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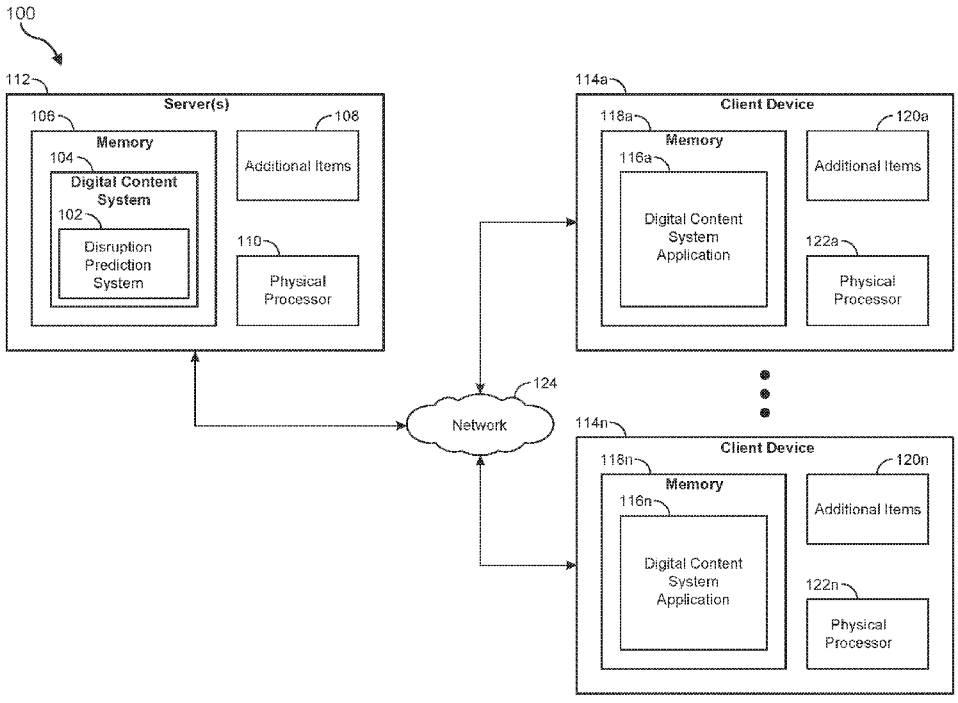



FIG. 1

(57) Abstract: The disclosed computer-implemented methods and systems leverage machine learning techniques to generate disruption predictions associated with digital media sessions. For example, the methods and systems discussed herein generate input features for a deep neural network that represent various characteristics associated with a session. By applying the deep neural network to the generated input features, the methods and systems described herein generate an accurate disruption prediction in addition to an attribution report detailing which of the characteristics represented among the input features had the greatest impact on the disruption prediction. Various other methods, systems, and computer-readable media are also disclosed.

*[Continued on next page]*

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# SYSTEMS AND METHODS FOR PREDICTING DISRUPTIONS IN DIGITAL CONTENT SYSTEM SESSIONS

## CROSS-REFERENCE

**[0001]** This application is related to U.S. Application No. 18/525,486 entitled "SYSTEMS AND METHODS FOR PREDICTING USER EXPERIENCES DURING DIGITAL CONTENT SYSTEMS SESSIONS" filed November 30, 2023 and claims the benefit of U.S. Application No. 18/524,197 entitled "SYSTEMS AND METHODS FOR PREDICTING DISRUPTIONS IN DIGITAL CONTENT SYSTEM SESSIONS" filed November 30, 2023, the disclosures of each of which are incorporated, in their entirety, by this reference.

## BACKGROUND

**[0002]** Streaming digital content is a very common and popular form of entertainment. For example, most digital content streaming platforms make client-based applications available for users to install on their client devices. Users then select and play digital media via these applications. In this way, users interact with digital media on their smartphones, tablet computers, laptops, or even via set-top devices and smart TVs.

**[0003]** In some instances, these digital content streaming applications become a significant point of pain for digital content system subscribers. To illustrate, digital content streaming applications sometimes experience instabilities (e.g., slow-downs, crashes) when new features and experiences are released. Additionally, digital content streaming applications sometimes experience instability based on geographical location from which they are operating, or the device on which they are installed.

**[0004]** There are many reasons why a digital content streaming application may experience instabilities and other problems that cause user disruptions. Despite this,

uncovering root causes of these disruptions is often technically challenging. For example, application problems may arise for a host of different reasons, and may affect users in different ways. To illustrate, a new feature release may cause a digital content streaming application to load a media item for playback slowly. For some users, this slow load may be a significant point of disruption because they pay for a high-tier subscription plan or for a super-fast Internet connection. For other users, slow loading may not be bothersome at all because they have a slow Internet connection and are used to things loading slowly.

**[0005]** In another example, a digital content streaming application may experience crashes when used on a particular type of client device. As such, users with that type of client device may experience lots of disruptions when trying to stream media, while other users with different client devices will not notice any disruption at all. As such, making an initial determination that a user disruption has occurred is often challenging because of the wide range of devices used in connection with the digital content streaming application, the wide range of user expectations associated with the digital content streaming application, and so forth.

**[0006]** Additionally, determining why the disruption occurred and trying to prevent it from happening in the future is typically a task that requires brute force analysis of vast amounts of data. For example, uncovering session disruptions often requires analysis of data at a session-level. When large numbers of users often have multiple sessions every day, such session-level data aggregates into a huge data dump. Moreover, when a digital content streaming platform is widely distributed across many regions and even countries, this data aggregates even further to create analytical tasks that are often so slow and cumbersome that results are only arrived at when an excessive amount of time has elapsed since the

disruption occurred—making any subsequent solution seem unhelpful to a user or group of users who experienced the disruption.

## SUMMARY

**[0007]** As will be described in greater detail below, the present disclosure describes implementations that predict disruptions in digital content system sessions and determine root causes for the predicted disruptions without a need for manual and/or repetitive analytical tasks. For example, implementations include generating a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system, applying a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session, determining contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction, and generating an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

**[0008]** In some implementations, generating the device-specific feature includes determining device characteristics of the client device and a digital content system account identifier associated with the client device, and generating the device-specific feature based on the device characteristics of the client device and the digital content system account identifier associated with the client device. In some examples, the device characteristics of the client device include a type of the client device, a model of the client device, a current power level of the client device, and a network connectivity status of the client device.

**[0009]** Additionally, in some implementations, generating the geographic feature includes determining geographic characteristics associated with the client device and geographic characteristics associated with the session between the client device and the digital content system, and generating the geographic feature based on the geographic characteristics associated with the client device and the geographic characteristics associated with the session between the client device and the digital content system. In some examples, geographic characteristics associated with the client device include a current location of the client device and a current time associated with the client device, and geographic characteristics associated with the session between the client device and the digital content system comprise a country and region associated with the session.

**[00010]** In some implementations, generating the application-level feature includes determining application characteristics associated with a digital content system application installed on the client device, and generating the application-level feature based on one or more of the application characteristics. In some examples, the application characteristics include a version of the digital content system application, an amount of time it takes the digital content system application to load on the client device, a number of sessions that have been initialized on the digital content system application, an amount of qualified playback time that has occurred on the digital content system application, an amount of delay the digital content system application has experienced, a number of crashes the digital content system application has experienced, and types and numbers of errors experienced by the digital content system application.

**[00011]** In at least one implementation, the disruption prediction is binary. Moreover, in one or more examples, determining the contribution levels of the device-

specific feature, the geographic feature, and the application-level feature includes determining positive contribution levels and negative contribution levels for the device-specific feature, the geographic feature, and the application-level feature relative to the disruption prediction for the session. Furthermore, in some examples, a positive contribution level indicates that an associated feature contributed to a favorable disruption prediction, and a negative contribution level indicates that an associated feature contributed to an unfavorable disruption prediction. At least one implementation further includes automatically selecting and applying one or more experience features to future sessions between the client device and the digital content system based on the attribution report.

**[00012]** Some examples described herein include a system with at least one physical processor and physical memory including computer-executable instructions that, when executed by the at least one physical processor, cause the at least one physical processor to perform various acts. In at least one example, the computer-executable instructions, when executed by the at least one physical processor, cause the at least one physical processor to perform acts including generating a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system, applying a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session, determining contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction, and generating an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

**[00013]** In some examples, the above-described method is encoded as computer-readable instructions on a computer-readable medium. In one example, the computer-readable instructions, when executed by at least one processor of a computing device, cause the computing device to generate a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system, apply a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session, determine contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction, and generate an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

**[00014]** In one or more examples, features from any of the implementations described herein are used in combination with one another in accordance with the general principles described herein. These and other implementations, features, and advantages will be more fully understood upon reading the following detailed description in conjunction with the accompanying drawings and claims.

## BRIEF DESCRIPTION OF THE DRAWINGS

**[00015]** The accompanying drawings illustrate a number of exemplary implementations and are a part of the specification. Together with the following description, these drawings demonstrate and explain various principles of the present disclosure.

**[00016]** FIG. 1 is a block diagram of an exemplary environment for implementing a disruption prediction system in accordance with one or more implementations.

**[00017]** FIG. 2 illustrates steps taken by the disruption prediction system to predict

whether a disruption has occurred during a session and determining one or more root causes for the disruption in accordance with one or more implementations.

**[00018]** FIG. 3 is a flow diagram of an exemplary computer-implemented method for predicting disruptions in sessions and determining root causes for the predicted disruptions in accordance with one or more implementations.

**[00019]** FIG. 4 is a detailed diagram of the disruption prediction system in accordance with one or more implementations.

**[00020]** Throughout the drawings, identical reference characters and descriptions indicate similar, but not necessarily identical, elements. While the exemplary implementations described herein are susceptible to various modification and alternative forms, specific embodiments have been shown by way of example in the drawings and will be described in detail herein. However, the exemplary embodiments described herein are not intended to be limited to the particular forms disclosed. Rather, the present disclosure covers all modifications, equivalents, and alternatives falling within the scope of the appended claims.

## DETAILED DESCRIPTION OF EXEMPLARY EMBODIMENTS

**[00021]** As discussed above, determining whether a disruption has occurred during a digital content system session is often extremely difficult. This is typically due to the wide range of connectivity levels, client device capabilities, membership tiers, user expectations, etc. associated with each session. What may be a disruption for one user during a digital content system session may not even register as problematic for another user. Once a disruption is identified, determining a root cause for the disruption is often even more difficult. This is particularly true when a digital content streaming system is widely distributed

among vast ranges of users, regions, countries, etc.

**[00022]** Identifying and determining root causes of digital content system session disruptions are generally computationally intensive and inefficient tasks. For example, to determine that a session disruption has occurred, session-level data is collected across hundreds or even thousands of sessions and users. Specific and diverse metrics are then analyzed using brute force techniques to potentially determine that a session disruption has occurred in one or more of the sessions. Reports are often manually configured and run multiple times until a picture develops of a session disruption and factors that led to the disruption occurring. Attempting to scale this process to larger numbers of sessions and users is often impossible because of the amount of data that must be analyzed across a wide and diverse range of users, connection levels, device types, and so forth.

**[00023]** As such, the present disclosure describes systems and methods that predict session disruptions with a high level of accuracy and illuminate root causes of the predicted disruptions such that action may be taken quickly and efficiently to solve digital content system session problems. For example, the systems and methods described herein generate targeted, session-level input features based on client device characteristics, geographic characteristics of the sessions, and characteristics of the digital content system applications installed on the client devices used during those sessions. In one or more examples, the systems and methods further include applying a disruption prediction deep neural network to the generated input features to generate a disruption prediction for individual sessions indicating whether or not disruptions occurred during those sessions. The systems and methods also include determining contribution levels of each of the input features that indicate how each feature contributed to the disruption predictions. Thus, the

disruption prediction indicates whether a disruption occurred while the contribution levels point to root causes of the disruption. From this information, the systems and methods described herein further generate an attribution report that is used in some examples to automatically select features for future sessions that avoid disturbances and enhance viewing experiences.

**[00024]** Features from any of the implementations described herein may be used in combination with one another in accordance with the general principles described herein. These and other implementations, features, and advantages will be more fully understood upon reading the following detailed description in conjunction with the accompanying drawings and claims.

**[00025]** The following will provide, with reference to FIGS. 1-4, detailed descriptions of a disruption prediction system that predicts whether a disruption occurred during a session and, if so, what specific factors and/or characteristics of the session led to the disruption. For example, an exemplary network environment is illustrated in FIG. 1 to show the disruption prediction system operating in connection with one or more client devices where digital content system sessions occur. FIG. 2 illustrates the prediction pipeline utilized by the disruption prediction system, while FIG. 3 illustrates steps taken by the disruption prediction system in prediction disruptions and disruption root causes. Finally, FIG. 4 provides additional detail with regard to the features and functionality of the disruption prediction system.

**[00026]** As just mentioned, FIG. 1 illustrates an exemplary networking environment 100 implementing aspects of the present disclosure. For example, the networking environment 100 includes server(s) 112, client devices 114a-114n, and a network 124. As

further shown, the server(s) 112 and the client devices 114a-114n include memories 106 and 118a-118n, additional items 108 and 120a-120n, and physical processors 110 and 122a-122n, respectively.

**[00027]** In one or more implementations, as shown in FIG. 1, the client devices 114a-114n are devices that are capable of digital content item playback. For example, in some implementations, the client devices 114a-114n are any of smartphones, tablets, laptop computers, desktop computers, smart wearables, virtual reality headsets, and so forth. In at least one implementation any of the client devices 114a-114n are set-top devices that receive streamed input from the server(s) 112 and provide the streamed content to a television for playback.

**[00028]** As further shown in FIG. 1, a disruption prediction system 102 is implemented as part of a digital content system 104 within the memory 106 on the server(s) 112. In one or more implementations, the digital content system 104 includes a subscription streaming service for providing digital media content to subscribers. In one or more examples, this digital media content includes non-interactive content such as movies and TV shows, as well as interactive content such as video games. Moreover, the digital content system 104 also provides static information such as menus and selectable thumbnails associated with digital media items.

**[00029]** As further shown in FIG. 1, the client devices 114a-114n include digital content system applications 116a-116n within the memories 118a-118n, respectively. In some implementations, the digital content system applications 116a-116n include some or all of the functionality of the disruption prediction system 102. In at least one implementation, the digital content system applications 116a-116n transmit session data to the disruption

prediction system 102. For example, in one or more examples, the digital content system application 116a initiates a session with the digital content system 104 in response to one or more detected user selections. Once a session is initiated, the digital content system 104 establishes a communication channel with the digital content system application 116a. Utilizing this communication channel, the digital content system 104 provides streamed media content to the digital content system application 116a while the digital content system application 116a transmits session data back to the disruption prediction system 102. In some implementations, this session data is associated with a current session. In additional implementations, the session data is associated with past sessions, or both.

**[00030]** As mentioned above, the client devices 114a-114n are communicatively coupled with the server(s) 112 through the network 124. In one or more implementations, the network 124 represents any type or form of communication network, such as the Internet, and includes one or more physical connections, such as a LAN, and/or wireless connections, such as a WAN. In some implementations, the network 124 represents a telecommunications carrier network. In at least one implementation, the network 124 represents combinations of networks.

**[00031]** Although FIG. 1 illustrates components of the exemplary networking environment 100 in one arrangement, other arrangements are possible. For example, in one implementation, the disruption prediction system 102 operates as a native application installed on any of the client devices 114a-114n. In another implementation, the disruption prediction system 102 operates across multiple servers. In additional implementations, the exemplary networking environment 100 includes any number of client devices across any number of users, regions, geofenced areas, countries, and so forth.

**[00032]** In one or more implementations, and as will be explained in greater detail below, the methods and steps performed by the disruption prediction system 102 reference multiple terms. To illustrate, in one example, a "disruption" refers to an occurrence that interferes with a session. In some examples, a disruption is performance-based. To illustrate, a disruption may occur when the digital content system application on the client device crashes or freezes. In additional examples, a disruption is preference-based. For example, a disruption may occur when a digital media item plays at a lower resolution even though the client device user is subscribed to a membership tier that allows streaming digital media items at a higher resolution. In that example, the digital content system application may be playing the digital media item without any slow-downs or freezes—the resolution is just not what the user prefers.

**[00033]** As used herein, a "session" refers to a period of time during which the digital content system application on a client device is initialized and sending and receiving data to and from the digital content system 104. In some examples, a session includes digital media item browsing and streamed playback of a selected digital media item. In additional examples, a session includes streamed playback of more than one digital media item. Additionally, in some examples, a session includes streamed video game play.

**[00034]** As mentioned above, the disruption prediction system 102 generates predictions as to whether disruptions occurred during one or more sessions and determines root causes associated with that disruption. FIG. 2 illustrates additional detail regarding the steps taken by the disruption prediction system 102 in generating disruption predictions and attribution reports as to the root causes of the predicted disruptions. For example, as shown in FIG. 2, the disruption prediction system 102 generates input features including a device-

specific feature 202, a geographic feature 204, and an application-level feature 206.

**[00035]** In one or more implementations, the disruption prediction system 102 generates the device-specific feature 202, the geographic feature 204 and the application-level feature 206 based on session-level data received from one or more client devices (e.g., the client devices 114a-114n). For example, in one or more implementations, the disruption prediction system 102 receives session data from the client device 114a (e.g., via the digital content system application 116a installed thereon) including information about the client device 114a and information about the digital content system application operating on the client device 114a.

**[00036]** In more detail, the disruption prediction system 102 receives data including or indicating device information associated with the client device 114a. For example, the disruption prediction system 102 receives device characteristics including a type of the client device 114a, an age of the client device 114a, a model of the client device 114a, a current power level of the client device 114a, processor architecture of the client device 114a, and a network connectivity status of the client device 114a. Additionally, in most examples, the disruption prediction system 102 also receives geographic information associated with the client device 114a including, but not limited to, GPS coordinates of the client device 114a, a current date and time associated with the client device 114a and/or the current session, a time zone associated with the client device 114a and/or the current session, a current region where the client device 114a and or the current session is located, and so forth.

**[00037]** Additionally, the disruption prediction system 102 receives session information for a session that occurred on the client device 114a. For example, the disruption prediction system 102 receives session information such as a duration of the session, how

many minutes of qualified playback (e.g., stable playback) occurred during the session, and any error logs associated with the session.

**[00038]** Furthermore, the disruption prediction system 102 receives information about the digital content system application 116a installed on the client device 114a. For example, the disruption prediction system 102 receives information including a version or version number of the digital content system application 116a, an amount of time it takes the digital content system application 116a to load on the client device 114a, a digital content system account identifier associated with the digital content system application 116a, a total amount of viewing time (e.g., qualified or stable playback) and/or a total number of sessions that have occurred via the digital content system application 116a, an amount of delay the digital content system application 116a has experienced, a number of crashes the digital content system application 116a has experienced, playback logs generated by the digital content system application 116a, and error logs generated by the digital content system application 116a indicating types and numbers of errors experienced by the digital content system application 116a.

**[00039]** In response to receiving all of this information, the disruption prediction system 102 generates the device-specific feature 202, the geographic feature 204, and the application-level feature 206. In one or more implementations, the disruption prediction system 102 generates the device-specific feature 202 as a representational vector reflecting device characteristics of the client device 114a. As such, in most examples, the device-specific feature 202 reflects any or all of the device characteristics discussed above. Similarly, the disruption prediction system 102 generates the geographic feature 204 as a representational vector reflecting geographic characteristics of the client device 114a, such as discussed above.

Furthermore, the disruption prediction system 102 generates the application-level feature 206 as a representational vector reflecting the application characteristics of the digital content system application 116a, such as discussed above.

**[00040]** In one or more implementations, the disruption prediction system 102 applies a disruption prediction deep learning network (DNN) 208 to the device-specific feature 202, the geographic feature 204, and the application-level feature 206. In one or more implementations, the disruption prediction DNN 208 is a binary classifier model that is trained to generate binary predictions. To illustrate, the disruption prediction system 102 trains the disruption prediction DNN 208 to generate a disruption prediction 210 that is either "Yes" (e.g., there was a disruption in the session) or "No" (e.g., there was not a disruption in the session). In some implementations, the disruption prediction system 102 trains the disruption prediction DNN 208 specifically for a single user account. In additional implementations, the disruption prediction system 102 trains the disruption prediction DNN 208 in connection with a geographic region, or a group of users of the digital content system 104. In additional implementations, the disruption prediction DNN 208 is any other type of machine learning model that can generate binary disruption predictions.

**[00041]** In one or more implementations, the disruption prediction system 102 augments the disruption prediction DNN 208 with model explainability features. For example, in one implementation, the disruption prediction system 102 incorporates SHAP values ("Shapley Additive Explanations") into the disruption prediction DNN 208. In that implementation, the disruption prediction system 102 applies SHAP methodology to determine how each of the device-specific feature 202, the geographic feature 204, and the application-level feature 206 contributed to the disruption prediction 210.

**[00042]** As such, along with the disruption prediction 210 the disruption prediction DNN 208 also outputs contribution levels 212. In one or more implementations, the contribution levels 212 indicate the degree to which each of the device-specific feature 202, the geographic feature 204, and the application-level feature 206 had a positive or negative impact on the disruption prediction 210.

**[00043]** In some implementations, the disruption prediction system 102 utilizes the disruption prediction 210 and the contribution levels 212 to generate an attribution report 214. In one or more implementations, the attribution report 214 explains characteristics of the features that had the largest impacts on the disruption prediction 210. To illustrate, in some examples, the disruption prediction system 102 generates the attribution report 214 including a ranked listing of the features that contributed most heavily to the disruption prediction 210. Additionally, in some implementations, the attribution report 214 includes ranked listings of the characteristics represented by each of the contributing factors. As such, the attribution report 214 explains the predicted disruption that occurred during the session associated with the device-specific feature 202, the geographic feature 204, and the application-level feature 206 and makes the root cause of that disruption clear.

**[00044]** As mentioned above, FIG. 3 is a flow diagram of an exemplary computer-implemented method 300 for predicting disruptions in sessions and determining root causes for the predicted disruptions. The steps shown in FIG. 3 may be performed by any suitable computer-executable code and/or computing system, including the system(s) illustrated in FIG. 4. In one example, each of the steps shown in FIG. 3 may represent an algorithm whose structure includes and/or is represented by multiple sub-steps, examples of which will be provided in greater detail below.

**[00045]** As illustrated in FIG. 3, at step 302 the disruption prediction system 102 generates a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system. For example, as discussed above, the disruption prediction system 102 generates the device-specific feature, the geographic feature, and the application-level feature by determining characteristics of the client device (e.g., the client device 114a), characteristics of the session, characteristics of the geographic location of the client device and the session, and characteristics of the digital content system application (e.g., the digital content system application 116a) operating on the client device. The disruption prediction system 102 then generates the input features (e.g., the device-specific feature, the geographic feature, and the application-level feature) based on these characteristics.

**[00046]** As further illustrated in FIG. 3, at step 304 the disruption prediction system 102 applies a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session. As discussed above, the disruption prediction system 102 generates the disruption prediction DNN (e.g., the disruption prediction DNN 208) as a binary classifier model that is trained to generate disruption predictions based on the input features discussed above. In some implementations, the disruption prediction system 102 trains the disruption prediction DNN on session-level data such that the generated disruption predictions are personalized and specific.

**[00047]** As further illustrated in FIG. 3, at step 306 the disruption prediction system 102 determines contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction. For example, in many

implementations, the disruption prediction system 102 determines how each of the input features contributed to the disruption prediction both positively and negatively. To illustrate, the disruption prediction system 102 determines that positive contribution levels indicate that a particular feature contributed to a favorable disruption prediction (e.g., the session did not experience a disruption). Conversely, the disruption prediction system 102 determines that negative contribution levels indicate that a particular feature contributed to an unfavorable disruption prediction (e.g., the session experienced a disruption).

**[00048]** As further illustrated in FIG. 3, at step 308 the disruption prediction system 102 generates an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction. For example, the disruption prediction system 102 generates the attribution report with explanations of how each of the input features—and the characteristics represented by those input features—contributed to the generated disruption prediction. As such, the attribution report gives a full picture of whether a disruption occurred during the session as well as the one or more root causes of that disruption.

**[00049]** As mentioned above, and as shown in FIG. 4, the disruption prediction system 102 performs various functions in connection with predicting disruptions in sessions and determining root causes for the predicted disruptions. FIG. 4 is a block diagram 400 of the disruption prediction system 102 operating within the memory 106 of the server(s) 112 while performing these functions. As such, FIG. 4 provides additional detail with regard to these functions. For example, in one or more implementations as shown in FIG. 4, the disruption prediction system 102 includes a feature manager 402, a disruption prediction DNN manager 404, and an attribution manager 406. As further shown in FIG. 4, the additional

items 108 stores and maintains session data 408.

**[00050]** In certain implementations, the disruption prediction system 102 represents one or more software applications, modules, or programs that, when executed by a computing device, may cause the computing device to perform one or more tasks. For example, and as will be described in greater detail below, one or more of the feature manager 402, the disruption prediction DNN manager 404, and the attribution manager 406 may represent software stored and configured to run on one or more computing devices, such as the server(s) 112. One or more of the feature manager 402, the disruption prediction DNN manager 404, or the attribution manager 406 of the disruption prediction system 102 shown in FIG. 4 may also represent all or portions of one or more special purpose computers to perform one or more tasks.

**[00051]** As mentioned above, and as shown in FIG. 4, the disruption prediction system 102 includes the feature manager 402. In one or more implementations, the feature manager 402 collects data (e.g., such as the session data 408) associated with sessions. For example, as discussed above, the feature manager 402 identifies session information associated with client devices, digital content system applications installed on those client devices, and current and previous sessions that are occurring or have occurred on those client devices.

**[00052]** From all of this information, the feature manager 402 generates input features. For example, as discussed above, the feature manager 402 generates device-specific features, geographic features, and application-level features. In most implementations, the feature manager 402 generates these features at the session level—meaning that these features are relative to a single session between a client device and the digital content system

104. In some implementations, the feature manager 402 aggregates features for sessions associated with a particular client device and/or digital content system user. For example, in one implementation, the feature manager 402 generates an application-level feature that reflects information for a current session in addition to a number of previous sessions between a single client device and the digital content system 104.

**[00053]** As mentioned above, and as shown in FIG. 4, the disruption prediction system 102 includes the disruption prediction DNN manager 404. In one or more implementations, the disruption prediction DNN manager 404 generates the disruption prediction deep neural network (e.g., the disruption prediction DNN 208). For example, as discussed above, the disruption prediction DNN manager 404 generates the disruption prediction DNN as a binary classifier that generates binary disruption predictions. In some implementations, as part of generating the disruption prediction DNN, the disruption prediction DNN manager 404 also trains the disruption prediction DNN.

**[00054]** In most examples, the disruption prediction DNN manager 404 trains the disruption prediction DNN with training input features and ground truth outputs. To illustrate, the disruption prediction DNN manager 404 applies the disruption prediction DNN to the training input features and compares the output predictions of the disruption prediction DNN to the corresponding ground truth outputs. The disruption prediction DNN manager 404 then back-propagates the results of these comparisons back through the disruption prediction DNN. The disruption prediction DNN manager 404 repeats these training epochs until the comparisons converge. Once trained, the disruption prediction DNN manager 404 applies the disruption prediction DNN to new input features at run time. In some implementations, the disruption prediction DNN manager 404 periodically retrains the disruption prediction DNN

to ensure accuracy of the generated disruption predictions.

**[00055]** In one or more implementations, the disruption prediction DNN manager 404 further employs model explainability techniques in connection with the disruption prediction DNN to determine contribution levels of the input features to the generated disruption predictions. In some examples, as discussed above, the disruption prediction DNN manager 404 applies the SHAP methodology to determine SHAP values for each of the input features and/or characteristics represented by the input features. In most implementations, the SHAP values indicate whether and how a feature or characteristic contributed positively or negatively to a disruption prediction. In at least one implementation, the disruption prediction DNN manager 404 determines that the features and/or characteristics with the most negative SHAP values are the root cause of a predicted disruption (e.g., they contributed most significantly to a predicted disruption). In additional implementations, the disruption prediction DNN manager 404 utilizes other model explainability techniques beyond or in addition to the SHAP methodology.

**[00056]** As mentioned above, and as shown in FIG. 4, the disruption prediction system 102 includes the attribution manager 406. In one or more implementations, the attribution manager 406 generates an attribution report in response to the disruption prediction DNN predicting that a disruption occurred during a particular session. For example, in some implementations, the attribution manager 406 generates the attribution report including the most significant SHAP values determined by the disruption prediction DNN manager 404.

**[00057]** In at least one implementation, the attribution manager 406 utilizes the attribution report to automatically select experience features for future sessions. To

illustrate, in one example an attribution report indicates that a session between a particular client device and the digital content system 104 experienced a disruption because the associated digital content system account was configured with a picture quality that was too high for the client device's level of network connectivity—thereby leading to freezes and re-buffers during that session. In light of this, the attribution manager 406 automatically re-configures the picture quality associated with that digital content system account such that the next session between that client device and the digital content system 104 experiences fewer or no freezes or re-buffers.

**[00058]** As shown in FIGS. 1 and 4, the server(s) 112 and the client devices 114a-114n include one or more physical processors, such as the physical processors 110 and 122a-122n, respectively. The physical processors 110 and 122a-122n generally represent any type or form of hardware-implemented processing unit capable of interpreting and/or executing computer-readable instructions. In one implementation, the physical processors 110 and 122a-122n access and/or modify one or more of the components of the disruption prediction system 102. Examples of physical processors include, without limitation, microprocessors, microcontrollers, Central Processing Units (CPUs), Field-Programmable Gate Arrays (FPGAs) that implement softcore processors, Application-Specific Integrated Circuits (ASICs), portions of one or more of the same, variations or combinations of one or more of the same, and/or any other suitable physical processor.

**[00059]** Additionally as shown in FIGS. 1 and 4, the server(s) 112 and the client devices 114a-114n include memories 106 and 118a-118n, respectively. In one or more implementations, the memories 106 and 118a-118n generally represent any type or form of volatile or non-volatile storage device or medium capable of storing data and/or computer-

readable instructions. In one example, the memories 106 and 118a-118n store, load, and/or maintain one or more of the components of the disruption prediction system 102. Examples of the memories 106 and 118a-118n include, without limitation, Random Access Memory (RAM), Read Only Memory (ROM), flash memory, Hard Disk Drives (HDDs), Solid-State Drives (SSDs), optical disk drives, caches, variations or combinations of one or more of the same, and/or any other suitable storage memory.

**[00060]** Moreover, as shown in FIG. 4, the server(s) 112 includes the additional items 108. On the server(s) 112, the additional items 108 include the session data 408. In one or more implementations, the session data 408 includes client device characteristic information, geographic characteristic information, application-level characteristic information, and so forth. As described above, the feature manager 402 accesses the session data 408 to generate input features for the disruption prediction DNN.

**[00061]** In summary, the disruption prediction system 102 avoids the inefficiencies and waste generated by other analytical systems that rely on repetitive, brute force data analysis in order to identify disruptions during sessions. As discussed above, the disruption prediction system 102 trains a disruption prediction deep neural network to generate accurate disruption predictions based on input features representing device characteristics, geographic characteristics, and digital content system application characteristics. The disruption prediction system 102 also goes a step further by utilizing model explainability techniques to determine which of the characteristics represented by the input features contributed most significantly to the disruption prediction. In this way, the disruption prediction system 102 quickly and accurately determines not only whether a disruption occurred during a session but also why the disruption occurred.

**Example Embodiments**

**[00062]** Example 1: A computer-implemented method for predicting disruptions in digital content system sessions and determining root causes for the predicted disruptions. For example, the method may include generating a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system, applying a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session, determining contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction, and generating an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

**[00063]** Example 2: The computer-implemented method of Example 1, further including generating the device-specific feature by determining device characteristics of the client device and a digital content system account identifier associated with the client device, and generating the device-specific feature based on the device characteristics of the client device and the digital content system account identifier associated with the client device.

**[00064]** Example 3: The computer-implemented method of any of Examples 1 and 2, wherein the device characteristics of the client device include a type of the client device, a model of the client device, a current power level of the client device, and a network connectivity status of the client device.

**[00065]** Example 4: The computer-implemented method of any of Examples 1-3, further including generating the geographic feature by determining geographic characteristics associated with the client device and geographic characteristics associated

with the session between the client device and the digital content system, and generating the geographic feature based on the geographic characteristics associated with the client device and the geographic characteristics associated with the session between the client device and the digital content system.

**[00066]** Example 5: The computer-implemented method of any of Examples 1-4, wherein geographic characteristics associated with the client device include a current location of the client device and a current time associated with the client device, and geographic characteristics associated with the session between the client device and the digital content system comprise a country and region associated with the session.

**[00067]** Example 6: The computer-implemented method of any of Examples 1-5, further including generating the application-level feature by determining application characteristics associated with a digital content system application installed on the client device, and generating the application-level feature based on one or more of the application characteristics.

**[00068]** Example 7: The computer-implemented method of any of Examples 1-6, wherein the application characteristics include a version of the digital content system application, an amount of time it takes the digital content system application to load on the client device, a number of sessions that have been initialized on the digital content system application, an amount of qualified playback time that has occurred on the digital content system application, an amount of delay the digital content system application has experienced, a number of crashes the digital content system application has experienced, and types and numbers of errors experienced by the digital content system application.

**[00069]** Example 8: The computer-implemented method of any of Examples 1-7,

wherein the disruption prediction is binary, and determining the contribution levels of the device-specific feature, the geographic feature, and the application-level feature includes determining positive contribution levels and negative contribution levels for the device-specific feature, the geographic feature, and the application-level feature relative to the disruption prediction for the session

**[00070]** Example 9: The computer-implemented method of any of Examples 1-8, wherein a positive contribution level indicates that an associated feature contributed to a favorable disruption prediction, and a negative contribution level indicates that an associated feature contributed to an unfavorable disruption prediction.

**[00071]** Example 10: The computer-implemented method of any of Examples 1-9, further including automatically selecting and applying one or more experience features to future sessions between the client device and the digital content system based on the attribution report.

**[00072]** In some examples, a system may include at least one processor and a physical memory including computer-executable instructions that, when executed by the at least one processor, cause the at least one processor to perform various acts. For example, the computer-executable instructions may cause the at least one processor to perform acts including generating a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system, applying a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session, determining contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction, and generating an

attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

**[00073]** In some examples, a method may be encoded as non-transitory, computer-readable instructions on a computer-readable medium. In one example, the computer-readable instructions, when executed by at least one processor of a computing device, cause the computing device to generate a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system, apply a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session, determine contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction, and generate an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

**[00074]** Unless otherwise noted, the terms "connected to" and "coupled to" (and their derivatives), as used in the specification and claims, are to be construed as permitting both direct and indirect (i.e., via other elements or components) connection. In addition, the terms "a" or "an," as used in the specification and claims, are to be construed as meaning "at least one of," Finally, for ease of use, the terms "including" and "having" (and their derivatives), as used in the specification and claims, are interchangeable with and have the same meaning as the word "comprising."

## CLAIMS

What is claimed is:

1. A computer-implemented method comprising:

generating a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system;

applying a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session;

determining contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction; and

generating an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

2. The computer-implemented method of claim 1, further comprising generating the device-specific feature by:

determining device characteristics of the client device and a digital content system account identifier associated with the client device; and

generating the device-specific feature based on the device characteristics of the client device and the digital content system account identifier associated with the client device.

3. The computer-implemented method of claim 2, wherein the device characteristics of the client device comprise a type of the client device, a model of the client

device, a current power level of the client device, and a network connectivity status of the client device.

4. The computer-implemented method of claim 1, further comprising generating the geographic feature by:

determining geographic characteristics associated with the client device and geographic characteristics associated with the session between the client device and the digital content system; and

generating the geographic feature based on the geographic characteristics associated with the client device and the geographic characteristics associated with the session between the client device and the digital content system.

5. The computer-implemented method of claim 4, wherein:

geographic characteristics associated with the client device comprise a current location of the client device and a current time associated with the client device; and

geographic characteristics associated with the session between the client device and the digital content system comprise a country and region associated with the session.

6. The computer-implemented method of claim 1, further comprising generating the application-level feature by:

determining application characteristics associated with a digital content system application installed on the client device; and

generating the application-level feature based on one or more of the application characteristics.

7. The computer-implemented method of claim 6, wherein the application characteristics comprise a version of the digital content system application, an amount of time it takes the digital content system application to load on the client device, a number of sessions that have been initialized on the digital content system application, an amount of qualified playback time that has occurred on the digital content system application, an amount of delay the digital content system application has experienced, a number of crashes the digital content system application has experienced, and types and numbers of errors experienced by the digital content system application.

8. The computer-implemented method of claim 1, wherein:

the disruption prediction is binary; and

determining the contribution levels of the device-specific feature, the geographic feature, and the application-level feature comprises determining positive contribution levels and negative contribution levels for the device-specific feature, the geographic feature, and the application-level feature relative to the disruption prediction for the session.

9. The computer-implemented method of claim 8, wherein:

a positive contribution level indicates that an associated feature contributed to a favorable disruption prediction; and

a negative contribution level indicates that an associated feature contributed to an unfavorable disruption prediction.

10. The computer-implemented method of claim 1, further comprising automatically selecting and applying one or more experience features to future sessions between the client device and the digital content system based on the attribution report.

11. A system comprising:

at least one physical processor; and

physical memory comprising computer-executable instructions that, when executed by the at least one physical processor, cause the at least one physical processor to perform acts comprising:

generating a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system;

applying a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session;

determining contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction; and

generating an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

12. The system of claim 11, further comprising computer-executable instructions that, when executed by the at least one physical processor, cause the at least one physical processor to generate the device-specific feature by:

determining device characteristics of the client device and a digital content system account identifier associated with the client device; and

generating the device-specific feature based on the device characteristics of the client device and the digital content system account identifier associated with the client device.

13. The system of claim 12, wherein the device characteristics of the client device comprise a type of the client device, a model of the client device, a current power level of the client device, and a network connectivity status of the client device.

14. The system of claim 11, further comprising computer-executable instructions that, when executed by the at least one physical processor, cause the at least one physical processor to generate the geographic feature by:

determining geographic characteristics associated with the client device and geographic characteristics associated with the session between the client device and the digital content system; and

generating the geographic feature based on the geographic characteristics associated with the client device and the geographic characteristics associated with the session between the client device and the digital content system.

15. The system of claim 14, wherein:

geographic characteristics associated with the client device comprise a current location of the client device and a current time associated with the client device; and

geographic characteristics associated with the session between the client device and the digital content system comprise a country and region associated with the session.

16. The system of claim 11, further comprising computer-executable instructions that, when executed by the at least one physical processor, cause the at least one physical processor to generate the application-level feature by:

determining application characteristics associated with a digital content system application installed on the client device; and

generating the application-level feature based on one or more of the application characteristics.

17. The system of claim 16, wherein the application characteristics comprise a version of the digital content system application, an amount of time it takes the digital content system application to load on the client device, a number of sessions that have been initialized on the digital content system application, an amount of qualified playback time that has occurred on the digital content system application, an amount of delay the digital content system application has experienced, a number of crashes the digital content system application has experienced, and types and numbers of errors experienced by the digital content system application.

18. The system of claim 11, further comprising computer-executable instructions that, when executed by the at least one physical processor, cause the at least one physical processor to determine the contribution levels of the device-specific feature, the geographic feature, and the application-level feature by determining positive contribution levels and negative contribution levels for the device-specific feature, the geographic feature, and the application-level feature relative to the disruption prediction for the session.

19. The system of claim 18, wherein:

a positive contribution level indicates that an associated feature contributed to a favorable disruption prediction; and

a negative contribution level indicates that an associated feature contributed to an unfavorable disruption prediction.

20. A non-transitory computer-readable medium comprising one or more computer-executable instructions that, when executed by at least one processor of a computing device, cause the computing device to:

generate a device-specific feature, a geographic feature, and an application-level feature associated with a session between a client device and a digital content system;

apply a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the session;

determine contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction; and

generate an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction.

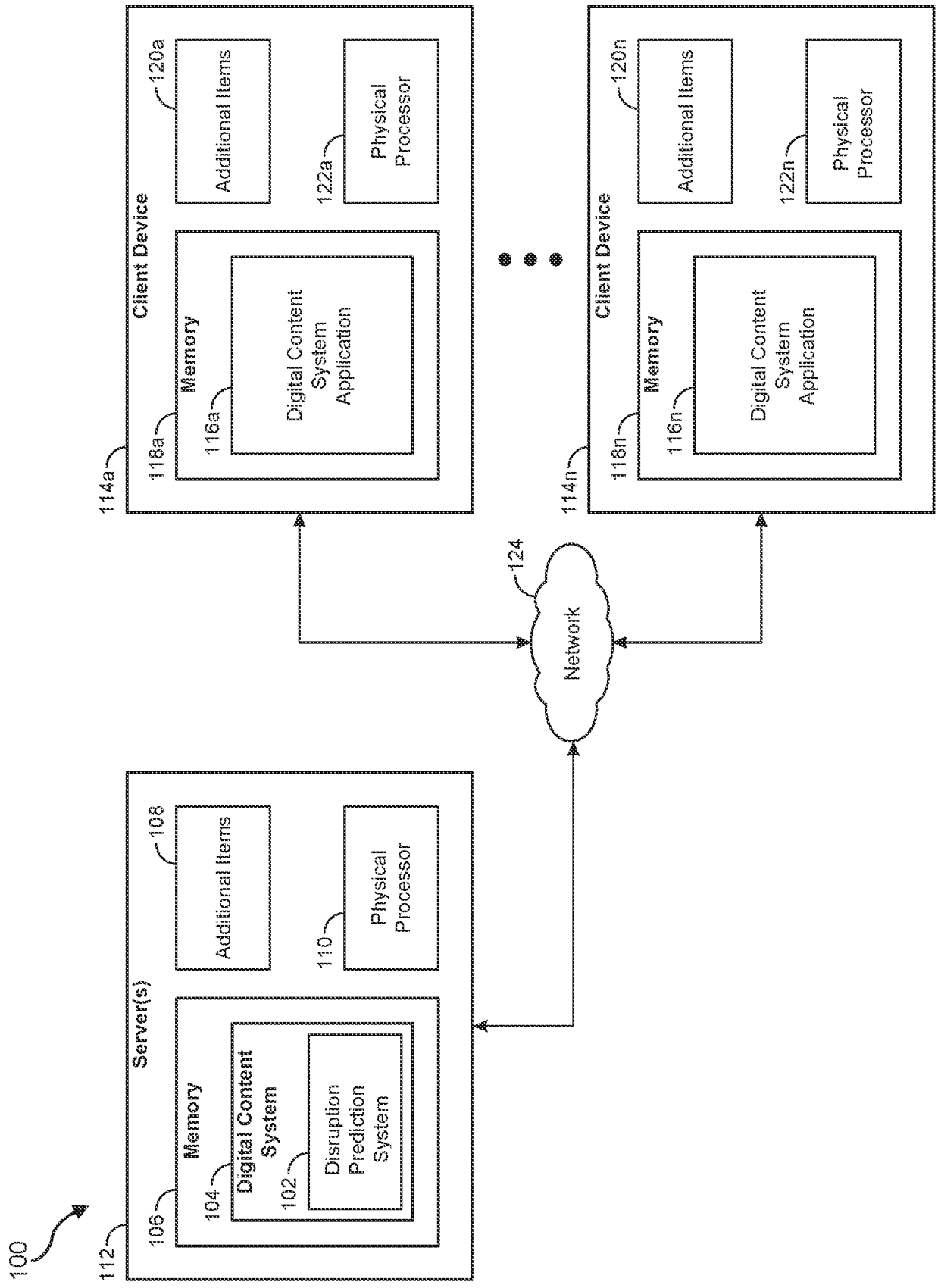

100
Server(s)
112
Memory
106
Digital Content System
104
Disruption Prediction System
102
Additional Items
108
Physical Processor
110
Network
124
Client Device
114a
Memory
118a
Digital Content System Application
116a
Additional Items
120a
Physical Processor
122a
Client Device
114n
Memory
118n
Digital Content System Application
116n
Additional Items
120n
Physical Processor
122n

FIG. 1

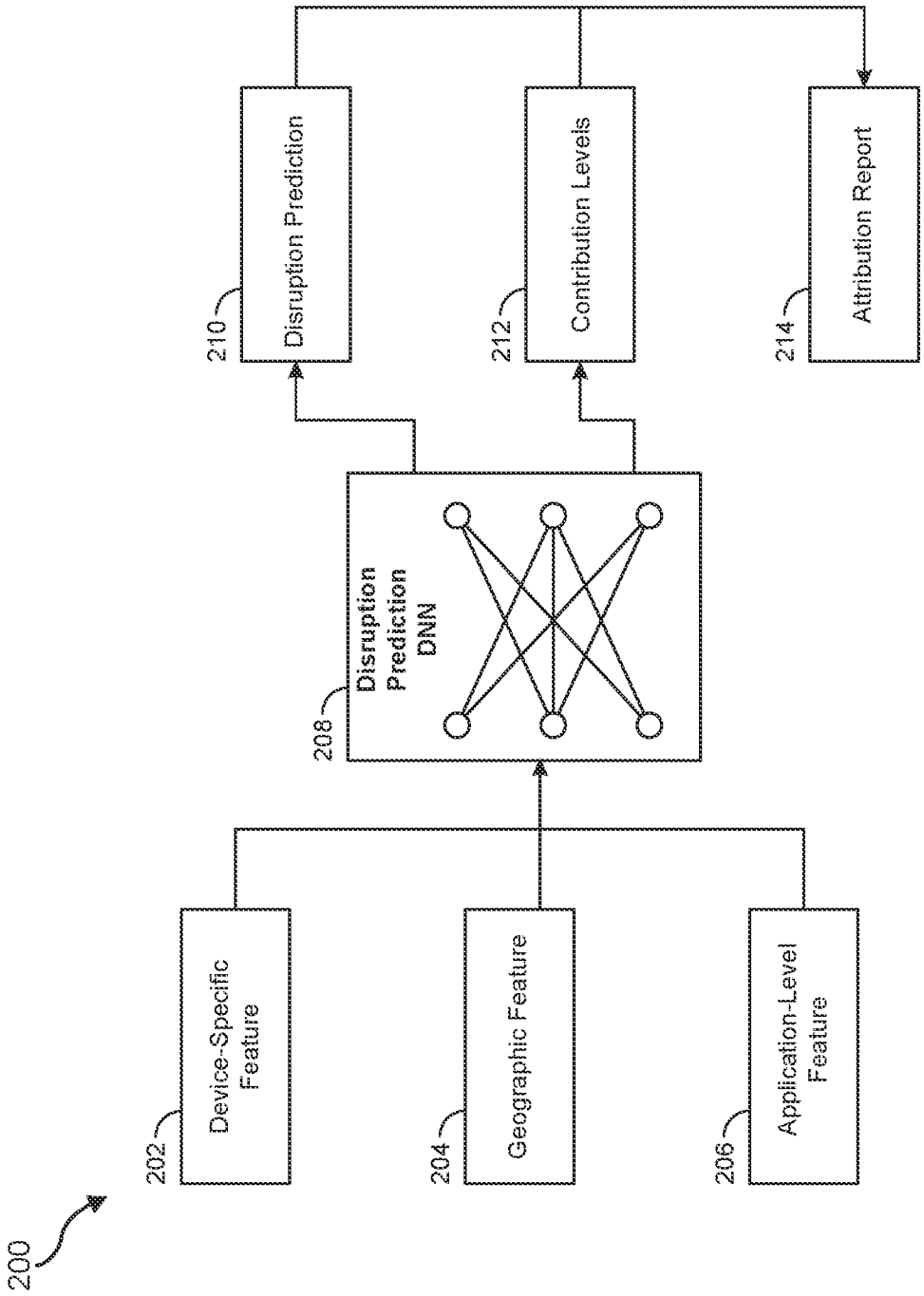

200
202
Device-Specific Feature
204
Geographic Feature
206
Application-Level Feature
208
Disruption Prediction DNN
210
Disruption Prediction
212
Contribution Levels
214
Attribution Report

FIG. 2

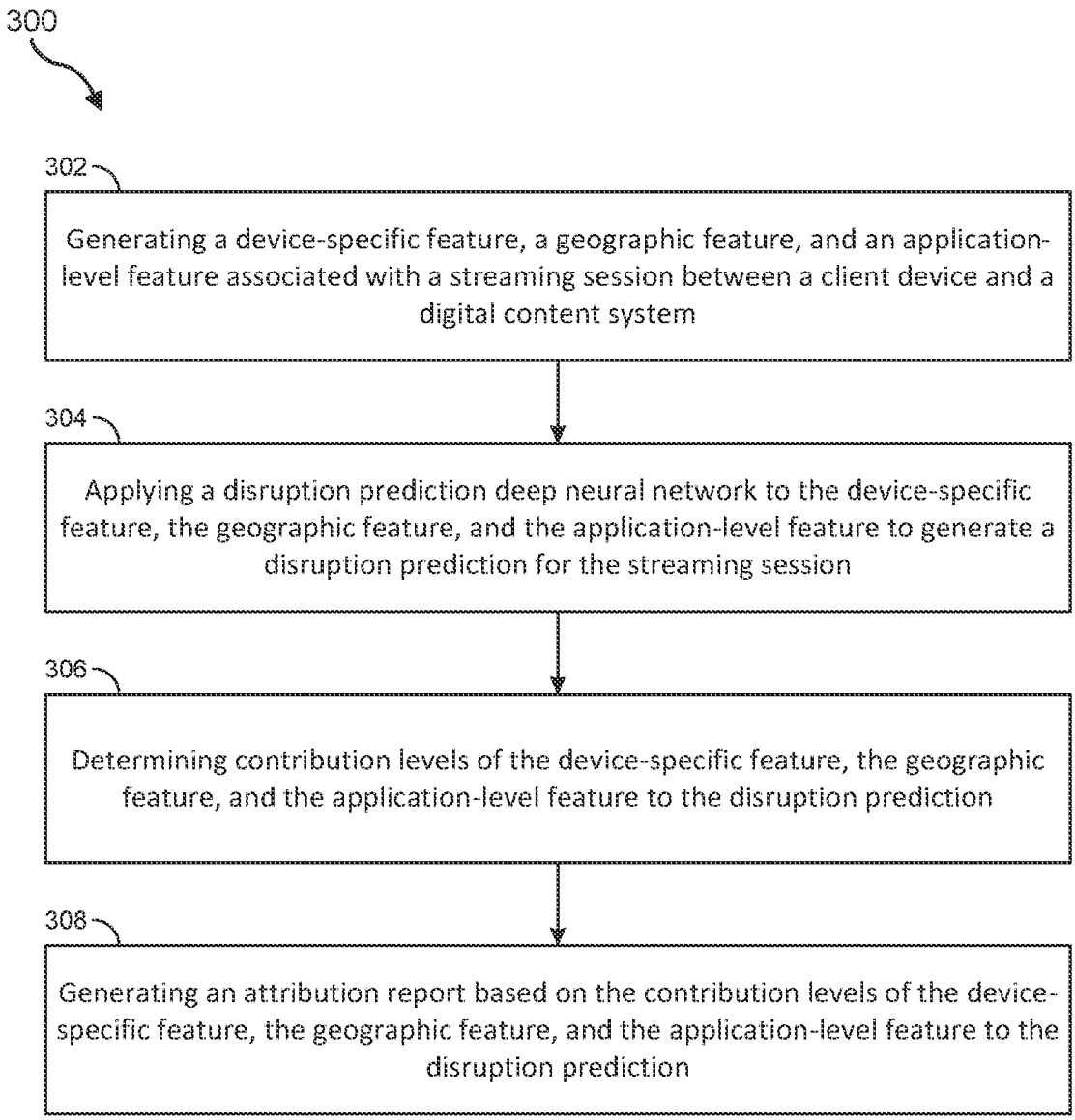

300
302
Generating a device-specific feature, a geographic feature, and an application-level feature associated with a streaming session between a client device and a digital content system
304
Applying a disruption prediction deep neural network to the device-specific feature, the geographic feature, and the application-level feature to generate a disruption prediction for the streaming session
306
Determining contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction
308
Generating an attribution report based on the contribution levels of the device-specific feature, the geographic feature, and the application-level feature to the disruption prediction

*FIG. 3*

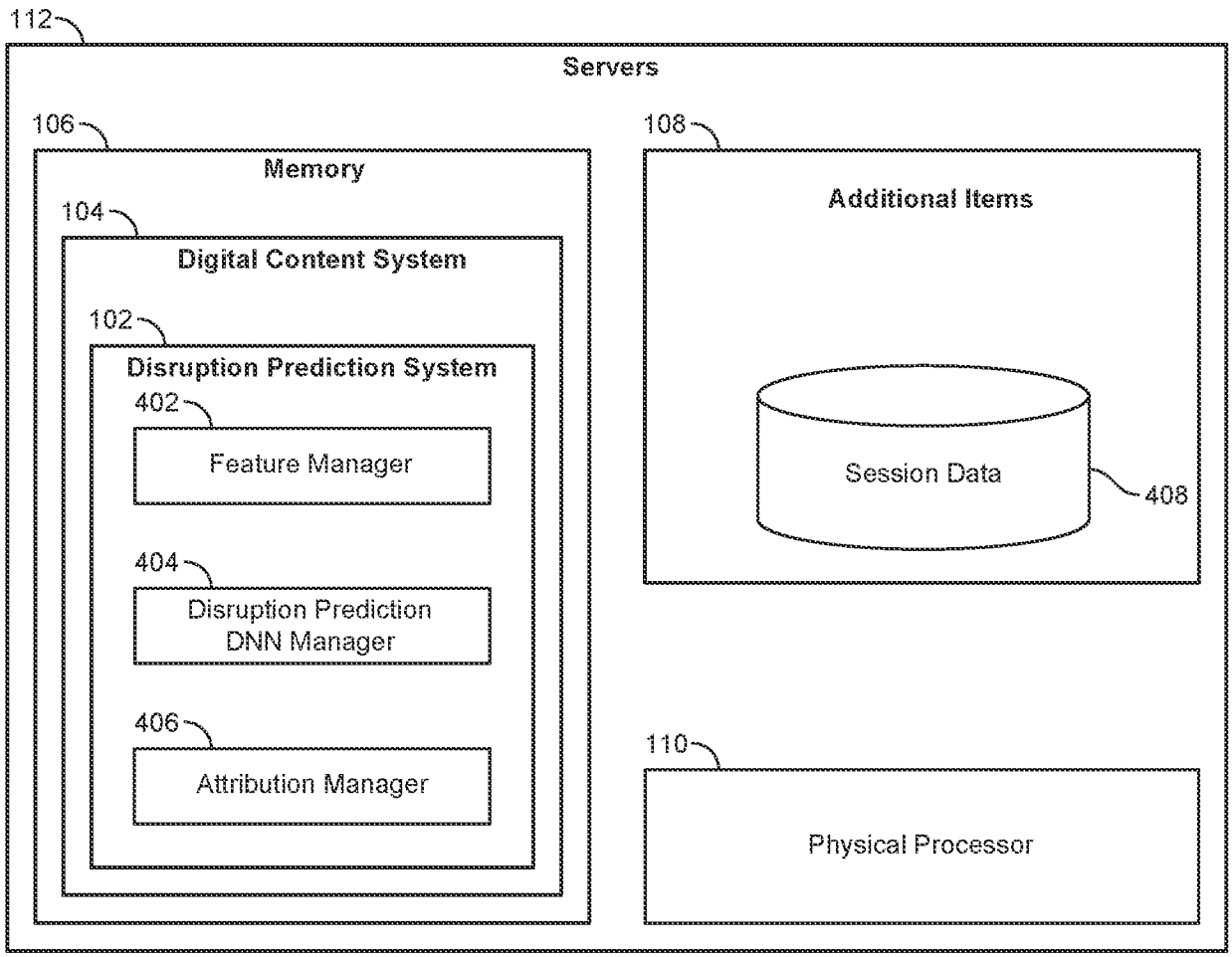

112
Servers
106
Memory
104
Digital Content System
102
Disruption Prediction System
402
Feature Manager
404
Disruption Prediction DNN Manager
406
Attribution Manager
108
Additional Items
Session Data
408
110
Physical Processor

*FIG. 4*

# INTERNATIONAL SEARCH REPORT

International application No
PCT/US2024/057765

**A. CLASSIFICATION OF SUBJECT MATTER**
INV. H04N21/25 H04N21/466
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

**B. FIELDS SEARCHED**

Minimum documentation searched (classification system followed by classification symbols)
H04N G06N

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)
EPO-Internal, WPI Data

**C. DOCUMENTS CONSIDERED TO BE RELEVANT**

| Category* | Citation of document, with indication, where appropriate, of the relevant passages | Relevant to claim No. |
|---|---|---|
| X | Wehner Nikolas ET AL: "Explainable Data-Driven QoE Modelling with XAI ¦ IEEE Conference Publication ¦ IEEE Xplore", , 18 July 2023 (2023-07-18), pages 112-115, XP093249715, Retrieved from the Internet: URL:https://ieeexplore.ieee.org/abstract/document/10178499/authors#authors [retrieved on 2025-02-12] the whole document | 1-20 |
| X | US 2023/362420 A1 (MANG XIAOWEN [US] ET AL) 9 November 2023 (2023-11-09) paragraphs [0046], [0059], [0089], [0099] - [0100] | 1-20 |

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[x] Further documents are listed in the continuation of Box C.

[x] See patent family annex.

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"P" document published prior to the international filing date but later than the priority date claimed

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"X" document of particular relevance;; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

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"&" document member of the same patent family

| Date of the actual completion of the international search | Date of mailing of the international search report |
|---|---|
| 20 February 2025 | 11/03/2025 |

| Name and mailing address of the ISA/ | Authorized officer |
|---|---|
| European Patent Office, P.B. 5818 Patentlaan 2<br>NL - 2280 HV Rijswijk<br>Tel. (+31-70) 340-2040,<br>Fax: (+31-70) 340-3016 | Bertrand, Frédéric |

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Form PCT/ISA/210 (second sheet) (April 2005)

# INTERNATIONAL SEARCH REPORT

International application No
PCT/US2024/057765

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

| Category* | Citation of document, with indication, where appropriate, of the relevant passages | Relevant to claim No. |
|---|---|---|
| A | US 2022/405603 A1 (MANCHANDA SANJEEV [IN] ET AL) 22 December 2022 (2022-12-22) the whole document | 1-20 |

1

# INTERNATIONAL SEARCH REPORT

**Information on patent family members**

**International application No**
PCT/US2024/057765

| Patent document cited in search report | Publication date | Patent family member(s) | Publication date |
|---|---|---|---|
| US 2023362420 A1 | 09-11-2023 | NONE | |
| US 2022405603 A1 | 22-12-2022 | NONE | |