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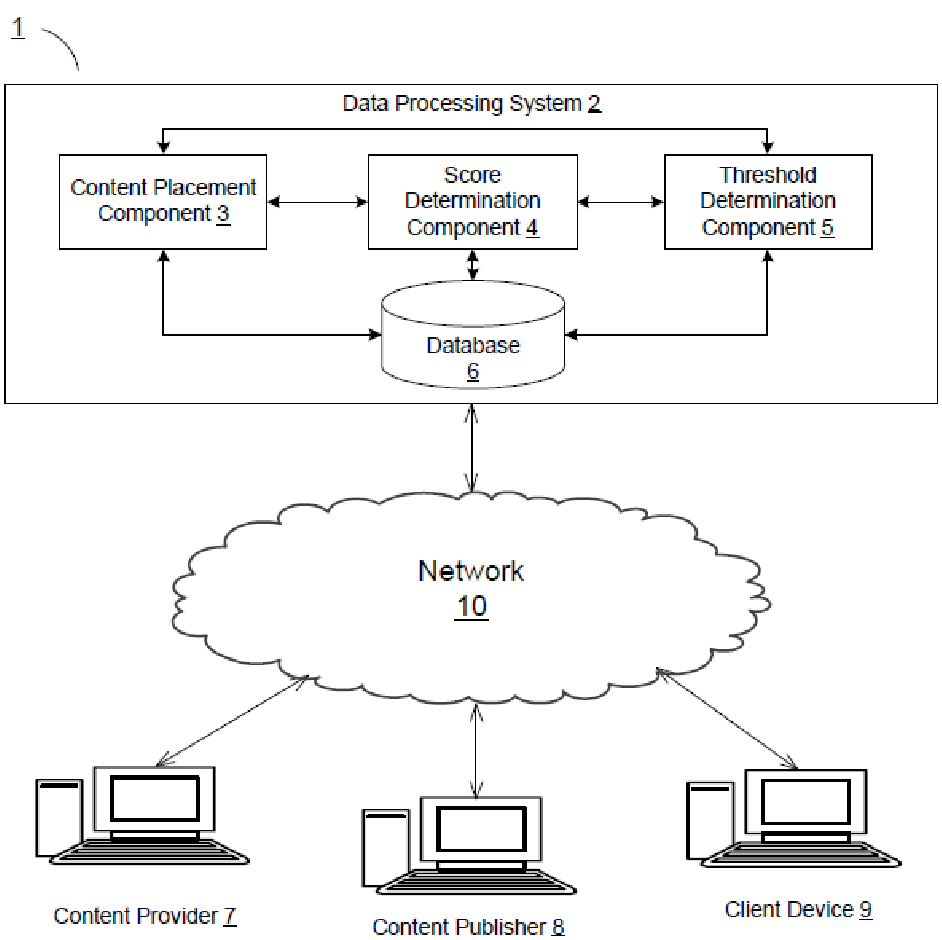
DYNAMIC THROTTLING OF IN-APP PROMOTIONS TO REDUCE MARKETING SPEND BASED ON MACHINE-LEARNING

In online content placement systems, third-party content items, such as ads, can be displayed on information resources to increase the chance that users will purchase, or take other actions with respect to, products or services associated with the third-party content items. In the context of mobile applications, apps often run growth campaigns where in-app promotions are shown to users to increase awareness about a particular brand, product, or application feature. Examples may include promotions for new digital media (e.g., shows, music) which may appeal only to certain audiences, and free-to-paid upsell for increasing brand awareness to promote products that are commonly bought on a recurring basis. The promotions are commonly shown to each user multiple times in order to make the message stick and increase the possibility of conversion (i.e., taking the desired action, for example, clicking on a promotion, clicking through to a brand's website, clicking through a page to watch a show, clicking a button to buy a product).

The above described systems may have problems. Because content providers or marketers generally pay on a cost per-impression basis, most systems put frequency caps on the promotions. However, as noted above, each particular promotion is likely to appeal only to certain users. Since the frequency caps may not take into account a particular user's attributes, the above described systems may not provide the best use of the marketing dollars. For example, if a user has a higher affinity for products similar to "product A" than for "product B," it may make more economic sense for a marketer to show a promotion for "product A" more frequently than for "product B" to the user. Another problem is user satisfaction. Showing a promotion or third-party content item may have a negative impact if the user is being annoyed by the display of the promotion or the content item. Publishers, ad networks, content and application providers and other entities do not want to annoy users as a result of showing promotions or ads because users may be less likely to visit the site or use the application which can translate into financial loss over the long run. On the other hand, a user may be less likely to be annoyed if promotions appealing to the user are repeated more frequently than promotions that do not appeal to the user.

One technique for solving these problems is throttling (not showing) a promotion or third party content item when a score (e.g., a click score, an auction score) is under a certain threshold. The proposed technique adds an additional machine learning model (or a set of machine learning models) that predicts the user annoyance effect of showing a promotion or third party content item, as opposed to not showing one. Because the machine learning model takes into account the current context, ad spending may not be wasted and user satisfaction can be retained by not showing a promotion that is predicted as unlikely to lead to a conversion. Furthermore, the present technique can translate the user annoyance effect into a monetary amount such that an intelligent decision can be made with respect to whether the cost of showing a promotion or ad may outweigh the revenue of showing the promotion or ad.

Figure 1 is a block diagram depicting an exemplary environment 1 for implementing the present technique. The environment 1 includes at least one data processing system 2, one or more content providers 7, one or more content publishers 8, one or more client devices 9, and a network 10. The data processing system 2 can include at least one content placement component 3, at least one score determination component 4, at least one threshold determination component 5, and at least one database 6. The data processing system 2, the content placement component 3, the score determination component 4, and the threshold determination component 5 can include one or more processors, servers, computing devices, memory, logic arrays, circuitry, software or hardware modules, logic elements, or digital logic blocks configured to communicate with the database 6 and with other computing devices (e.g., the content provider 7, the content publisher 8, and the client device 9) via the network 10. The memory of the data processing system 2, the content placement component 3, the score determination component 4, and the threshold determination component 5 can store machine instructions that, when executed by the one or more processors, cause the one or more processors to perform one or more of the operations described herein. The content placement component 3, the score determination component 4, and the threshold determination component 5 can be or be within separate devices, or can be or be within one device.



The network 10 can include one or more of any type of computer networks such as the Internet, cellular network, WIFI network, WiMAX network, mesh network, Bluetooth, near field communication, satellite network, or other data network that facilitates communications between the data processing system 2, the content provider 7, the content publisher 8, and the client device 9. The network 10 can also include any number of computing devices (e.g., computers, servers, routers, network switches, etc.) that are configured to receive and/or transmit data within the network 10. The network 10 can further include any number of hardwired and/or wireless connections.

The content provider 7 can refer to, or include, an advertiser or other providers of content items, such as online documents, blogs, media or advertisements. The content provider 7 can establish an advertisement campaign with advertisements and advertisement selection criteria, such as keywords and geographic location. The content publisher 8 can refer to or include a web site operator, such as an entity that operates a web page. The web site operator or content publisher 8 can include at least one web page server that communicates with the network 10 to make the web page available to the client device 9.

The client device 9 can include, for example, mobile computing devices, mobile telecommunications devices, smartphones, personal digital assistants, laptop computers, notebooks, tablet computers, smart watches, or wearable devices. The client device 9 can include a display such as a liquid crystal display, light emitting diode (LED) based display, organic light emitting diode based display, bitmap display, pixel display, electronic ink display, or other display configured to visually output content including text, characters, strings, symbols, images, or multimedia content provided by the data processing system 2. The content provider

7, the content publisher 8, and the client device 9 can each include one or more processors and memory.

The data processing system 2 can receive a request for a promotion or content item. In some implementations, the content placement component 3 can receive a request from the content provider 7 or another component of the data processing system 2 for starting a promotional campaign. A campaign can be constructed in a user interface (UI) and launched by marketing teams for messaging users with in-app popups, push notifications, emails, and advertisements. The request can also be received from the client device 9 or the content publisher 8 for requesting a third party content item, such as an ad, to be displayed at the client device 9. In some implementations, the request received by the data processing system 2 can include various data, including a logged-in user identifier, a cookie identifier or other identifiers associated with the user at the client device 9, and contextual information (e.g., placement, device information, web page that is being loaded, user's location, time of day, etc.). Historical data, such as content browsed by users can be logged and stored in a database (e.g., database 6) and aggregated on a server (e.g., a server in the data processing system 2, the content provider 7 or the content publisher 8.). User interaction with the promotions can also be logged and aggregated. These site activities and promotion interaction logs can be fed into a pipeline where they can be joined with information (e.g., demographics, language, user's purchase history, user's preferred form of payment) about the user represented by a user/device identifier, and information about the promotions (title text, body text, colors, choice of image). A machine-learning model can be trained on an ongoing basis using those items of information. In some implementations, the model can be trained to predict a probability of a user's conversion, which can be proxied by a probability of a click on an appropriate call-to-action button. For example, the score determination component 4 can determine the probability of a click in the form of a click score. Various machine learning algorithms, for example logistic regression, can be used.

For situations in which the systems discussed here collect personal information about users, or may make use of personal information, the users may be provided with an opportunity to control whether programs or features that may collect personal information (e.g., information about a user's social network, social actions or activities, a user's preferences, or a user's current location), or to control whether or how to receive content from the content server that may be more relevant to the user. In addition, certain data may be treated in one or more ways before it is stored or used, so that certain information about the user is removed when generating parameters (e.g., demographic parameters). For example, a user's identity may be treated so that no identifying information can be determined for the user, or a user's geographic location may be generalized where location information is obtained (such as to a city, ZIP code, or state level), so that a particular location of a user cannot be determined. Thus, the user may have control over how information is collected about the user and used by a content server.

In some implementations, the content placement component 3 can fetch a list of content item candidates from the database 6 and select one content item by conducting an auction. The content placement component 3 can run one or more predictive models to predict the value of showing the content item by estimating a click-through rate and estimating whether the user will convert if the user clicks on the content item. The score determination component 4 can determine an auction score for each candidate according to the predictions of the predictive models. The auction score may also take another multiplier in addition to the output of the predictive model, for example, the importance or value of this ad relative to other ads, usually in the form of a bid that the content provider has agreed to pay if the content provider's ad is clicked. The auction score is usually denominated in the form of a monetary amount. For example, the expected dollar value of showing a particular candidate can be determined by multiplying the amount that the content provider will pay if the content item is clicked on with the likelihood that the user will click the content item if the content item is shown. The content placement component 3 can select a content item based on the auction scores of the candidates.

In either the promotional campaign context or the content item (e.g., ad) placement context, it is possible that showing a promotion or ad can have a negative impact greater than the revenue generated. For example, a user may be annoyed by a promotion or ad displayed to him or her, and in turn may stay away from the web site or mobile application. Thus, the possible revenue of showing the promotion or ad to the user can be outweighed by the negative impact that the user may be annoyed. The data processing system 2 can determine whether the negative impact of the showing the promotion or ad outweighs the possible revenue generated by comparing a score (e.g., a click score or an auction score) with a threshold. If the score is less than the threshold, the promotion or ad placement can be throttled by the data processing system 2. As discussed above, the score, such as a click score or an auction score, can be determined by the score determination component 4 based on various factors.

The threshold determination component 5 can be configured to determine the threshold. In some implementations, the threshold can be determined with machine learning using multiple different thresholds during a warm-up period. For example, the threshold determination component 5 can start each promotion in a warm-up period. Instead of serving the promotion to all traffic, the promotion is served with throttling on different thresholds to small fractions of the traffic. For instance, the different thresholds can include “no threshold,” “threshold=0.001,” “threshold=0.005,” “threshold=0.01.” Each of these thresholds can be applied to a small fraction of the traffic (e.g., 1% of traffic). Thus, it can be expected that as the threshold increases, throttling causes the number of impressions to decrease. The threshold determination component 5 can determine a good threshold where while impressions have decreased, the number of conversions is still at an acceptable level (e.g., on a use-case basis, 100% of the original conversions or 80% of original conversions). The threshold determination component 5 can immediately choose this threshold, or repeat the experiment trying several thresholds near the earlier chosen threshold, similar to a binary search, until finding an acceptable loss of conversions.

In some implementations, the threshold determination component 5 can determine the threshold by first showing the promotion to all users or a small fraction of traffic during a warm-up period without throttling. The threshold determination component 5 can then analyze the data from the warm-up period, which can be visualized as a scatter plot of click scores against user identifiers. Business (e.g., the content provider 7 or the content publisher 8) can articulate a guide, such as throttling out promotions from the bottom 10% of user requests that are least likely to convert on the promotion. This guide can be used by the data processing system 2 to dynamically determine the threshold based on the data, which can be the place to draw the horizontal line on that chart. Once an appropriate threshold is chosen, the warm-up period is over. The data processing system 2 can serve the promotion to all traffic, applying throttling using the appropriate threshold.

In some implementations, the threshold determination component 5 can calculate a cost amount of showing an ad, and dynamically determine an auction score threshold. For example, the threshold determination component 5 can predict that showing an ad to a particular user on a particular ad impression may reduce the expected amount of time that the user spends on the site by, for instance, 0.5%. Continuing with this example, assuming that the average spending on the site to buy items is $50 over a user's lifetime. The threshold determination component 5 can determine that a predicted cost of showing the ad is $0.25 as opposed to not showing it. The threshold determination component 5 can choose this value of $0.25 as a threshold for showing any ad to this particular user on this particular impression.

By dynamically and intelligently determining a threshold, and throttling a promotion or ad placement if a click score or auction score is below the determined threshold, the present technique can avoid annoying users with promotions or ads when they do not have enough value to merit the annoyance. As a result, ad spending may not be wasted and user satisfaction can be retained.

Abstract

This document describes a technique of dynamically throttling a promotion or content item placement to reduce marketing spending using machine-learning. A data processing system can determine a click score or an auction score based on various factors. The data processing system can further determine a threshold, for example, by predicting an annoyance effect of showing the promotion or the content item to a user. If the click score or the auction score is below the threshold, the data processing system can throttle the promotion or the content item placement such that the promotion or the content item is not shown to the user.