedding vectors via aggregation of embedding vectors of neighboring nodes in the graph. The model in Reference [156] is built using the message-passing architecture and defining a model via layerwise message constructing and aggregating operations. A recent study [74] addresses the limitation of methods like DeepFM [44], by considering a graph structure for feature fields in the input data in which nodes corresponding to feature fields interact with others through weighted edges to reflect the importance of field interactions. A GNN-based model is developed to model complex interaction between input field features. In this model, field feature as the nodes in graph are attributed by hidden state vector that is updated using a recurrent approach. An interaction step parameter is defined to consider higher and lower interactions between nodes and their neighbor nodes that are located in one or more hops away. The ending point of the model includes an attention layer to predict CTR values.

One essential challenge of network embedding for the user response prediction is that the embedding learning might not be directly optimized toward the underlying user response prediction. Following an unsupervised learning, nodes are represented using embedding vectors, however,

they may not be optimized for downstream tasks like the click-through rate prediction. This issue can be considered as the bottleneck to improve the task. Therefore, the user intention modeling is considered as an alternative [189, 190]. Considering the sequence of the user behavior from the interaction between users and ads in the user intent modeling still have some challenges like the data sparsity and weak generalization. A study [71] showed that sequence of user behavior can be organized as a co-occurrence commodity graph with node representing clicked commodities and weighted edges describing number of co-occurrence times. To address the sparsity problem, a multi-layered neighbor diffusion is performed on the commodity graph. The preceding result is combined with using an attention layer to generate user intention features. These features combine with other ones, such as user profiles, query keywords, and context in fully connected network, for the click-through prediction.

Knowledge graph-based methods. Knowledge graphs are semantic heterogeneous networks including a collection of entities with attributes that are inter-connected together through edges. They are usually described through a triplet with relation connecting head and tail entities like (Head, Relation, Tail). This structure of data has been studied for different applications like link prediction [30] and Web search analysis [143]. The advantages of the knowledge graph for applications suffering from data sparsity and cold start problems, such as recommendation systems, have been observed from different perspectives. First, networks can provide additional semantic relationship information to improve the recommendation performance. Moreover, the diversity of information in the knowledge graph can extend the information for matching with user interests. In addition, the historical information linked to items in recommender systems can provide implication ability for the system. In summary, we separate knowledge graph-based methods for recommender systems and online advertising into three categories: embedding-based, path-based, and hybrid methods.

Network embedding methods. This category of methods aim to map the components of the knowledge graph, including entities and relations, into low-dimensional embedding space to preserve network structural information [153]. Some jointly incorporate heterogeneous attributes and content that are assigned to nodes in the graph for modeling [174].

For example, knowledge graph-based representation for news recommendation [147] has been studied to address the challenge of topic and time sensitivity for news items selected and visited by users. It means that users generally visit selected news at a short specific of time that may not happen later. In addition, news content usually has brief words and diverse topics. To handle these challenges, a deep neural network is proposed to take advantage of a customized CNN module as the key component to model user interest through multiple channels that consider both word semantics information and corresponding information from a generated knowledge graph data. This leads to generating three categories of embedding vectors for words in the body of news, the associated entity and immediate neighbors in knowledge graph. In the design, an attention mechanism is used to aggregate embedding vectors of user behavior sequences. They avoid using concatenation strategy for the aggregation in this step, since entity and word embeddings may have different dimension generated from different contexts. The output are fed into a fully connected neural network to learn the probability of user's click for a selected news piece. Likewise, a study [174] presents a heterogeneous graph neural network model that adopts the aggregation of feature information with regard to a sampled neighboring nodes. A node sampling procedure is suggested to aggregate selected neighbors grouped by their types and their frequency in a designed random walks. Using attention mechanism, the content embedding of neighbor nodes with the same type are first aggregated. It is then followed by another attention round to aggregate embedding vectors of neighbor nodes from different types in the graph. They train embeddings using heterogeneous skip-gram learning. To compare the performance of proposed model, element-wise

multiplication and inner-product operations of user and items embedding vectors are used to simulate user response for link prediction and recommendation experiments.

Meta-path-based methods. This category contains knowledge graph embedding methods that employ meta-path schemes as the guideline to generate random walks and in turn embedding vectors. Although many studies in the category have shown a decent performance for recommender systems [35, 175], current methods heavily rely on manually building random walk corpus for further processes. The selection of meta-path schemes are generally considered as the hyper-parameters set differently by researchers in experiments. So this can be an issue in practice. To tackling this problem, attention mechanism has been employed in recent studies. Authors in [157] design a heterogeneous graph neural network to automatically address the effect of different neighboring nodes and meta-paths using two-level attention layers. In the first level, node-level attention is applied to train the weights for meta-path guided neighbors of each node in the graph. It is then fed to a semantic attention step to calculate weighted combination of different meta-paths for the node embeddings. The predicted interaction between different node types in heterogeneous graph is modelled through training a fully connected neural network at the end.

Other knowledge-based methods. In this section, we present hybrid knowledge-based methods that learn user/item embeddings by exploiting structural information in the knowledge graphs [116, 148]. Recently, a study [148] discusses the extension of GNN method made for a knowledge graph where the edge weights between user and item nodes are not available beforehand. So a personalized scoring function is proposed for training to determine the edge weights via a supervised approach following a relational heterogeneity principle in the knowledge graph. To address the data sparsity issue in recommendation systems, a leave-one-out loss function is used as a label smoothness regularization to calculate predicted weight values. It leads to calculating node embeddings through aggregating node's feature information over the local neighborhood of the item node with different weights.

A common approach to model user response in knowledge graph-based methods is to apply aggregation mechanism to combine embedding vectors of user and items entities via average pooling or attention units over their neighbors. The authors of Reference [116] consider this as early summarization problem. They argue that modeling user response using the inner product of embedding vectors of user and item can have a limitation for user response prediction. Accordingly, a neighborhood interaction model is proposed to integrate a higher-order neighbor-neighbor interactions through a bi-attention network in the aggregation step to improve user click through rate prediction.

4.5 Stream-based Framework

Online advertising is essentially a streaming platform, where users, auctions, and ads are continuously and dynamically changing [151]. In this context, data stream refers to continuous feeds of news and information generated by users in an interactive way [69]. Social media platforms are examples of these systems in which millions of users generate data continuously being uploaded. The stream environment provides an opportunity to emerge in-stream advertising with commercials in stream of data. Also known as native advertising, in-stream ads look similar to regular feeds. They are differentiated by an assigned tag indicating a commercial target or the content of feed.

The performance of advertising strategies for stream data has been studied from different aspects according to the condition and policies in online platforms. Click-through rate value is not only a metric to evaluate user experiences. Many studies have developed methods to address pre-click and post-click user experiences [9, 67, 192]. From a different perspective, user response prediction was cast to evaluate ad quality. The high rate of quality value is considered as the positive

Table 5. Overview of Main Ideas of User Response Prediction Methods along with Pros and Cons

Learning Strategy	Algorithm	Advantages	Disadvantages
Data Hierarchy Analysis	Clustering based	+ Using clusters as an auxiliary information for samples with insufficient observations	- May have a variation in user response rates
Matrix Factorization	Collaborative Filtering	+ Good scalability along with simplicity + It can provide robust performance against sparse data	-Explore all historical data -Weak on anonymous behaviour sequences - No promised performance in case of lack of user info due to privacy issues
Training a classifier	LR	+ Scalability	- Needs feature engineering
	FM based	+ Have a closed form equation that can be calculated in a linear time	- Limited to model second-order feature interactions
Feature Learning + Training a classifier	DNN based	+ end-to-end interface with representation learning and non-linear transformation + High flexibility using a modular implementation via open source frameworks	- Interpretability - Prone to over-fitting due to requirement of large amount of input data - Hyper-parameter tuning issue
	RNN based	+ Can learn from sequential data with variable lengths + Robust performance with regard to data sparsity	- Rely on linear sequential structure; - Hard to take full advantages of GPU/TPU computing architectures; - Long training time
	GNN based	+ Addressing the network structure in the input data to aggregate feature information of neighboring nodes + Joining with attention mechanism to provide good interpretability	- A model trained cannot be directly applied to an input graph with different structure - Computational cost
Stream-based framework		+ Adjust prediction in user preferences over time + Joining with external memory network for increment updates + Reservoir technique to use more samples to update the model	- Unpractical to stack up the training data for modeling

influence for users to use the platform more and produce even more click responses for the long run. There are some studies experimenting a model to address the impact of ads quality for predicting user response and user engagement, based on in-app advertising such as Yahoo Gemini platform [9, 67]. To this end, a post-click experience instead of click-through rate value is used to evaluate the user experience on the landing page of advertising web-sites. Post-click experience is attributed by metrics like dwell time and the bounce rate. The former measures the spending time in the landing page where the latter indicates the percentage of short and momentary dwell times. The level of user engagement with ads is considered to have a natural connection to the time length users spend in landing websites.

Aside from ad quality metric, in the context of social media, CTR prediction for stream data in Twitter is first studied [70], where positive use responses are defined as retweet, reply, and actual click on promoted tweets. They also use a dismiss feature in Twitter to identify explicit negative instances for the analysis. According to the fact that the number of spots dedicated for promoted tweets are limited, in this study a learning-to-rank method with a calibration mechanism is proposed to combine traditional classification with pairwise learning to address data sparsity and scalability issues. They formalize two problems of classification and ranking in the framework.

Table 6. Comparing User Response Prediction Methods in Terms of Feature Characteristics, Application Domains, and Downstream Tasks

Feature Types /Organization		Application Domain			Prediction Task (Publications)
		E-commerce	Display Advertising	Recomm. Systems	
Feature Engineering			✓		(1) CVR ([68, 86, 145]); (2) CTR ([17, 27, 48, 65, 121, 180, 193]); (3) Ranking ([25]
Feature Learning	Collaborative Filtering Based	✓	✓	✓	(1) CTR ([82, 95]); (2) Ranking ([82]); (3) Product Rating ([161])
	Multi-field (categorical)			✓	(1) CTR ([22, 53]), (2) Ranking ([51])
	Textual		✓	✓	(1) CTR ([6, 33], Deep(Char) Word-Match [32], DSM [41]); (2) Ranking ([41])
	Visual	✓			(1) CTR (DICM [38], [19]), (2) Ranking (ACF [20], PinSage [169])
	Sequential	✓	✓	✓	(1) CTR(DSIN [36], DIEN [189], DIN [190], RNN [181], MIMN [110]), (2) CVR(GMP [15], DTAIN [40]), (3) Ranking(FGNN [115], GAG [126], LGSR [170])
	Network based	✓	✓		(1) CTR(FiGNN [74], GIN [71],[150], KNI [116]); (2) Ranking(KGNN-LS [148])
	Hybrid	✓		✓	(1) CTR ([5], RippleNet [146], MKR [149], DKN [147]), (2) Ranking(RippleNet [146], MKR [149])

Table 7. Summary of Selected Practical Solution Applied in Industrial Environments

Algorithm	Challenge	Introduced Strategy	Application Domain	Provider
AdPredictor [42]	Scalability	Bayesian probit regression model, Weight pruning, Parallel training	Sponsored search ads	Microsoft Bing
EtsyCTR [5]	Dealing with image data	Transfer learning, Feature Hashing, Ensemble model	E-commerce	Etsy
FBCTR [48]	Massive data	Uniform sub-sampling, Cascade of classifiers, Ensemble model	Display ads	Facebook
DLRM [96]	Memory constraints in embeddings and computational costs of DL components	Using PyTorch and Caffe2 for model and data parallelism	Recomm. Sys	Facebook
DeepFM [45] PIN [118]	Insensitive gradient issue in DNN-based models and space complexity of FFM-based models	Shared embedding vectors, an end-to-end prediction model [45], Net-in-Net architecture to combine FM and DNN units [118]	Recomm. Sys	Huawei

(Continued)

Table 7. Continued

Algorithm	Challenge	Introduced Strategy	Application Domain	Provider
DIN [190] DIEN [189]	Large number of DNN parameters, Addressing temporal drifts in user interests representation	Mini-batch aware regularization and local adaptive activation function [190], Attention-based user interest extractor layer [189]	Display ads	Alibaba
MIMN [110]	Handling long user behavior sequences	Multi-channel memory network	Display ads	Alibaba
HPMN [120] UBR4CTR [114] SIM [113]	Tackling long sequential user behaviours	Memory network model along with a GRU network [120]. Self-attentive retrieval module to select relevant user behaviors [114]. Cascaded two-stage search model [113].	E-commerce	Alibaba
EGES [150]	Scalability	Graph Embedding Using XTensorflow	Recomm. Sys	Taobao
DICM [38]	Dealing with images to represent user behaviours	A distributed model server to handle image data embedding and reduce the communication latency	Display ads	Taobao
RAM [185]	Balance immediate advertising revenue and long-run user experience	Joint optimization using two-level reinforcement learning	Recomm. Sys	ByteDance
HPS-4 [184]	Massive model with large number of parameters	A distributed hierarchical GPU parameter server	Display ads	Baidu
PinSage [169]	Massive input graph with billions of links	Highly scalable graph convolutional network	Recomm. Sys	Pinterest
DCN_V2 [155]	Controlling the number of model parameters to learn feature interactions for real-time data	Mixture of low-rank approximation of DCN method [154] organized in stacked and parallel structures	Recomm. Sys	Google

In an alternative work [29], time-sensitivity of streaming data in Twitter and the short memory issue for online learning are studied to exclude obsolete tweets from being considered. Therefore, authors propose to analyze hashtags[3] in social media as the indicators of user interests to provide a personalized ranking of topics. They present an online collaborative filtering method following pairwise ranking approach for matrix factorization (Stream Ranking Matrix Factorization), and propose a pairwise learning to optimize an ordinal loss and a selective negative sampling based on a selective active learning, using three objective losses, including hinge loss, SVM, and RankSVM for training.

[3]Hashtags are prefixed expressions using the symbol of # to be used for marking a specific topic in Twitter.

Recently, the authors of Reference [64] have centered their work on delayed positive feedback at stream media to study the effect of two factors, such as the trend and seasonality, in online advertising. In live streams, the predicting models are dealt with the cold start issue. This is because in online real-time scenarios, fresh data lack enough label information and the few appearance of the positive response of users, which leads to the underestimation of CTR values. They conduct experiments to estimate CTR values for video ads in Twitter platform, and examine predicting models with logistic regression and Wide& Deep [22] models using five loss function designed for delayed positive samples to identify the combination of learners and loss functions for continuous stream data.

4.6 Summary

To summarize different framework covered in the above sections, Table 5 outlines main learning strategies used by different methods. In Table 6, we also outline studied methods from a different aspects, including feature engineering, downstream tasks used for the evaluation of models, and domain applications. Recent years have witnessed a significant growth in networking technologies and a larger number of online users across the world. As a result, scalability is a major challenge for recommender and online advertising. In Table 7 we overview different efforts made to provide technical solutions for user response prediction in real-world applications. Comparing with academic scale solutions, models deployed for production system need massive resources to store and execute internal processes. To address these requirements, industry attempts to devise paralleled model and data architectures that data can be processed with high throughput and remarkably low latency. Recently some work [90, 96] focus on developing benchmark framework suites to provide adequate flexibility along with good test results to make fair comparisons between academic and industrial models. In Appendix D.4, we also outline some potential directions for future studies.

5 CONCLUSION

This survey provides a comprehensive overview of computational methods for user response prediction in online advertising. Our goal is to provide a detailed review and categorization of the online advertising ecosystem, stakeholders, data sources, and technical solutions. To achieve the goal, we review and categorize online advertising platforms, type of user responses, data sources and features, and propose a taxonomy to characterize main stream approaches for user response prediction. For each type of user response prediction methods, we also briefly study technical details of representative methods, with a focus on machine learning-based, especially deep learning-based, approaches. In addition to the algorithms, we also review user response prediction applications, benchmark data, and open source codes. The survey delivers a first-hand guideline for industry and academia to comprehend the state of the art. It also serves as a technical reference for practitioners and developers to design their own computational approaches for user response prediction.

REFERENCES

[1] Deepak Agarwal, Rahul Agrawal, Rajiv Khanna, and Nagaraj Kota. 2010. Estimating rates of rare events with multiple hierarchies through scalable log-linear models. In *KDD*. 213–222.

[2] Deepak Agarwal, Andrei Zary Broder, Deepayan Chakrabarti, Dejan Diklic, Vanja Josifovski, and Mayssam Sayyadian. 2007. Estimating rates of rare events at multiple resolutions. In *KDD*. 16–25.

[3] Qingquan Song, Dehua Cheng, Hanning Zhou, Jiyan Yang, Yuandong Tian, and Xia Hu. 2020. Towards automated neural interaction discovery for click-through rate prediction. In *Proceedings of the KDD*. ACM, 945–955.

[4] Ethem Alpaydin. 2010. *Introduction to Machine Learning* (2nd ed.). The MIT Press.

[5] Kamelia Aryafar, Devin Guillory, and Liangjie Hong. 2017. An ensemble-based approach to click-through rate prediction for promoted listings at Etsy. In *Proceedings of the ADKDD*. ACM, 6 pages. DOI: 10.1145/3124749.3124758

[6] Afroze Ibrahim Baqapuri and Ilya Trofimov. 2014. Using neural networks for click prediction of sponsored search. *CoRR* abs/1412.6601 (2014).
[7] D. Barbará, Y. Li, and J. Couto. 2002. COOLCAT: An entropy-based algorithm for categorical clustering. In *CIKM*. 582–589.
[8] Eduardo Barbaro, Eoin Martino Grua, Ivano Malavolta, Mirjana Stercevic, Esther Weusthof, and Jeroen van den Hoven. 2020. Modelling and predicting User Engagement in mobile applications. *J. Data Sci.* 3, 2 (2020), 61–77. DOI: 10.3233/DS-190027
[9] Nicola Barbieri, Fabrizio Silvestri, and Mounia Lalmas. 2016. Improving post-click user engagement on native ads via survival analysis. In *WWW*. 761–770.
[10] Shawn D Baron, Caryn Brouwer, and Amaya Garbayo. 2014. A model for delivering branding value through high-impact digital advertising. *J. Advert. Res.* 54, 3 (2014), 286–291. DOI: 10.2501/jar-54-3-286-291
[11] Sonja Bidmon and Johanna Röttl. 2018. *Advertising Effects of In-Game-Advertising vs. In-App-Advertising*. Springer, 73–86.
[12] L. Bigon, G. Cassani, C. Greco, L. Lacasa, M. Pavoni, A. Polonioli, and J. Tagliabue. 2019. Prediction is very hard, especially about conversion. Predicting user purchases from clickstream data in fashion e-commerce. *CoRR* abs/1907.00400 (2019).
[13] M. Blondel, A. Fujino, N. Ueda, and M. Ishihata. 2016. Higher-order factorization machines. In *NIPS*. 3359–3367.
[14] Patrick P. K. Chan, Xian Hu, Lili Zhao, Daniel S. Yeung, Dapeng Liu, and Lei Xiao. 2018. Convolutional neural networks based click-through rate prediction with multiple feature sequences. In *IJCAI*. 2007–2013.
[15] Xuchao Zhang Chuxu Zhang Jiashu Zhao Dawei Yin Chao Huang, Xian Wu and Nitesh Chawla. 2019. Online purchase prediction via multi-scale modeling of behavior dynamics. In *KDD*, 2613–2622.
[16] Olivier Chapelle. 2014. Modeling delayed feedback in display advertising. In *KDD*. 1097–1105.
[17] Olivier Chapelle, Eren Manavoglu, and Rómer Rosales. 2014. Simple and scalable response prediction for display advertising. *ACM Trans. Intell. Syst. Technol.* 5, 4, Article 61 (2014), 61:1–61:34. DOI: 10.1145/2532128
[18] Gong Chen, Jacob H. Cox, A. Selcuk Uluagac, and John A. Copeland. 2016. In-depth survey of digital advertising technologies. *IEEE Commu. Surv. Tutor.* 18 (2016), 2124–2148.
[19] Junxuan Chen, Baigui Sun, Hao Li, Hongtao Lu, and Xian-Sheng Hua. 2016. Deep CTR prediction in display advertising. In *Proceedings of the MM*. ACM, 811–820. DOI: 10.1145/2964284.2964325
[20] Jingyuan Chen, Hanwang Zhang, Xiangnan He, Liqiang Nie, Wei Liu, and Tat-Seng Chua. 2017. Attentive collaborative filtering: Multimedia recommendation with item- and component-level attention. In *SIGIR*. 335–344.
[21] Wenqiang Chen, Lizhang Zhan, Yuanlong Ci, Minghua Yang, Chen Lin, and Dugang Liu. 2019. FLEN: Leveraging field for scalable CTR prediction. *CoRR* abs/1911.04690 (2019).
[22] H. Cheng, L. Koc, J. Harmsen, and et al. 2016. Wide & deep learning for recommender systems. In *DLRS*. 7–10.
[23] Hana Choi, Carl F. Mela, Santiago R. Balseiro, and Adam Leary. 2019. Online display advertising markets: A literature review and future directions. *J. Inf. Syst. Res.* 31 (2019), 556–575.
[24] Shu-Chuan Chu. 2011. Viral advertising in social media: Participation in Facebook groups and responses among college-aged users. *J. Interact. Advert.* 12 (2011), 30–43.
[25] P. Covington, J. Adams, and E. Sargin. 2016. Deep neural networks for YouTube recommendations. In *RecSys*. 191–198.
[26] Brian Dalessandro, Daizhuo Chen, Troy Raeder, Claudia Perlich, Melinda Han Williams, and Foster Provost. 2014. Scalable hands-free transfer learning for online advertising. In *KDD*. 1573–1582.
[27] Brian Dalessandro, Rod Hook, Claudia Perlich, and Foster Provost. 2015. Evaluating and optimizing online advertising: Forget the click, but there are good proxies. *J. Big Data* 3 (2015), 90–102.
[28] Y. Deng, Y. Shen, and H. Jin. 2017. Disguise adversarial networks for click-through rate prediction. In *IJCAI*. 1589–1595.
[29] Ernesto Diaz-Aviles, Lucas Drumond, Lars Schmidt-Thieme, and Wolfgang Nejdl. 2012. Real-time top-n recommendation in social streams. In *RecSys*. 59–66.
[30] Daniel M. Dunlavy, Tamara G. Kolda, and Evrim Acar. 2011. Temporal link prediction using matrix and tensor factorizations. *ACM Trans. Knowl. Discov. Data* 5 (2011), 10:1–10:27.
[31] N. Ebadi, B. Lwowski, M. Jaloli, and P. Rad. 2019. Implicit life event discovery from call transcripts using temporal input transformation network. *IEEE Access* 7 (2019), 172178–172189.
[32] Bora Edizel, Amin Mantrach, and Xiao Bai. 2017. Deep character-level click-through rate prediction for sponsored search. In *Proceedings of the SIGIR*. ACM, 305–314. DOI: 10.1145/3077136.3080811
[33] Muhammad Junaid Effendi and Syed Abbas Ali. 2017. Click through rate prediction for contextual advertisment using linear regression. *CoRR* abs/1701.08744 (2017).
[34] F. Maurizio, C. Paolo, and J. Dietmar. 2020. Methodological issues in recommender systems research. In *IJCAI*. 4706–4710.

[35] Shaohua Fan, Junxiong Zhu, Xiaotian Han, Chuan Shi, Linmei Hu, Biyu Ma, and Yongliang Li. 2019. Metapath-guided heterogeneous graph neural network for intent recommendation. *ACM Trans. Knowl. Discov. Data* (2019), 2478–2486.
[36] Yufei Feng, Fuyu Lv, Weichen Shen, Menghan Wang, Fei Sun, Yu Zhu, and Keping Yang. 2019. Deep session interest network for click-through rate prediction. In *IJCAI*. 2301–2307.
[37] Hongchang Gao, Deguang Kong, Miao Lu, Xiao Bai, and Jian Yang. 2018. Attention convolutional neural network for advertiser-level click-through rate forecasting. In *WWW*. 1855–1864.
[38] T. Ge, L. Zhao, G. Zhou, and et al. 2018. Image matters: Visually modeling user behaviors using advanced model server. In *CIKM*, 2087–2095.
[39] Zhabiz Gharibshah, Xingquan Zhu, Arthur Hainline, and M. Conway. 2020. Deep learning for user interest and response prediction in online display advertising. *Data Sci. Eng.* 5 (2020), 12–26.
[40] Djordje Gligorijevic, Jelena Gligorijevic, and A. Flores. 2019. Time-aware prospective modeling of users for online display advertising. *CoRR* abs/1911.05100 (2019).
[41] Jelena Gligorijevic, Djordje Gligorijevic, Ivan Stojkovic, Xiao Bai, Amit Goyal, and Zoran Obradovic. 2018. Deeply supervised semantic model for click-through rate prediction in sponsored search. *CoRR* abs/1803.10739 (2018).
[42] Thore Graepel, Joaquin Quiñonero Candela, Thomas Borchert, and Ralf Herbrich. 2010. Web-scale bayesian click-through rate prediction for sponsored search advertising in Microsoft's bing search engine. In *ICML*. 13–20.
[43] Cheng Guo and Felix Berkhahn. 2016. Entity embeddings of categorical variables. *CoRR* abs/1604.06737 (2016).
[44] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. 2017. DeepFM: A factorization-machine based neural network for CTR prediction. In *IJCAI*. 1725–1731.
[45] H. Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, X. He, and Zhenhua Dong. 2018. DeepFM: An end-to-end wide & deep learning framework for CTR prediction. *CoRR* abs/1804.04950 (2018).
[46] Rajan T. Gupta and Saibal K. Pal. 2019. Click-through rate estimation using CHAID classification tree model. In *Advances in Analytics and Applications*. 45–58.
[47] H. Dustin, S. Stefan, M. Eren, R. Hema, and L. Chirs. 2010. Improving ad relevance in sponsored search. In *WSDM*. 361–370.
[48] Xinran He, Stuart Bowers, Joaquin Quiñonero Candela, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Atallah, and Ralf Herbrich. 2014. Practical lessons from predicting clicks on ads at Facebook. In *ADKDD*. 1–9.
[49] Xiangnan He and Tat-Seng Chua. 2017. Neural factorization machines for sparse predictive analytics. In *SIGIR*. 355–364.
[50] X. He, K. Deng, X. Wang, Y. Li, Yongdong Zhang, and Meng Wang. 2020. LightGCN: Simplifying and powering graph convolution network for recommendation. In *SIGIR*, 639–648.
[51] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T. Chua. 2017. Neural collaborative filtering. In *WWW*. 173–182.
[52] Y. Hu, Y. Koren, and C. Volinsky. 2008. Collaborative filtering for implicit feedback datasets. In *ICDM*, 263–272.
[53] Tongwen Huang, Zhiqi Zhang, and Junlin Zhang. 2019. FiBiNET: Combining feature importance and bilinear feature interaction for click-through rate prediction. In *RecSys*. 169–177.
[54] Dietmar Jannach, Gabriel de Souza P. Moreira, and Even Oldridge. 2020. Why are deep learning models not consistently winning recommender systems competitions yet? A position paper. In *RecSys*. 44–49.
[55] Zilong Jiang, Shu Gao, and Wei Dai. 2016. Research on CTR prediction for contextual advertising based on deep architecture model. *Contr. Eng. Appl. Inf.* 18 (Mar. 2016), 11–19.
[56] Zilong Jiang, S. X. Gao, and Mingjiang Li. 2018. An improved advertising CTR prediction approach based on the fuzzy deep neural network. *PLoS ONE*.
[57] Yuchin Juan, Damien Lefortier, and Olivier Chapelle. 2017. Field-aware factorization machines in a real-world online advertising system. In *Proceedings of the WWW*. International World Wide Web Conferences Steering Committee, 680–688.
[58] Shubhra Karmaker, Parikshit Sondhi, and ChengXiang Zhai. 2017. On application of learning to rank for E-commerce search. In *SIGIR*.
[59] K-M Kim, D. Kwak, H. Kwak, Y-J Park, S. Sim, J-H Cho, M. Kim, J. Kwon, Nako Sung, and J-W Ha. 2019. Tripartite heterogeneous graph propagation for large-scale social recommendation. In *RecSys*. 56–60.
[60] Michael A. King, Alan S. Abrahams, and Cliff T. Ragsdale. 2015. Ensemble learning methods for pay-per-click campaign management. *Expert Syst. Appl.* 42 (2015), 4818–4829.
[61] Y. Koren. 2008. Factorization meets the neighborhood: A multifaceted collaborative filtering model. In *KDD*. 426–434.
[62] N. Kota and D. Agarwal. 2011. Temporal multi-hierarchy smoothing for estimating rates of rare events. In *KDD*. 1361–1369.
[63] S. Krishnan and R. Sitaraman. 2013. Understanding the effectiveness of video ads: A measurement study. In *IMC*. 149–162.

[64] S. Ktena, A. Tejani, L. Theis, P. Myana, D. Dilipkumar, F. Huszar, S. Yoo, and W. Shi. 2019. Addressing delayed feedback for continuous training with neural networks in CTR prediction. In *Proceedings of the RecSys*. ACM, 187–195.
[65] Ashish Kumar and Jari Salo. 2016. Effects of link placements in email newsletters on their click-through rate. *J. Market. Commun.* 24, 5 (Mar. 2016), 535–548.
[66] Rohan Kumar, Mohit Kumar, Neil Shah, and Christos Faloutsos. 2018. Did we get it right? Predicting query performance in e-commerce search. *CoRR* abs/1808.00239 (2018).
[67] Mounia Lalmas, Janette Lehmann, Guy Shaked, Fabrizio Silvestri, and Gabriele Tolomei. 2015. Promoting positive post-click experience for in-stream Yahoo Gemini users. In *KDD*. 1929–1938.
[68] Kuang-chih Lee, Burkay Orten, Ali Dasdan, and Wentong Li. 2012. Estimating conversion rate in display advertising from past erformance data. In *KDD*. 768–776.
[69] S. Leong, M. Mahdian, and S. Vassilvitskii. 2014. Advertising in a stream. In *WWW*.
[70] Cheng Li, Yue Lu, Qiaozhu Mei, Dong Wang, and Sandeep Pandey. 2015. Click-through prediction for advertising in Twitter timeline. In *KDD*. 1959–1968.
[71] Feng Li, Zhenrui Chen, Pengjie Wang, Yi Ren, Di Zhang, and Xiaoyu Zhu. 2019. Graph intention network for click-through rate prediction in sponsored search. In *SIGIR*, 961–964.
[72] Xiang Li, Chao Wang, Jiwei Tan, Xiaoyi Zeng, Dan Ou, and Bo Zheng. 2020. Adversarial multimodal representation learning for click-through rate prediction. In *Proceedings of the Web Conference*. ACM, 827–836. DOI: 10.1145/3366423.3380163
[73] Zeyu Li, Wei Cheng, Yang Chen, Haifeng Chen, and Wei Wang. 2020. Interpretable click-through rate prediction through hierarchical attention. In *WSDM*, 313–321.
[74] Zekun Li, Zeyu Cui, Shu Wu, Xiaoyu Zhang, and Liang Wang. 2019. Fi-GNN: Modeling feature interactions via graph neural networks for CTR prediction. In *CIKM*. 539–548.
[75] J. Lian, X. Zhou, F. Zhang, Z. Chen, X. Xie, and G. Sun. 2018. xDeepFM: Combining explicit and implicit feature interactions for recommender systems. In *KDD* (2018).
[76] X. Lin, H. Chen, C. Pei, F. Sun, X. Xiao, H. Sun, Y. Zhang, W. Ou, and P. Jiang. 2019. A pareto-efficient algorithm for multiple objective optimization in e-commerce recommendation. In *RecSys*. 20–28.
[77] X. Ling, W. Deng, C. Gu, and et al. 2017. Model ensemble for click prediction in bing search ads. In *WWW*. 689–698.
[78] Bin Liu, Ruiming Tang, Yingzhi Chen, Jinkai Yu, Huifeng Guo, and Yuzhou Zhang. 2019. Feature generation by convolutional neural network for click-through rate prediction. In *WWW*. 1119–1129.
[79] Bin Liu, Niannan Xue, Huifeng Guo, Ruiming Tang, Stefanos Zafeiriou, Xiuqiang He, and Zhenguo Li. 2020. AutoGroup: Automatic feature grouping for modelling explicit high-order feature interactions in CTR prediction.
[80] Bin Liu, Chenxu Zhu, Guilin Li, Weinan Zhang, Jincai Lai, Ruiming Tang, X. He, Z. Li, and Y. Yu. 2020. AutoFIS: Automatic feature interaction selection in factorization models for click-through rate prediction. In *KDD*. 2636–2645.
[81] Hui Liu, Xingquan Zhu, Kristopher Kalish, and Jeremy Kayne. 2017. ULTR-CTR: Fast page grouping using URL truncation for real-time click through rate estimation. In *IEEE IRI*.
[82] Qiang Liu, Shu Wu, and Liang Wang. 2015. Collaborative prediction for multi-entity interaction with hierarchical representation. In *CIKM*. 613–622.
[83] Qiang Liu, Feng Yu, Shu Wu, and Liang Wang. 2015. A convolutional click prediction model. In *CIKM*. 1743–1746.
[84] Xun Liu, Wei Xue, Lei Xiao, and Bo Zhang. 2017. PBODL: Parallel Bayesian online deep learning for click-through rate prediction in tencent advertising system. *CoRR* abs/1707.00802 (2017).
[85] Yozen Liu, Xiaolin Shi, Lucas Pierce, and Xiang Ren. 2019. Characterizing and forecasting user engagement with in-app action graph: A case study of Snapchat. In *KDD*, 2023–2031.
[86] Zhe Liu, Xianzhi Wang, Lina Yao, Jake An, Lei Bai, and Ee-Peng Lim. 2020. Face to purchase: Predicting consumer choices with structured facial and behavioral traits embedding. *CoRR* abs/2007.06842 (2020).
[87] Amit Livne, Roy Dor, Eyal Mazuz, Tamar Didi, Bracha Shapira, and Lior Rokach. 2020. Iterative boosting deep neural networks for predicting click-through rate. *CoRR* abs/2007.13087 (2020).
[88] Xiao Ma, Liqin Zhao, Guan Huang, Zhi Wang, Zelin Hu, Xiaoqiang Zhu, and Kun Gai. 2018. Entire space multi-task model: An effective approach for estimating post-click conversion rate. In *SIGIR*. 1137–1140.
[89] Miriam Marciel, Rubén Cuevas, Albert Banchs, Roberto González, Stefano Traverso, Mohamed Ahmed, and Arturo Azcorra. 2016. Understanding the detection of view fraud in video content portals. In *WWW*. 357–368.
[90] P. Mattson, C. Cheng, C. Coleman, G. Diamos, and et al. 2019. MLPerf training benchmark. *CoRR* abs/1910.01500.
[91] Stephen McCreery and Dean M. Krugman. 2017. Tablets and TV advertising: Understanding the viewing experience. *J. Curr. Issues Res. Advert.* 38, 2 (Mar. 2017), 197–211.
[92] B. McMahan, G. Holt, D. Sculley, and et al. 2013. Ad click prediction: A view from the trenches. In *KDD*. 1222–1230.
[93] Tao Mei, Xian-Sheng Hua, Linjun Yang, and Shipeng Li. 2007. VideoSense: Towards effective online video advertising. In *MM*. 1075–1084.

[94] Wei Meng, Xinyu Xing, Anmol Sheth, Udi Weinsberg, and Wenke Lee. 2014. Your online interests: Pwned! A pollution attack against targeted advertising. In *CCS*. 129–140.
[95] Aditya Krishna Menon, Krishna-Prasad Chitrapura, Sachin Garg, Deepak Agarwal, and Nagaraj Kota. 2011. Response prediction using collaborative filtering with hierarchies and side-information. In *KDD*. 141–149.
[96] M. Naumov, D. Mudigere, H. Michael Shi, and et. al. 2019. Deep learning recommendation model for personalization and recommendation systems. *CoRR* abs/1906.00091 (2019).
[97] Chenglei Niu, Guojing Zhong, Y. Liu, Yandong Zhang, Y. Sun, Ailong He, and Zhaoji Chen. 2018. Unstructured semantic model supported deep neural network for click-through rate prediction. *CoRR* abs/1812.01353 (2018).
[98] R. Oentaryo, E. Lim, M. Finegold, and et al. 2014. Detecting click fraud in online advertising: A data mining approach. *J. Mach. Learn. Res.* 15 (2014), 99–140.
[99] R. Oentaryo, E. Lim, J. Low, D. Lo, and M. Finegold. 2014. Predicting response in mobile advertising with hierarchical importance-aware factorization machine. In *WSDM*. 123–132.
[100] Wentao Ouyang, Xiuwu Zhang, Li Li, Heng Zou, Xin Xing, Zhaojie Liu, and Yanlong Du. 2019. Deep spatio-temporal neural networks for click-through rate prediction. In *KDD* (2019), 2078–2086.
[101] Wentao Ouyang, Xiuwu Zhang, Shukui Ren, Li Li, Zhaojie Liu, and Yanlong Du. 2019. Click-through rate prediction with the user memory network. In *Proceedings of the DLP-KDD*. ACM, 4 pages. DOI: 10.1145/3326937.3341258
[102] Wentao Ouyang, Xiuwu Zhang, Shukui Ren, Chao Qi, Zhaojie Liu, and Yanlong Du. 2019. Representation learning-assisted click-through rate prediction. In *IJCAI*.
[103] Feiyang Pan, Shuokai Li, Xiang Ao, Pingzhong Tang, and Qing He. 2019. Warm up cold-start advertisements: Improving CTR predictions via learning to learn ID embeddings. In *SIGIR*, 695–704.
[104] Junwei Pan, Yizhi Mao, Alfonso Lobos Ruiz, Yu Sun, and Aaron Flores. 2019. Predicting different types of conversions with multi-task learning in online advertising. In *KDD'19* (2019), 2689–2697.
[105] Jing Pan, Weian Sheng, and Santanu Dey. 2019. Order matters at fanatics recommending sequentially ordered products by LSTM embedded with Word2Vec. *CoRR* abs/1911.09818 (2019).
[106] Junwei Pan, Jian Xu, Alfonso Lobos Ruiz, Wenliang Zhao, Shengjun Pan, Yu Sun, and Quan Lu. 2018. Field-weighted factorization machines for click-through rate prediction in display advertising. In *WWW*. 1349–1357.
[107] Zhen Pan, Enhong Chen, Qi Liu, Tong Xu, Haiping Ma, and Hongjie Lin. 2016. Sparse factorization machines for click-through rate prediction. In *Proceedings of the IEEE 16th Intl. Conf. on Data Mining (ICDM'16)*. 400–409.
[108] Changhua Pei, Xinru Yang, Qing Cui, Xiao Lin, Fei Sun, Peng Jiang, Wenwu Ou, and Yongfeng Zhang. 2019. Value-aware recommendation based on reinforcement profit maximization. In *WWW*. 3123–3129.
[109] Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. 2014. DeepWalk: Online learning of social representations. In *Proceedings of the KDD*. ACM, 701–710. DOI: 10.1145/2623330.2623732
[110] Qi Pi, Weijie Bian, Guorui Zhou, Xiaoqiang Zhu, and Kun Gai. 2019. Practice on long sequential user behavior modeling for click-through rate prediction. In *ACM SIGKDD*.
[111] M. Safaei Pour, A. Mangino, K. Friday, Matthias Rathbun, E. Bou-Harb, F. Iqbal, Kh. Shaban, and A. Erradi. 2019. Data-driven curation, learning and analysis for inferring evolving IoT botnets in the wild. In *ARES*. Article 6.
[112] S. Punjabi and P. Bhatt. 2018. Robust factorization machines for user response prediction. In *WWW*. 669–678.
[113] P. Qi, X. Zhu, G. Zhou, Y. Zhang, Z. Wang, L. Ren, Y. Fan, and K. Gai. 2020. Search-based user interest modeling with lifelong sequential behavior data for click-through rate prediction. In *Proceedings of the CIKM*. ACM, 2685–2692.
[114] Jiarui Qin, Weinan Zhang, Xin Wu, Jiarui Jin, Yuchen Fang, and Yong Yu. 2020. User behavior retrieval for click-through rate prediction. In *Proceedings of the SIGIR*. ACM, 2347–2356.
[115] Ruihong Qiu, Zi Huang, Jingjing Li, and Hongzhi Yin. 2020. Exploiting cross-session information for session-based recommendation with graph neural networks. *ACM Transactions on Information Systems* 38 (2020).
[116] Yanru Qu, Ting Bai, Weinan Zhang, Jianyun Nie, and Jian Tang. 2019. An end-to-end neighborhood-based interaction model for knowledge-enhanced recommendation. In *Proceedings of the DLP-KDD*. ACM, 9 pages. DOI: 10.1145/3326937.3341257
[117] Yanru Qu, Han Cai, Kan Ren, Weinan Zhang, Yong Yu, Ying Wen, and Jun Wang. 2016. Product-based neural networks for user response prediction. In *ICDM*, 1149–1154.
[118] Yanru Qu, Bohui Fang, Wei-Nan Zhang, Ruiming Tang, Minzhe Niu, Huifeng Guo, yong Yu, and Xiuqiang He. 2018. Product-based neural networks for user response prediction over multi-field categorical data. *ACM Transactions on Information Systems* (2018).
[119] Regelson, Moira, Fain, and Daniel C. 2006. Predicting click-through rate using keyword clusters.
[120] K. Ren, J. Qin, Y. Fang, W. Zhang, L. Zheng, W. Bian, G. Zhou, J. Xu, Y. Yu, X. Zhu, and K. Gai. 2019. Lifelong sequential modeling with personalized memorization for user response prediction. In *SIGIR'19*.
[121] Kan Ren, Weinan Zhang, Yifei Rong, Haifeng Zhang, Yong Yu, and Jun Wang. 2016. User response learning for directly optimizing campaign performance in display advertising. In *CIKM*. 679–688.
[122] Steffen Rendle. 2010. Factorization machines. In *ICDM*, 995–1000.

[123] S. Rendle, L. Zhang, and Y. Koren. 2019. On the difficulty of evaluating baselines: A study on recommender systems. *CoRR* abs/1905.01395 (2019).
[124] Jenna Reps, Uwe Aickelin, Jonathan Garibaldi, and Chris Damski. 2014. Personalising mobile advertising based on users' installed apps. In *ICDM Workshop*, 338–345.
[125] Matthew Richardson, Ewa Dominowska, and Robert Ragno. 2007. Predicting clicks: Estimating the click-through rate for new ads. In *WWW*. 521–530.
[126] Qiu Ruihong, Yin Hongzhi, Huang Zi, and Tong Chen. 2020. GAG: Global attributed graph neural network for streaming session-based recommendation. In *Proceedings of the SIGIR*. ACM, 669–678. DOI: 10.1145/3397271.3401109
[127] Oliver Rutz, Ashwin Aravindakshan, and Olivier Rubel. 2019. Measuring and forecasting mobile game app engagement. *Int. J. Res. Market.* 36, 2 (Jun. 2019), 185–199.
[128] Oliver J. Rutz and Randolph E. Bucklin. 2011. From generic to branded: A model of spillover in paid search advertising. *J. Market. Res.* (2011), 87–102.
[129] Rubén Saborido, Foutse Khomh, Giuliano Antoniol, and Yann-Gaël Guéhéneuc. 2017. Comprehension of ads-supported and paid android applications: Are they different? In *ICPC*, 143–153.
[130] Ying Shan, T. Ryan Hoens, Jian Jiao, Haijing Wang, Dong Yu, and J. C. Mao. 2016. Deep crossing: Web-scale modeling without manually crafted combinatorial features. In *KDD*. 255–262.
[131] Neha Sharma and Nirmal Gaud. 2015. K-modes clustering algorithm for categorical data. *Int. J. Comput. Appl.* 127 (2015), 1–6.
[132] Weichen Shen. 2018. Easy-to-use, Modular and Extendible Package of Deep-learning Based CTR Models. Retrieved from https://github.com/shenweichen/DeepCTR.
[133] Weichen Shen. 2019. (PyTorch) Easy-to-use, Modular and Extendible Package of Deep-learning Based CTR Models. Retrieved from https://github.com/shenweichen/DeepCTR-Torch.
[134] Shu-Ting Shi, Wenhao Zheng, Jun Tang, Qing-Guo Chen, Yao Hu, Jianke Zhu, and Ming Li. 2020. Deep time-stream framework for click-through rate prediction by tracking interest evolution. *AAAI* 34, 4 (2020), 5726–5733. DOI: 10.1609/aaai.v34i04.6028
[135] Enno Shioji and Masayuki Arai. 2017. Neural feature embedding for user response prediction in real-time bidding (RTB). *CoRR* abs/1702.00855 (2017).
[136] Qingquan Song, Dehua Cheng, Hanning Zhou, Jiyan Yang, Yuandong Tian, and Xia Hu. 2020. Towards automated neural interaction discovery for click-through rate prediction. In *Proceedings of the KDD*. ACM, 945–955.
[137] Weiping Song, Chence Shi, Zhiping Xiao, Zhijian Duan, Yewen Xu, Ming Zhang, and Jian Tang. 2019. AutoInt: Automatic feature interaction learning via self-attentive neural networks. In *Proceedings of the CIKM*. ACM, 1161–1170. DOI: 10.1145/3357384.3357925
[138] Yuhan Su, Zhongming Jin, Ying Chen, Xinghai Sun, Yaming Yang, Fangzheng Qiao, Fen Xia, and Wei Xu. 2017. Improving click-through rate prediction accuracy in online advertising by transfer learning. In *WI*. 1018–1025.
[139] Anh-Phuong Ta. 2015. Factorization machines with follow-the-regularized-leader for CTR prediction in display advertising. In *IEEE Big Data* (2015), 2889–2891.
[140] G. S. Thejas, Kianoosh G. Boroojeni, Kshitij Chandna, Isha Bhatia, S. S. Iyengar, and N. R. Sunitha. 2019. Deep Learning-based Model to Fight Against Ad Click Fraud. In *ACM SE*. 176–181.
[141] T. Tian, J. Zhu, F. Xia, X. Zhuang, and T. Zhang. 2015. Crowd fraud detection in internet advertising. In *WWW*. 1100–1110.
[142] Gabriele Tolomei, Mounia Lalmas, Ayman Farahat, and Andrew Haines. 2018. You must have clicked on this ad by mistake! Data-driven identification of accidental clicks on mobile ads with applications to advertiser cost discounting and click-through rate prediction. *Data Sci. Analyt.* 7 (2018), 53–66.
[143] Sergio Duarte Torres, Ingmar Weber, and Djoerd Hiemstra. 2014. Analysis of search and browsing behavior of young users on the web. *ACM Trans. Web* 8 (2014), 7:1–7:54.
[144] Vinh Truong, Mathews Nkhoma, and Wanni Pansuwong. 2019. An integrated effectiveness framework of mobile in-app advertising. *Australas. J. Inf. Syst.* 23 (2019).
[145] Flavian Vasile, Damien Lefortier, and Olivier Chapelle. 2017. Cost-sensitive learning for utility optimization in online advertising auctions. In *Proceedings of the ADKDD*. 1–6. DOI: 10.1145/3124749.3124751
[146] Hongwei Wang, Fuzheng Zhang, Jialin Wang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. 2018. RippleNet: Propagating user preferences on the knowledge graph for recommender systems. In *CIKM'18*, 417–426.
[147] Hongwei Wang, Fuzheng Zhang, Xing Xie, and Minyi Guo. 2018. DKN: Deep knowledge-aware network for news recommendation. In *Proceedings of the WWW*. International World Wide Web Conferences Steering Committee, 1835–1844.
[148] H. Wang, F. Zhang, M. Zhang, J. Leskovec, M. Zhao, W. Li, and Z. Wang. 2019. Knowledge-aware graph neural networks with label smoothness regularization for recommender systems. In *KDD* (2019), 968–977.

[149] Hongwei Wang, Fuzheng Zhang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. 2019. Multi-task feature learning for knowledge graph enhanced recommendation. In *WWW*. 2000–2010.
[150] Jizhe Wang, Pipei Huang, Huan Zhao, Zhibo Zhang, Binqiang Zhao, and Dik Lun Lee. 2018. Billion-scale commodity embedding for E-commerce recommendation in Alibaba. *KDD*, 839–848.
[151] Jun Wang, Weinan Zhang, and Shuai Yuan. 2016. Display advertising with real-time bidding (RTB) and behavioural targeting. *Found. Trends Inf. Retr.* 11 (2016), 297–435.
[152] Qianqian Wang, Fang'ai Liu, Shuning Xing, and Xiaohui Zhao. 2018. A new approach for advertising CTR prediction based on deep neural network via attention mechanism. *Comp. Math. Methods Med.* 2018 (2018), 1–11. DOI: 10.1155/2018/8056541
[153] Quan Wang, Zhendong Mao, Bin Wang, and Li Guo. 2017. Knowledge graph embedding: A survey of approaches and applications. *IEEE Trans. Knowl. Data Eng.* 29 (2017), 2724–2743.
[154] Ruoxi Wang, Bin Fu, Gang Fu, et al. 2017. Deep & cross network for ad click predictions. In *Proceedings of the ADKDD*. ACM, 7 pages.
[155] Ruoxi Wang, Rakesh Shivanna, D. Cheng, S. Jain, D. Lin, L. Hong, and Ed Huai hsin Chi. 2020. DCN V2: Improved deep & cross network and practical lessons for web-scale learning to rank systems. *arXiv arXiv:2008.13535*.
[156] X. Wang, X. He, M. Wang, F. Feng, and T. Chua. 2019. Neural graph collaborative filtering. In *Proceedings of the SIGIR*. ACM, 165–174. DOI: 10.1145/3331184.3331267
[157] Xiao Wang, Houye Ji, Chuan Shi, Bai Wang, Peng Cui, P. Yu, and Yanfang Ye. 2019. Heterogeneous graph attention network. In *Proceedings of the World Wide Web Conference*. ACM, 2022–2032. DOI: 10.1145/3308558.3313562
[158] X. Wang, W. Li, Y. Cui, R. Zhang, and J. Mao. 2011. Click-through rate estimation for rare events in online advertising.
[159] Hong Wen, Jing Zhang, Quan Lin, Keping Yang, and Pipei Huang. 2019. Multi-level deep cascade trees for conversion rate prediction. *AAAI* 33 (2019), 338–345. DOI: 0.1609/aaai.v33i01.3301338
[160] Hong Wen, Jing Zhang, Yuan Wang, Wentian Bao, Quan Lin, and Keping Yang. 2019. Entire space multi-task modeling via post-click behavior decomposition for conversion rate prediction. In *Proceedings of the SIGIR*. ACM, 2377–2386. DOI: 10.1145/3397271.3401443
[161] Xian Wu, Baoxu Shi, Yuxiao Dong, Chao Huang, and Nitesh V. Chawla. 2019. Neural tensor factorization for temporal interaction learning. In *WSDM*. 537–545.
[162] Jun Xiao, Hao Ye, Xiangnan He, Hanwang Zhang, Fei Wu, and Tat-Seng Chua. 2017. Attentional factorization machines: Learning the weight of feature interactions via attention networks. In *Proceedings of the IJCAI*. AAAI Press, 3119–3125.
[163] Chen Xu, Quan Li, Junfeng Ge, Jinyang Gao, Xiaoyong Yang, Changhua Pei, Fei Sun, Jian Wu, Hanxiao Sun, and Wenwu Ou. 2020. Privileged features distillation at Taobao recommendations. In *Proceedings of the KDD*. ACM, 2590–2598.
[164] C. Xu and M. Wu. 2020. Learning feature interactions with lorentzian factorization machine. In *AAAI*. 6470–6477.
[165] Hongxia Yang, Quan Lu, Angus Xianen Qiu, and Chun Han. 2016. Large scale CVR prediction through dynamic transfer learning of global and local features. In *Proceedings of Machine Learning Research*, Vol. 53. 103–119.
[166] Xiao Yang, Tao Deng, Weihan Tan, Xutian Tao, Junwei Zhang, Shouke Qin, and Zongyao Ding. 2019. Learning compositional, visual and relational representations for CTR prediction in sponsored search. In *CIKM*. 2851–2859.
[167] Y. Yang, X. Guan, and J. You. 2002. CLOPE: A fast and effective clustering algorithm for transactional data. In *KDD*.
[168] Yi Yang, Baile Xu, Furao Shen, and Jian Zhao. 2019. Operation-aware neural networks for user response prediction. *Neural Netw.* 121 (2019), 161–168.
[169] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L. Hamilton, and Jure Leskovec. 2018. Graph convolutional neural networks for web-scale recommender systems. *CoRR* abs/1806.01973 (2018).
[170] Xu Yong, Chen Jiahui, Huang Chao, Zhang Bo, Xing Hao, Dai Peng, and Bo Liefeng. 2020. Joint modeling of local and global behavior dynamics for session-based recommendation*. In *ECAI*, 545–552.
[171] Fajie Yuan, Xiangnan He, Alexandros Karatzoglou, and Liguang Zhang. 2020. Parameter-efficient transfer from sequential behaviors for user modeling and recommendation. In *SIGIR*. 1469–1478.
[172] Yuan Yuan, Xiaojing Dong, Chen Dong, Yiwen Sun, Zhenyu Yan, and Abhishek Pani. 2018. Dynamic hierarchical empirical Bayes: A predictive model applied to online advertising. *CoRR* abs/1809.02213 (2018).
[173] Y. Yuan, F. Wang, J. Li, and R. Qin. 2014. A survey on real time bidding advertising. In *IEEE SOLI*. 418–423.
[174] C. Zhang, D. Song, C. Huang, A. Swami, and N. Chawla. 2019. Heterogeneous graph neural network. In *KDD*. 793–803.
[175] Chuxu Zhang, A. Swami, and Nitesh V. Chawla. 2019. SHNE: Representation learning for semantic-associated heterogeneous networks. In *WSDM* (2019).
[176] J. Zhang, T. Huang, and Z. Zhang. 2019. FAT-DeepFFM: Field attentive deep field-aware factorization machine. In *ICDM*.

[177] Li Zhang, Weichen Shen, Shijian Li, and Gang Pan. 2019. Field-aware neural factorization machine for click-through rate prediction. *IEEE Access* 7 (2019), 75032–75040.
[178] Weinan Zhang, Lingxi Chen, and Jun Wang. 2016. Implicit look-alike modelling in display ads - Transfer collaborative filtering to CTR estimation. *CoRR* abs/1601.02377 (2016).
[179] Weinan Zhang, Tianming Du, and Jun Wang. 2016. Deep learning over multi-field categorical data - - A case study on user response prediction. In *ECIR*.
[180] Weinan Zhang, Tianxiong Zhou, Jun Wang, and Jian Xu. 2016. Bid-aware gradient descent for unbiased learning with censored data in display advertising. In *KDD*. 665–674.
[181] Yuyu Zhang, Hanjun Dai, Chang Xu, Jun Feng, Taifeng Wang, Jiang Bian, Bin Wang, and Tie-Yan Liu. 2014. Sequential click prediction for sponsored search with recurrent neural networks. In *AAAI*. 1369–1375.
[182] Yang Zhang, Fuli Feng, Chenxu Wang, Xiangnan He, Meng Wang, Yan Li, and Yongdong Zhang. 2020. How to retrain recommender system? A sequential meta-learning method. In *SIGIR*. 1479–1488.
[183] Y. Zhang, P. Zhao, Y. Guan, L. Chen, K. Bian, L. Song, B. Cui, and X. Li. 2020. Preference-aware mask for session-based recommendation with bidirectional transformer. In *ICASSP*. 3412–3416.
[184] Weijie Zhao, Deping Xie, Ronglai Jia, Yulei Qian, Ruiquan Ding, Mingming Sun, and Ping Li. 2020. Distributed hierarchical GPU parameter server for massive scale deep learning ads systems. *CoRR* abs/2003.05622 (2020).
[185] Xiangyu Zhao, Xudong Zheng, Xiwang Yang, Xiaobing Liu, and Jiliang Tang. 2020. Jointly learning to recommend and advertise. In *Proceedings of the KDD*. ACM, 3319–3327.
[186] Yifei Zhao, Yu-Hang Zhou, Mingdong Ou, Huan Xu, and Nan Li. 2020. Maximizing cumulative user engagement in sequential recommendation: An online optimization perspective. In *KDD*. 2784–2792.
[187] Hua Zheng, Dong Wang, Qi Zhang, Hang Li, and Tinghao Yang. 2010. Do clicks measure recommendation relevancy? An empirical user study. In *RecSys*. 249–252.
[188] Guorui Zhou, Ying Fan, Runpeng Cui, Weijie Bian, Xiaoqiang Zhu, and Kun Gai. 2018. Rocket launching: A universal and efficient framework for training well-performing light net. *AAAI* 32, 1 (2018).
[189] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaoqiang Zhu, and Kun Gai. 2019. Deep interest evolution network for click-through rate prediction. *AAAI* 33 (2019), 5941–5948.
[190] Guorui Zhou, Chengru Song, Xiaoqiang Zhu, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. 2018. Deep interest network for click-through rate prediction. In *KDD* (2018), 1059–1068.
[191] Guorui Zhou, Kailun Wu, Weijie Bian, Zhao Yang, Xiaoqiang Zhu, and Kun Gai. 2019. Res-embedding for deep learning based click-through rate prediction modeling. In *Proceedings of the DLP-KDD*. ACM, 9 pages.
[192] K. Zhou, M. Redi, A. Haines, and et al. 2016. Predicting pre-click quality for native advertisements. In *WWW*. 299–310.
[193] Wen-Yuan Zhu, Chun-Hao Wang, Wen-Yueh Shih, W. Peng, and J. Huang. 2017. SEM: A softmax-based ensemble model for CTR estimation in real-time bidding advertising. In *IEEE BigComp*. 5–12.
[194] Xingquan Zhu and Ian Davidson. 2007. *Knowledge Discovery and Data Mining: Challenges and Realities*. IGI Global.
[195] X. Zhu, H. Tao, Z. Wu, J. Cao, K. Kalish, and J. Kayne. 2017. *Fraud Prevention in Online Digital Advertising*. Springer.
[196] B. Zoph and Q. Le. 2016. Neural architecture search with reinforcement learning. *CoRR* abs/1611.01578 (2016).
[197] Zhabiz Gharibshah and Xingquan Zhu. 2020. TriNE: Network representation learning for tripartite heterogeneous networks. In *IEEE International Conference on Knowledge Graph (ICKG'20)*. IEEE, 497–504. DOI: 0.1109/ICBK50248.2020.00076

Received April 2020; revised November 2020; accepted January 2021