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Machine-Learned Temporal Brand Scores for Video Ads

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BACKGROUND

Video ads that are presented to users, for example, can vary in their effectiveness. For example, the video ad's effectiveness can depend on how and when visual and audio content is presented.

SUMMARY

In general, a machine learning system is presented that can infer a "brand score" curve of a video across the run time for the video. The system can use a ground truth score obtained, for example, using user surveys, audio transcription of words spoken, video transcription of words displayed, the type of music being played, and computer-captured signals to learn and train a model for inferring brand scores. A given video can be segmented (e.g., by time), and a piecewise brand score for each segment can be generated using the model.

DESCRIPTION OF DRAWINGS

Figure 1 is a graph showing an example brand effectiveness of a video during its presentation over time.

DETAILED DESCRIPTION

Video ads (or other videos), such as video ads that are presented on video presentation and sharing sites, are often used by advertisers and/or other content sponsors to drive brand awareness and/or to improve users' affinities to certain brands. A typical video ad may be 30 seconds long, for example, which can make it challenging (but worthwhile) to determine which parts of the video ad are most effective in driving brand awareness and/or effectiveness/favorability of the video ad.

This document describes an automated way to generate, e.g., continuously over time, scores that indicate brand awareness and/or other related scores associated with the effectiveness and/or favorability of the video ad. For example, consider a 30-second video ad for a soft drink product. During the presentation of the video ad, for example, brand effectiveness (e.g., associated with an effect on a person watching the video ad) can vary significantly across different parts of the video ad (*See* Figure 1).

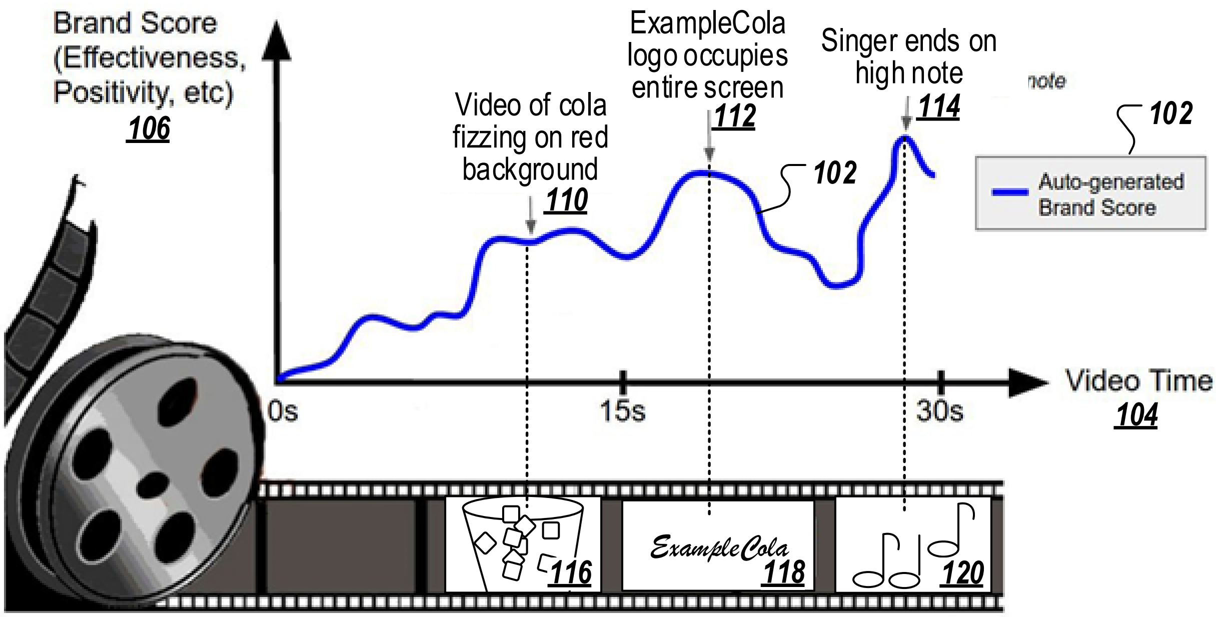

Figure 1

Figure 1 is a graph 100 showing an example brand effectiveness 102 of a video during its presentation over time. For example, the brand effectiveness 102 is temporal and is represented by a line that starts at 0 seconds of a video play time 104 and changes in height relative to a brand effectiveness score 106 over the 30-second length of the video. The graph 100 can apply to any types of brand scores and for other lengths of presentation that are not 30 seconds. The brand effectiveness represented by graph 100 can be an indication, for example, of whether people are more likely to retain brand awareness and/or remember the brand in the future. The graph 100 can also indicate brand favorability, e.g., indicating whether the ad improves favorability towards the brand, such as over time. The graph 100 can also be indicative of brand loyalty, e.g., did the video ad retain a person's (e.g., the video viewer's) loyalty to the brand? The graph 100 and processing associated with the graph can be general enough, for example, to handle video ads (including sound), audio-only ads, and soundless video ads, such as for various digital mediums (e.g., video sharing and presentation systems), television, radio, and other mediums.

The graph 100 can be annotated (e.g., if a likeness is presented to a user) to include temporal annotations 110-114. For example, the annotations 110-114 can indicate when a segment of the video ad shows the ExampleCola fizzing, when a logo for the ExampleCola is displayed, and when the audio of the video ad includes a high note (e.g., sung during a cola jingle), as indicated by mages 116-120, respectively. As displayed in Figure 1, the temporal annotations 110-114 (and corresponding images 116-120) can help to account for the height of the curve for the brand effectiveness 102.

Determining brand effectiveness, and developing models for measuring brand effectiveness, can be performed based on machine learning. For example, machine learning techniques can make it possible to infer a brand score curve across time for any arbitrary video ad. In some implementations, components of a machine learning system can include, for example, a ground truth component, a signals component, and an algorithms component. Ground truth, for example, can refer to determining and/or measuring the accuracy of output of machine learning techniques, in this case brand awareness or related information.

For the ground truth component, there can be several ways to obtain ground truth. For example, ground truth can be obtained by running brand surveys on users who have seen various temporal subsections of a given video ad, such as to obtain a ground truth temporal measurement for the video ad (e.g., for a soft drink product). In some implementations, domain experts (e.g., experts regarding soft drinks and/or advertising) can draw ground truth curves on various videos that they watch. In another example, negative values associated with user ground truth can be generated by evaluating timestamps associated with sections of video ads that users have skipped on video sharing sites and/or other resources.

For the signals component, many different types of signals can be used, both from video and ads sides. For example, from the presentation or recording of a video ad, an audio transcription of the words that are spoken or sung can be generated and used to detect mentions of brand name over time. In another example, video transcriptions of the words being displayed during presentation of the video can be used to locate mentions of the brand at certain times/positions of the video. In another example, signals can be determined from user preferences/demographics that are associated with types of music played during the presentation of a video ad. In another example, signals can be captured from computers used by users viewing video ads. The computer-captured signals can include, for example, eye movements, mouse movements and clicks, and durations associated with skipping or stopping a video ad. Timestamps associated with the computer-captured signals can be matched to temporal information associated with subsections of the video ad.

For the algorithms component, there are a variety of algorithms that can be used to infer the brand score curve. For example, a video can be split into various sub-regions (e.g., video segments associated with units of time). For each sub-region, a simple regression can be performed, e.g., using the signals and ground truth components described above. Based on the results, the regressions per sub-region can be pieced together to generate a piecewise brand score curve. In some implementations, more complex inferences can be made. e.g., using conditional random fields to optimize the whole curve globally.

The following example use cases can apply to using brand score curves. In some implementations, advertisers and ads network systems can use the brand score curves to improve advertising. For example, ads network systems can surface a tool (e.g., used by advertisers or content sponsors) for rating a given video ad. The tool can present a given brand score curve to an advertisers, for example, to identify which segments of the ads are most effective and to suggest segments to be deleted or shortened (e.g., using video ad editing tools that are also provided). In some implementations, displays can be presented that resemble the graph (or at least the curve) shown in Figure 1.

In some situations, video sharing and presentation systems can automatically skip to parts of the advertisement that are the most impactful, e.g., considered to affect brand awareness. The segments that are automatically skipped can vary, for example, by device type, by user type, or by specific user, e.g., if it is know that certain segments are likely to be skipped by the corresponding device types, user types, and/or individual users.

Advertising network systems can charge advertisers for ads based on brand awareness, e.g., that is proportional to brand-score-curve-weighted metrics. For example, if advertisers care about reach metrics such as gross rating point (GRP), a brand score curve can be used to weight each segment that the user watched.

ABSTRACT OF THE DISCLOSURE

A machine learning system infers a “brand score” curve of a video across the run time for the video. The system uses a ground truth score obtained using user surveys, audio transcription of words spoken, video transcription of words displayed, type of music being played, and computer vision signals to learn a model for inferring the brand score. A given video is segmented, and a piecewise brand score for each segment is generated using the model.