January 2021

DATA DRIVEN APPLICATION STORE LISTING OPTIMIZATION

Steve Suppe

Mike Davis

Jonathan Cheung

DATA DRIVEN APPLICATION STORE LISTING OPTIMIZATION

ABSTRACT

A computing system (e.g., a cloud server that hosts an application store) may predict the effect of modifying marketing assets (e.g., text, an image, a screenshot, a description, a video, etc.) of an application (hereinafter referred to as an “app”) on acquisitions (e.g., installations) for the app. The computing system may generate these predictions based on historical performance data (e.g., data relating to modifications to one or more marketing assets of the app and to acquisitions for the app) of marketing assets for a variety of types (e.g., lifestyle apps, social media apps, utility apps, productivity apps, entertainment apps including games, etc.) of apps on the app store. In some examples, the historical performance data may include the origin country, language, device type, purchase history, acquisition history, and/or the like of potential customers (e.g., customers of the app) such that the predictions generated by the computing system may be based on one or more of those factors. The computing system may then provide these predictions to a user (e.g., an app developer) of the application store to help (e.g., by providing benchmarks and/or recommendations) the user modify the marketing assets of the user’s app in a manner predicted to increase acquisitions for the user’s app in the app store. For example, the computing system may cause the user’s computing device (e.g., a smartphone, a tablet, a laptop) to display a statistical model (e.g., a cat and whisker plot, a bar graph, etc.) indicating the relationship between modifying one or more marketing assets and acquisitions for any type of app. The computing system may also provide statistics such as the average acquisition, the range of acquisition, the distribution of acquisition, the standard deviation of acquisition, and/or the like. Such statistics may represent acquisition benchmarks for guiding the user in modifying the user’s marketing assets.

DESCRIPTION

The present disclosure describes techniques for predicting the effect of modifying marketing assets (e.g., text, an image, a screenshot, a description, a video, etc.) of an application (hereinafter referred to as an "app") on acquisitions (e.g., installations) for the app. In particular, a computing system (e.g., a cloud server) that hosts an app store may generate these predictions based on historical performance data (e.g., data relating to modifications to one or more marketing assets of the app and to acquisitions for the app) of marketing assets for a variety of types (e.g., lifestyle apps, social media apps, utility apps, productivity apps, entertainment apps including games, etc.) of apps on the app store.

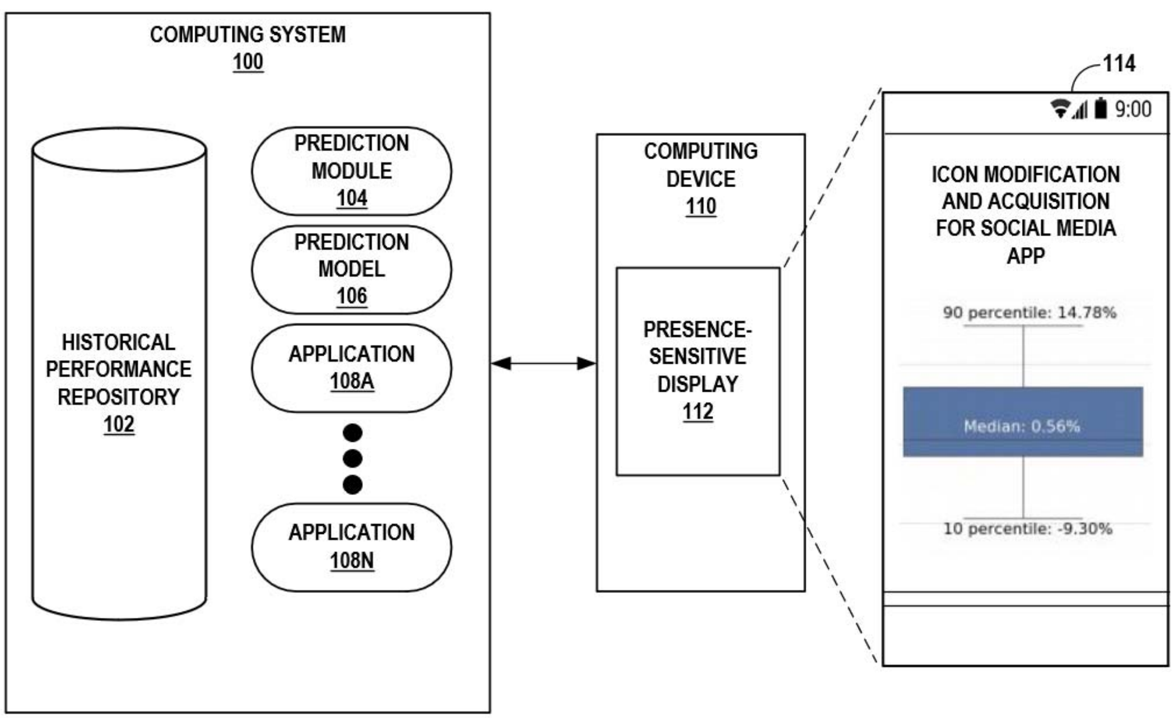

FIG. 1

FIG. 1 is a conceptual diagram illustrating a computing system 100. In some examples, computing system 100 is a remote cloud server hosting an app store. In other examples, computing system 100 is a supplemental computing system that supplements a remote cloud server hosting the app store. Computing system 100 may predict the effect of modifying one or more marketing assets of an app on acquisitions for one or more of apps 108A-108N (collectively, "apps 108"). Computing system 100 may be any suitable remote computing system, such as one or more desktop computers, laptop computers, mainframes, servers, cloud computing systems, virtual machines, and/or the like capable of sending and receiving information via a network. In some examples, computing system 100 may represent a cloud computing system that provides one or more services via the network. That is, in some examples, computing system 100 may be a distributed computing system. One or more computing devices, such as computing device 110, may access the services provided by computing system 100.

Computing system 100 includes one or more processors and one or more storage devices. The processors may implement functionality and/or execute instructions associated with computing system 100. Examples of the processors include application processors, display controllers, auxiliary processors, one or more sensor hubs, and any other hardware configured to function as a processor, a processing unit, or a processing device. Repositories (e.g., a historical performance repository 102), modules (e.g., a prediction module 104), models (e.g., a prediction model 106), and apps (e.g., apps 108) may be operable (or, in other words, executed) by the processors to perform various actions, operations, or functions of computing system 100. That is, historical performance repository 102, prediction module 104, prediction model 106, and apps 108 may form executable code, which when executed, cause the processors to perform specific operations in accordance with (e.g., causing computing system 100 to become a specific-purpose computer by which to perform) various aspects of the techniques described here.

The storage devices may store historical performance repository 102, prediction module 104, and prediction model 106. The storage devices may, in some examples, be described as a computer-readable storage medium. For example, the storage devices may be configured for long-term, as well as short-term storage of information, such as instructions, data, or other information used by computing system 100.

In the example of FIG. 1, computing device 110 is a smartphone. However, computing device 110 may be any mobile or non-mobile computing device, such as a cellular phone, a smartphone, a personal digital assistant (PDA), a desktop computer, a laptop computer, a tablet computer, a portable gaming device, a portable media player, an e-book reader, a watch (including a so-called smartwatch), an add-on device (such as a casting device), smart glasses, a gaming controller, and/or the like. Computing device 110 may communicate with computing system 100 via a network, such as a cellular radio, a third-generation (3G) radio, a fourth-generation (4G) radio, a fifth-generation (5G) radio, a Bluetooth® radio (or any other personal area network (PAN) radio), a near-field communication (NFC) radio, a WiFi® radio (or any other wireless local area network (WLAN) radio), and/or the like. Additionally or alternatively, computing device 110 may include wired communication devices capable of transmitting and/or receiving communication signals via a direct link over a wired communication medium (e.g., a universal serial bus (USB) cable).

Computing device 110 may include a presence-sensitive display ("display") 112. Display 112 may be a presence-sensitive display that functions as an input device and as an output device. For example, the presence-sensitive display may function as an input device using a presence-sensitive input component, such as a resistive touchscreen, a surface acoustic wave touchscreen, a capacitive touchscreen, a projective capacitive touchscreen, a pressure sensitive screen, an acoustic pulse recognition touchscreen, or another presence-sensitive display technology. Presence-sensitive display 112 may function as an output (e.g., display) device using any of one or more display components, such as a liquid crystal display (LCD), dot matrix display, light emitting diode (LED) display, microLED display, organic light-emitting diode (OLED) display, e-ink, active matrix organic light-emitting diode (AMOLED) display, or similar monochrome or color display capable of outputting visible information, such as a graphical user interface (GUI) 114 indicating at least a portion of the information from computing system 100 to computing device 110.

In accordance with techniques of this disclosure, computing system 100 may predict the effect of modifying one or more marketing assets of any of apps 108 (e.g., app 108A) on acquisitions for the app. In particular, computing system 100 may generate these predictions (and additional information based on these predictions, such as acquisition benchmarks) based on the historical performance data of marketing assets for a variety of apps 108, and thus a variety of types of apps 108, on the app store. The historical performance data of apps 108 may relate to modifications to one or more marketing assets of apps 108 and to acquisitions for apps 108. For example, the historical performance data for app 108A may identify the marketing asset of app 108A that was modified and the change in acquisitions for app 108A that occurred thereafter. In some examples, the historical performance data of apps 108 may include the origin country, language, device type, purchase history, acquisition history, and/or the like of potential customers (e.g., customers of the app). As such, the predictions generated by computing system 100 may be based on the origin country, language, device type, purchase history, acquisition history, and/or the like of potential customers.

In some examples, the historical performance data for apps 108 may be publicly available such that a user of computing system 100 can access the historical performance data, and information derived from the historical performance data in accordance with techniques of this disclosure, of apps not belonging to the user. In other examples, the historical performance data may not be publicly available such that a user of computing system 100 can only access the historical performance data, and information derived from the historical performance data in accordance with techniques of this disclosure, of apps belonging to the user.

Computing system 100 may collect the historical performance data for any of apps 108, and thus any type of app, on the app store. For example, computing system 100 may collect historical performance data on app 108A (e.g., a social media app), on app 108B (e.g., an entertainment app), and/or the like, to name a few examples. Computing system 100 may store the historical performance data in historical performance repository 102.

Based on the historical performance data, prediction module 104 of computing system 100 may generate predictions relating to the effect of modifying one or more marketing assets of any of apps 108 on acquisitions for the app. That is, prediction module 104 may aggregate the historical performance data and then analyze the historical performance data to determine a relationship between a modification to one or more marketing assets and acquisitions for any app (e.g., app 108A), and thus any type of app (e.g., a social media app), on the app store. For example, prediction module 104 may analyze the historical performance of all social media apps on the app store to determine that modifying the icon of app 108A (e.g., a social media app) is correlated with an average (e.g., mean, median, etc.) increase in acquisition of 0.56% for app 108A,as indicated in the example of FIG. 1. Similarly, prediction module 104 may analyze the historical performance of all entertainment apps on the app store to determine that modifying the icon of app 108B (e.g., an entertainment app) is correlated with an average decrease in acquisition of 1.23% for app 108B.

Prediction module 104 may determine the relationship between simultaneously modifying multiple assets and acquisitions. For example, prediction module 104 may analyze the historical performance of all lifestyle apps on the app store to determine that modifying the image and video of an app 108C (e.g., a lifestyle app) is correlated with an average increase in acquisition of 0.56% for app 108C. Like with the data relating to the effect of modifying one marketing asset on acquisitions, computing system 100 may store data relating to the effect of modifying a combination of marketing assets on acquisitions in historical data repository 102.

In some examples, prediction module 104 may determine statistics other than the average acquisition that may be helpful to a user (e.g., an app developer), such as the range of acquisition, the distribution of acquisition, the standard deviation of acquisition, and/or the like. These statistics may represent acquisition benchmarks for the user to guide the user in modifying the user's marketing assets. Such statistics may include data prior to and following a modification to one or more marketing assets such that prediction module 104 may determine relationships (e.g., correlations) between modifying marketing assets of an app and acquisitions for the app. For example, prediction module 104 may determine which marketing asset, if modified, is correlated with the largest increase in acquisition for the user's app and recommend (e.g., for output at display 112) that the user modify the marketing asset correlated with the largest increase in acquisition before modifying anything else. In some examples, prediction module 104 may measure the largest increase based on the average increase of acquisition, the maximum increase of acquisition, and/or the like.

Prediction module 104 may determine the relationship between a modification to one or more marketing assets and acquisitions for a specific segment of a population. For example, prediction module 104 may analyze the historical performance of all utility apps on the app store to determine that modifying the video of app 108D (e.g., a utility app) is correlated with an average (e.g., mean, median, etc.) increase in acquisition of 0.56% for app 108D in the United States but an average decrease in acquisition of 0.38% for app 108D in Brazil. In another example, prediction module 104 may analyze the historical performance of all lifestyle apps on the app store to determine that modifying the text of 108C is correlated with an average (e.g., mean, median, etc.) increase in acquisition of 0.12% for app 108C among English-speakers but an average decrease in acquisition of 0.22% for app 108C among French-speakers.

Prediction module 104 may output or otherwise use prediction model 106 during execution of prediction module 104. Prediction model 106 may represent one or more statistical models indicating statistical relationships of the historical performance data. For example, as shown in FIG. 1, prediction model 106 may represent a cat and whisker plot indicating the relationship between modifying the text of all lifestyle apps on the app store and the corresponding distribution of acquisition for all lifestyle apps. Computing system 100 may send an indication of prediction model 106 to computing device 110 to display via display 112 (e.g., as part of GUI 114).

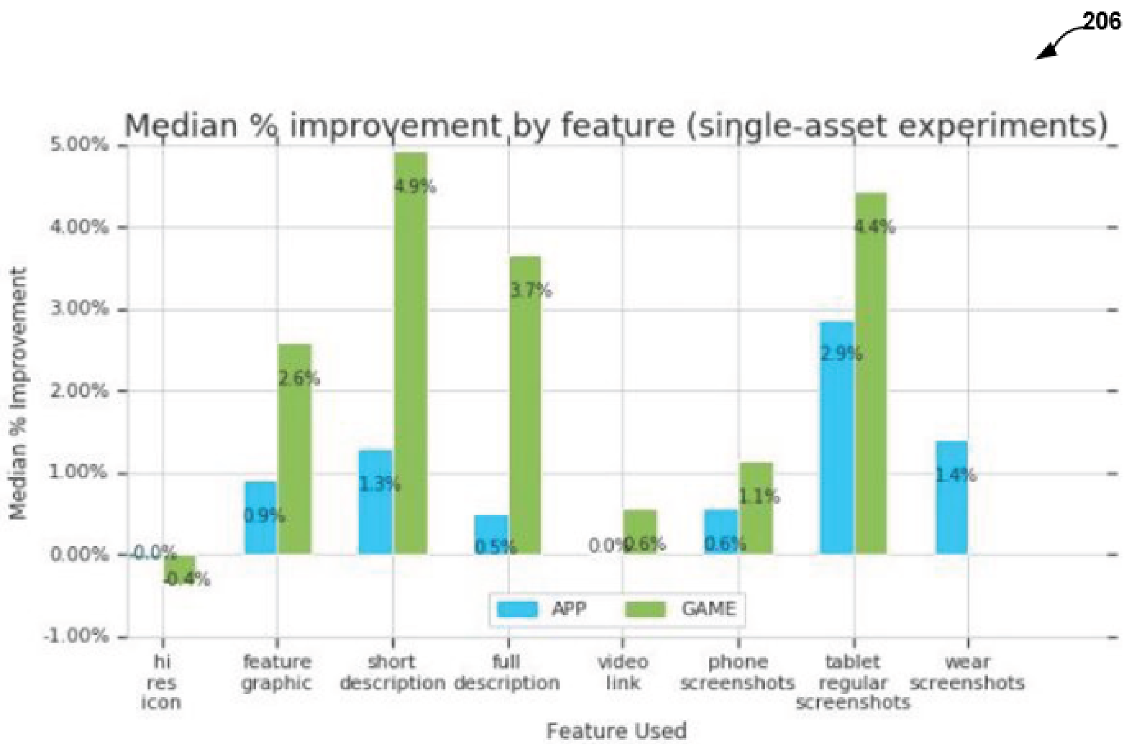

FIG. 2

FIG. 2 is a conceptual diagram illustrating another example of prediction model 206. In the example of FIG. 2, prediction model 206 represents a bar graph indicating the relationship between modifying each of the marketing assets or features (e.g., icons, graphics, short/full descriptions, links, screenshots, and the like) of all apps that are games and apps that are not games and the corresponding average change in acquisition for those types of apps. The data (e.g., statistics) illustrated in FIG. 2 is shown for purposes of illustration only.

Computing system 100 may send information (e.g., prediction model 106, 206, acquisition benchmarks, recommendations, etc.) to computing device 110 to help a user of computing device 110 modify the marketing assets of the user's app in a manner predicted to increase acquisitions for the user's app. In some examples, in response to a request (e.g., initiated by the user) from computing device 110, computing system 100 may send an indication of prediction model 106 as well as recommendation(s) and benchmark(s). Computing device 110 may then output for display (e.g., via display 112) GUI 114 of prediction model 106, recommendation(s), and/or benchmark(s).

One or more advantages of the techniques described in this disclosure include enabling a user, such as an app developer, to make a more informed decision when modifying and/or experimenting with one or more market assets of the user's app. Thus, rather than experimenting with modifications without any guidance, the user may more efficiently allocate resources (e.g., time, money, etc.) to improve acquisitions for the user's app by relying on predictions generated by the computing system. For example, in accordance with techniques of this disclosure, the computing system may analyze the historical performance of all social media apps to determine that modifying one or more marketing assets (e.g., the video and/or screenshot) of a social media app is correlated with an average increase in acquisition of 2.01% for that social media app. The computing system may further determine that modifying these one or more assets is correlated with the largest average increase in acquisition relative to modifying the other marketing assets and therefore recommend modifying these one or more assets before modifying anything else.

References

1. US Patent Application Publication No. US20170132123A1.
2. US Patent Application Publication No. US20190265971A1.
3. Martin et al., "A Survey of App Store Analysis for Software Engineering." IEEE Transactions on Software Engineering, September 2017.
4. Agicent App Development Company, "Prioritize Features For Your Mobile App MVP Agicent." Medium, March 14, 2019.