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Revenue sharing based on ECPM and video-quality metrics

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ABSTRACT

Advertisement-based revenue generated from content, e.g., videos, hosted on content-sharing sites is typically shared between the content-creator and the content-hosting site based on click-through rates, number of ad impressions, etc. However, user-generated content is of varying quality, e.g., different content items enjoy different levels of viewer attention. A user that watches an advertisement that precedes a video often does not know if the video they are about to watch is the one they're looking for. This disclosure addresses this problem by quantifying the value that content items bring to their viewer. The creator is paid based on the assessed value. For example, the value of a video may be based partially on the time a user spends viewing it, excluding time spent watching the ad. Basing payments to content creators on content value motivates creators to improve quality of their videos. Content quality also feeds into recommendation engines such that end-users are provided with higher quality of recommendations and search results.

KEYWORDS

User-generated content; content quality; search quality; revenue distribution; cost per click; cost per mille; CPC; CPM; ECPM; recommendation engine; click-through rate; CTR; ad impressions; video hosting; content hosting

BACKGROUND

Advertisement-based revenue generated from content, e.g., videos, hosted on content-sharing sites is typically shared between the content-creator and the content-hosting site based on click-through rates, number of ad impressions, etc. that are attributable to the content. In filling a user's watch session with entertaining videos, recommendations are based on user permitted factors such as viewing history, user demographic, etc. However, user-generated content is of varying quality, e.g., different content items enjoy different levels of viewer attention. A user that watches an advertisement that precedes a video often does not know if the video they are about to watch is the one they're looking for. The current procedure for finding and viewing videos or other content is thus characterized by some inefficiency, e.g., more search queries and browsing than necessary. This in turn leads to inefficiencies across the network, e.g., greater network traffic, greater use of memory and/or CPU at client as well as server, battery drain, etc.

DESCRIPTION

This disclosure presents techniques that efficiently identify content that likely satisfies a user. The value that contents bring to their viewer is quantified per techniques herein. For example, the value of a video may be based partially on the time a user spends viewing it (excluding time spent watching preceding or embedded ads, if any). Revenue arising from the video is shared with the video-creator based on the assessed value. Basing payments to content creators on content value motivates creators to improve quality of their videos. Content quality also feeds into recommendation engines such that end-users are provided with higher quality of recommendations and search results.

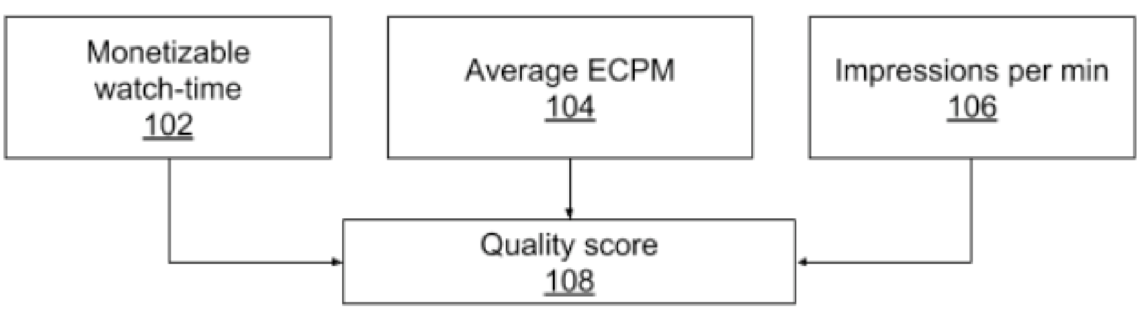

Fig. 1: Computing a quality score

Fig. 1 illustrates computing a quality score, also referred to as monetizable watch-time score, for a video or other user-generated content, per techniques of this disclosure. One or more of at least three factors, e.g., monetizable watch-time (102), average ECPM (104), impressions per minute (106), etc., are combined in order to compute a quality score (108).

Monetizable watch-time (102) is the total watch time from a collection of video content, e.g., from a particular content creator, that is monetizable. Watch times that are not monetizable arise from videos that have advertisements disabled by the creator, spam views, playback environment constraints that prevent advertisements, etc. Watch time monetizability may be contextually weighted, e.g., follow-on views in a playlist may be considered less monetizable than the view of a search result, e.g., since user engagement is typically lower during follow-on views.

Average ECPM (estimated cost per 1000 impressions) (104) is the expected cost of winning ad-auction bids for placing ads on videos. This factor can be applied on the basis of a group of video content items or on a per-video basis. In some implementations, application on a per-video basis is preferable because even videos from the same creator have differing appeals to audiences, e.g., when content is shared on third-party platforms. ECPM comprises several factors, e.g., cost per click (CPC), click-through rate (CTR), content quality, etc. The average ECPM of a video is a heuristic for the likelihood that a user will click on an advertisement, e.g., recommended video, and the value of that click, e.g., amount of time the video provides user satisfaction and the quality of that time.

Impressions per minute (106) is a constant dependent on the number of impressions across an entire session cluster. Typically, this calculation is done for clusters of user sessions based on defining characteristics of that cluster. For example, ad-impression frequencies and

ECPMs typically depend on the viewing device, e.g., smartphone, computer/web, TV, etc. Segregating sessions into different clusters based on device produces a more accurate description of the value distribution for each group of content items. Recommendations are also likely to be more accurate when the device in use is taken into account.

Quality score (108) is obtained by using a formula to combine constituent factors, e.g., Quality score = Monetizable watch-time × Avg. ECPM /Impressions per min. The quality score represents the value that the content brings to end-user sessions, and by extension, to the content-hosting platform. Per techniques of this disclosure, revenue is distributed between the content-creator and the content-hosting platform based on the quality score. The model of revenue distribution described herein is cognizant of the differences in the monetized values of watch time. In particular, the revenue distribution model is a mechanism that reflects the value-add of specific content based on the average monetized watch time.

In an example implementation, an average monetized value of watch time for content groups from a content creator is identified. This average is combined with the accumulated monetizable watch time for the content groups, e.g., via multiplication, to produce a new monetized watch-time score. A total score is calculated by adding up all of the monetized watch-time scores. Revenue is distributed to each content group in a manner proportional to their monetized watch-time score as a fraction of total monetized watch-time score.

The techniques of revenue distribution apply regardless of the source of the revenue, e.g., advertisements or subscription fees. For example, if revenue is derived from subscription fees, the techniques of this disclosure can be advantageously used to determine the distribution of subscription fees to contributing content-creators who bring differing values to the content-sharing platform.

Per the techniques of this disclosure, content creator revenue can be combined across advertising campaigns and distributed based on watch time, wherein watch-times are equally considered. Content groups included in a specific target subset get an apportioned part of revenue, rather than a disproportionately large portion of revenue from the respective advertisement campaign.

The techniques of this disclosure can also be applied to variable revenue sharing contracts. For example, some content providers negotiate different revenue-sharing rates with the content-distribution service. In such cases, the revenue-sharing rates can be multiplied by the monetized watch time scores to determine the fraction of revenue to be distributed to each content provider.

The techniques of this disclosure can also be applied to music and/or episodic content, which are often consumed in a series rather than as independent pieces. The techniques foster a content ecosystem with shorter bits of content; this is generally useful sine shorter pieces of content are easier for content creators to create than long-form content. Further, the techniques enable a content recommendation engine to compare the value of short-form content against episodic and/or long-form content.

In this manner, the techniques of this disclosure measure and employ user engagement with content as a heuristic for identifying recommended content. Content is recommended based on the likelihood of the user watching such content. Further, the techniques provide a revenue distribution model that reflects differences in cost per click and click-through rate across content groups. Revenue is distributed based on the value that content groups from a content creator bring to the content-sharing platform and to end-users.

CONCLUSION

Advertisement-based revenue generated from content, e.g., videos, hosted on content-sharing sites is typically shared between the content-creator and the content-hosting site based on click-through rates, number of ad impressions, etc. However, user-generated content is of varying quality, e.g., different content items enjoy different levels of viewer attention. A user that watches an advertisement that precedes a video often does not know if the video they are about to watch is the one they're looking for. This disclosure addresses this problem by quantifying the value that content items bring to their viewer. The creator is paid based on the assessed value. For example, the value of a video may be based partially on the time a user spends viewing it, excluding time spent watching the ad. Basing payments to content creators on content value motivates creators to improve quality of their videos. Content quality also feeds into recommendation engines such that end-users are provided with higher quality of recommendations and search results.