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(71) Applicant(s): Sony Interactive Entertainment Inc. 1-7-1 Konan, Minato-ku, Tokyo 108-0075, Japan		(56) Documents Cited:		
(72) Inventor(s): Oliver George Hume		WO 2014/107786 A1 US 20150099589 A1		
(74) Agent and/or Address for Service: D Young & Co LLP 120 Holborn, LONDON, EC1N 2DY, United Kingdom		US 20140274355 A1 US 20090197681 A1		
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(54) Title of the Invention: **A videogame search method and apparatus**
Abstract Title: **Videogame search and recommendation system using gameplay data**

(57) A method of videogame searching that comprises obtaining a plurality of different predetermined indicators of play behaviour of a user detected during play of one or more different videogames, generating a model of playing preferences of the player based on the play behaviour, and using the generated model to select a new videogame to recommend to the user from a set of videogames, based upon some or all of the respective possible indicators of play behaviour associated with each new videogame. The indicators of gameplay behaviour could comprise trophies or achievements that have been earned by the player.

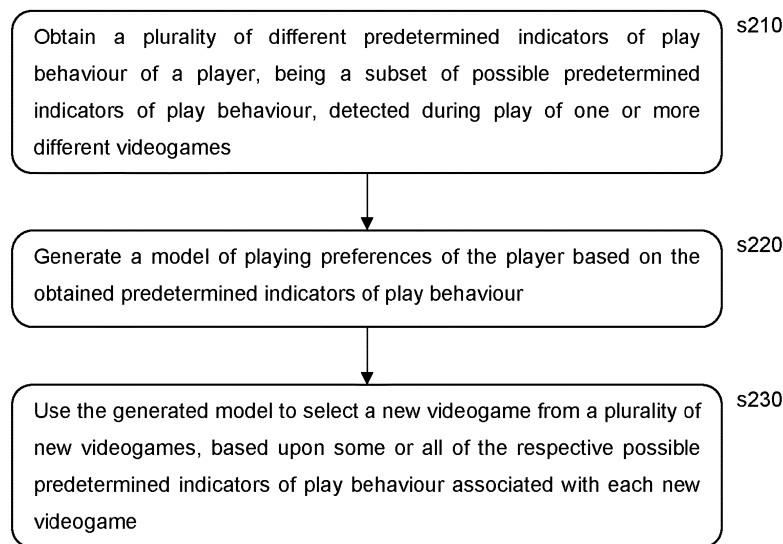


Figure 2

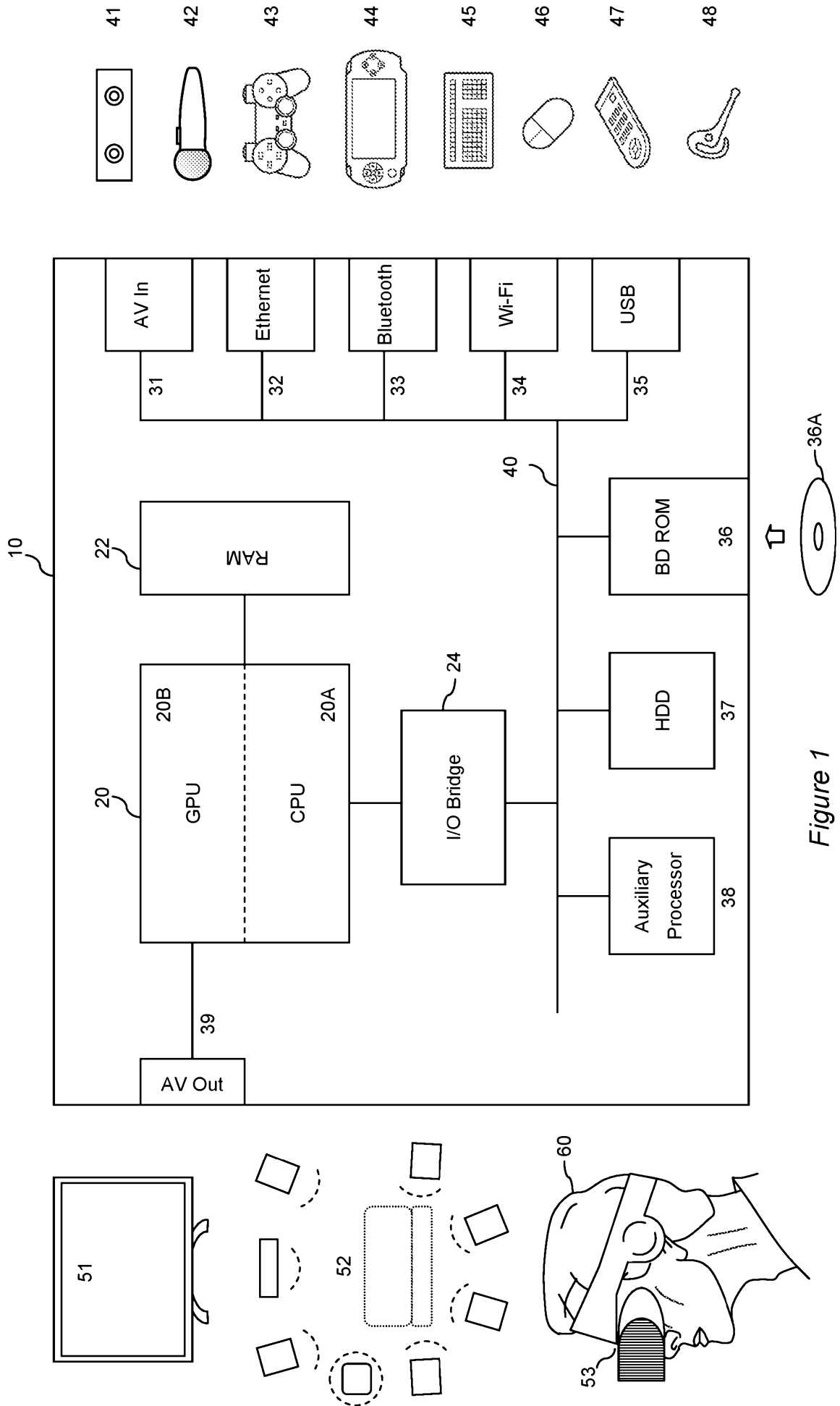
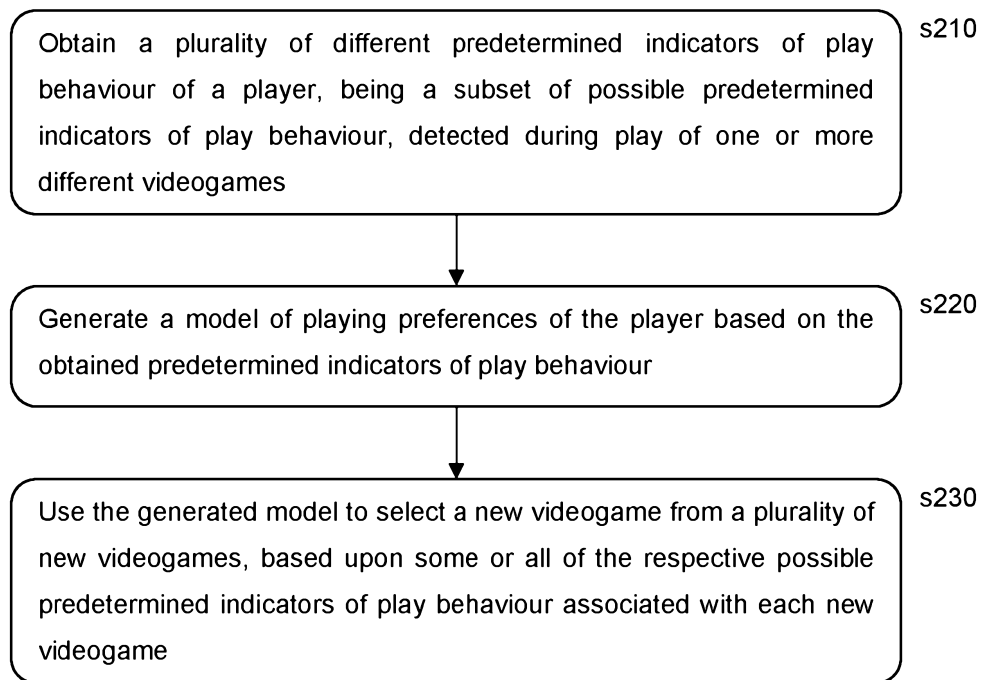


Figure 1

*Figure 2*

A VIDEOGAME SEARCH METHOD AND APPARATUS

The present invention relates to a videogame search method and apparatus.

Like other media such as music, film, TV, and books, it will be appreciated that videogames cover a diverse set of genres, and similarly vary widely in quality, budget and depth.

5 Consequently before choosing to engage with a videogame, a user may wish to read a review of the game, or watch a trailer for the game, in much the same manner as they might do for a film or TV programme.

However, the relevance of a review to a given user will depend upon them sharing similar tastes to the reviewer. Meanwhile, trailers can potentially be unrepresentative of a game due to
10 emphasising particular highlights rather than more representative aspects of gameplay, or to avoid revealing significant plot points that might otherwise have engaged the player.

As a result it is difficult to rely solely upon reviews or games trailers when making a decision on whether to engage with a given game.

This problem is compounded by the number of games available, and a user's limited time to play
15 them, or indeed assess them beforehand; by way of example, games distribution platform Steam® lists over 5000 different games, making the discovery of a particular game by a particular user a potentially arduous task.

Meanwhile it has been estimated that 37% of the games purchased from Steam® have not subsequently been played, meaning that most users own games they have yet to engage with.
20 Sometimes this is because the game was part of a bundle and not the focus of purchase, but often it is because games are bought during a time-limited sale, but the user subsequently does not find the time to prioritise playing them.

Comparable statistics can be expected for other games platforms.

As a consequence, the user may already own games that they are not aware that they would
25 enjoy playing, and most likely does not own some games that they would otherwise enjoy playing.

Clearly there is need to assist the user in searching for such games to play.

The present invention seeks to address or mitigate this problem.

In a first aspect, a method of videogame search is provided in accordance with claim 1.

In another aspect, a videogame search apparatus is provided in accordance with claim 13.

Further respective aspects and features of the invention are defined in the appended claims.

Embodiments of the present invention will now be described by way of example with reference to the accompanying drawings, in which:

- 5 - Figure 1 is a schematic diagram of videogame search apparatus in accordance with embodiments of the present invention; and
- Figure 2 is a flow diagram of a method of videogame search in accordance with embodiments of the present invention.

10 A videogame search method and apparatus are disclosed. In the following description, a number of specific details are presented in order to provide a thorough understanding of the embodiments of the present invention. It will be apparent, however, to a person skilled in the art that these specific details need not be employed to practice the present invention. Conversely, specific details known to the person skilled in the art are omitted for the purposes of clarity where appropriate.

15 A videogame search apparatus that may employ the method(s) described herein will typically be a server or similar general-purpose computer running suitable software instructions encapsulating the method(s), and operated by a service provider to which a video game playing device owned by a user may connect, for example via a network such as the Internet. Alternatively or in addition, the videogame search apparatus may comprise the videogame
20 playing device owned by the user. Alternatively or in addition, both apparatuses may operate cooperatively to implement the videogame search apparatus, or the videogame playing device may implement the method(s) locally (optionally only on games already owned by the user).

 As an example of the videogame playing device, and also in general terms exemplary of a general purpose computer or server, Figure 1 schematically illustrates the overall system
25 architecture of a Sony® PlayStation 4® entertainment device. A system unit 10 is provided, with various peripheral devices connectable to the system unit.

 The system unit 10 comprises an accelerated processing unit (APU) 20 being a single chip that in turn comprises a central processing unit (CPU) 20A and a graphics processing unit (GPU) 20B. The APU 20 has access to a random access memory (RAM) unit 22.

30 The APU 20 communicates with a bus 40, optionally via an I/O bridge 24, which may be a discreet component or part of the APU 20.

Connected to the bus 40 are data storage components such as a hard disk drive 37, and a Blu-ray ® drive 36 operable to access data on compatible optical discs 36A. Additionally the RAM unit 22 may communicate with the bus 40.

Optionally also connected to the bus 40 is an auxiliary processor 38. The auxiliary processor 38
5 may be provided to run or support the operating system.

The system unit 10 communicates with peripheral devices as appropriate via an audio/visual input port 31, an Ethernet ® port 32, a Bluetooth ® wireless link 33, a Wi-Fi ® wireless link 34, or one or more universal serial bus (USB) ports 35. Audio and video may be output via an AV output 39, such as an HDMI port.

10 The peripheral devices may include a monoscopic or stereoscopic video camera 41 such as the PlayStation Eye ®; wand-style videogame controllers 42 such as the PlayStation Move ® and conventional handheld videogame controllers 43 such as the DualShock 4 ®; portable entertainment devices 44 such as the PlayStation Portable ® and PlayStation Vita ®; a keyboard 45 and/or a mouse 46; a media controller 47, for example in the form of a remote control; and a
15 headset 48. Other peripheral devices may similarly be considered such as a printer, or a 3D printer (not shown).

The GPU 20B, optionally in conjunction with the CPU 20A, generates video images and audio for output via the AV output 39. Optionally the audio may be generated in conjunction with or instead by an audio processor (not shown).

20 The video and optionally the audio may be presented to a television 51. Where supported by the television, the video may be stereoscopic. The audio may be presented to a home cinema system 52 in one of a number of formats such as stereo, 5.1 surround sound or 7.1 surround sound. Video and audio may likewise be presented to a head mounted display unit 53 worn by a user 60.

In operation, the entertainment device defaults to an operating system such as a variant of
25 FreeBSD 9.0. The operating system may run on the CPU 20A, the auxiliary processor 38, or a mixture of the two. The operating system provides the user with a graphical user interface such as the PlayStation Dynamic Menu. The menu allows the user to access operating system features and to select games and optionally other content.

Referring now to Figure 2, in an embodiment of the present invention the server and/or the
30 videogame playing apparatus may implement a method of videogame searching, comprising:

a first step S210 of obtaining a plurality of different predetermined indicators of play behaviour of a player, being a subset of possible predetermined indicators of play behaviour, detected during play of one or more different videogames;

5 a second step S220 generating a model of playing preferences of the player based on the obtained predetermined indicators of play behaviour; and

a third step S230 using the generated model to search for a new videogame from a plurality of new videogames, based upon some or all of the respective possible predetermined indicators of play behaviour associated with each new videogame.

10 In the first step, the plurality of different predetermined indicators of play behaviour of a player may be obtained in one or more ways for a given videogame. For example, various parameters associated with the game state of a game may be obtained, such as a player character's average health level, percentage of shots that hit a valid target, time taken to complete a level, number of items collected, percentage of map explored, percentage of enemies killed, percentage of non-player characters interacted with, choice of player character development within a skill tree,
15 character class, in-game micro-transactions, relative time spent in solo and multiplayer campaigns, and any other measurable aspect of a game that can serve to differentiate one player's playing style, choices, and achievements from another players, may be obtained. Such game state information provides direct and/or indirect indications of a player's play behaviour.

20 However it will be appreciated that extracting some of this information from a given videogame may be difficult if the game is not specifically adapted to output the information in a manner recognised by the videogame search apparatus (for example via an API), as is likely to be the case for an existing back catalogue of games, and any such games already played by the player. Whilst it may be possible to interrogate certain memory addresses within such legacy games to obtain values relevant to parameters such as those above, this may be difficult, particularly if the
25 game developer is no longer available to provide these memory addresses, or if for any other reason they cannot provide such memory addresses. It may also add complexity to any game patching process that may cause such memory addresses, or internal representations of such information, to change during a game's lifetime.

30 Hence alternatively or in addition, to meet the need for backward compatibility with existing games, and for simplicity in achieving wide adoption of the technique for current and future games, the predetermined indicators of play behaviour of a player may take the form of trophies credited to the player by that videogame.

It will be appreciated that trophies have been in widespread use for some time. Moreover, it can be appreciated that trophies are direct or indirect acknowledgements of certain behaviours and/or achievements (potentially both positive and negative) within a game. Different trophies will be credited to a player depending on how much of a game they play (which in turn is typically an indicator of how much they enjoy the game), and how they play. Hence for example a player who likes to explore a game environment may receive a trophy for finding certain secrets or collecting a certain number of items of treasure, whilst a player who likes to run around with guns blazing may receive a trophy for clearing an area within a certain period of time, or shooting a certain number of enemies. A typical game will have between 30 and 60 trophies, enabling a relatively nuanced reflection of gameplay by the user, depending on which of these trophies they earn.

Hence in the first step s210, the set of possible predetermined indicators of play behaviour in a given game may correspond to all the available trophies associated with that game, whilst the obtained predetermined indicators of play behaviour of a player for that game may correspond to those trophies credited to the player during their play of the game.

As noted above, optionally other possible predetermined indicators of play may be obtained from various in game parameters.

It will be appreciated that trophies are typically relevant to the subject matter of an individual videogame, and described in terms consistent with the language and ethos of the individual game. However, as noted above, these trophies typically nevertheless reflect certain universal traits, as they are expressed within the specific game these traits may relate to players who are completionists, liking to collect resources or bonus objects, or players who enjoy competing side-quests, rather than running through the main story arc of a game. Some traits might be genre specific, such as behaviours and achievements peculiar to racing games, whilst some traits might span genres, so that some behaviours and achievements found in racing games also apply to platform games or auto-running games. Finally some traits may be universal most or all genres, such as the tendency to save games frequently, or to replay completed levels (for example to improve performance).

It can be envisaged therefore that the trophies of a specific videogame can be mapped to a global set of predetermined indicators of play behaviour. Put another way, specific trophies can be at least approximately mapped to a larger a set of archetypal trophies. This set may comprise any number of archetypes, but for the purposes of explanation there may be 256 archetypal trophies,

as a non-limiting example. Hence a specific game's trophies could each be associated with a single byte indicating the corresponding archetype. Optionally, a trophy could indicate a correspondence with several archetypes, and further optionally could indicate a degree of correspondence with one or more archetypes (for example, on a scale of 1 to 256).

- 5 Hence for example a trophy for stealing all the treasure in an enemy camp could map to an archetypal trophy for completed loot collection, and may also indicate a degree of correspondence with a player-style alignment chart, for example as 'chaotic good'. Meanwhile stealing all the treasure from a set of villagers could also map to an archetypal trophy for completed loot collection, but may also indicate a degree of correspondence to 'chaotic evil'.
- 10 It will be appreciated that a combination of trophies may thus contribute to a global trophy profile, but also to a heat-map of player alignment.

A typical 3x3 player alignment chart may comprise the categories:

Lawful Good	Neutral Good	Chaotic Good
Lawful Neutral	Neutral Neutral	Chaotic Neutral
Lawful Evil	Neutral Evil	Chaotic Evil

- 15 A more nuanced 5x5 chart may insert 'social' and 'rebel' columns on either side of the 'neutral' column, and similarly add 'moral' and 'impure' rows on either side of the 'neutral' row. In either case, each cell can be thought of as another example of an archetypal trophy.

- It will be appreciated that these are just examples. It will also be appreciated that a different alignment chart may be used for games that have less freedom of choice, for example progressing from 'slow' to 'fast' on one axis, and from 'Follows Path' to 'Strays'. This could be
- 20 used for example to characterise players who explore a race track, platform game or open world, either to find shortcuts or to find extra content.

Other examples will be understood by the person skilled in the art.

It will be appreciated that multiple trophies may map to a single archetype, both within a single game and when aggregated over a plurality of games.

- 25 Thus more generally, the global set of predetermined indicators of play behaviour that is maintained for a given player may take the form of a histogram, with counts being added as appropriate to histogram bins for given archetypal trophies. Where the mapping from a game is a

simple flag (e.g. a byte indicating the given trophy in the global set) then the histogram may be a simple count. Where the mappings include a degree of correspondence value, then this value may be added to the histogram bin for a given trophy in the global set. Where, for whatever reason, some games use the flag scheme and others provide correspondence values, then a predetermined correspondence value may be used in lieu of a flag count. This may assist by making it possible to only assign a global trophy to trophies of older games, whilst providing more informative data for new games.

Hence the histogram for a given player may take the form of a binary set, a set of values, or a combination of the two. Optionally where the histogram comprises non-binary values, these may be normalised as a function of the number of games that contributed to the histogram count and optionally also the range values used.

Hence for example if a set of five of the player's games were analysed to create a histogram, and in two of these the user was credited with a trophy corresponding to 'completed loot collection', then the normalised value would be 0.4 (i.e. two fifths). Meanwhile if a correspondence value was also used to that, for example, only a 50% correspondence was given (e.g. a score of 128 out of 256), then the normalised value would be 0.2 (i.e. $(128 * 2) / (256 * 5)$).

As will be described in more detail later herein, at least a subset of a user's existing games (i.e. games they have played) are analysed to populate the predetermined indicators of play behaviour of a player, which as noted above typically then takes the form of a histogram corresponding to global set of trophies, populated by a mapping of trophies credited to the player during play of the analysed games.

Turning now to the second step s220, several methods of generating the model may be employed, with either a single method being employed, or a sequence of methods being employed, or optionally a combination of methods at once, as will now be described.

In a first method, generating a model of playing preferences of the player comprises the step of training a machine learning system, using the obtained predetermined indicators of play behaviour for first subset of the player's videogames, to predict possible predetermined indicators of play behaviour in a second subset of the player's videogames.

The machine learning system may be a neural network such as a 'deep learning' network, or a Bayesian expert system, or any suitable scheme operable to learn a correlation between a first set

of data points and a second set of one or more data points, such as a genetic algorithm, a decision tree learning algorithm, an associative rule learning scheme, or the like.

In the first method, the credited trophies of a subset of games played by the player are provided as an input to the machine learning system. Typically they are first mapped to a global representation scheme, as described previously, and presented as a training set either for each individual game or as an aggregate, as described previously. The target output is a second subset of games played by the player, again typically mapped to a global representation scheme, as described previously, and typically presented as an aggregate (but optionally as individual games).

Hence in a first example, the obtained predetermined indicators of play behaviour for a first subset of the player's videogames (in the form of individual trophy sets represented using a global scheme) are input, and the machine learning system learns to predict a global representation scheme as the target output.

Similarly as an example, at least a majority of the videogames in the first subset of videogames was purchased by the player earlier than the videogames in the second subset of videogames.

Together these provide a means of predicting any change in preferences of the player over the time frame between the first and second sets.

Meanwhile in a second example, the obtained predetermined indicators of play behaviour for a first subset of the player's videogames (in the form of individual trophy sets represented using a global scheme) are input, and the machine learning system learns to predict obtained predetermined indicators of play behaviour for a second subset of the player's videogames (in the form of individual trophy sets represented using a global scheme) as the target.

In this case, to provide some correlation between input and target, tags associated with the games (for example provided by the developer, publisher, and/or provided by users when reviewing the game) may be used to select first and second subsets of games having similar genres (e.g. 'racing') or features (e.g. 'female protagonist'). Different pairs of subsets may be used to generate different models.

Optionally the above examples can be combined. For example an aggregate input of a first subset of games, or an input for individual game from that subset (for example based on a random half of games played), may be concatenated with an input for an individual game from a tagged subset to create an input, and this may then be trained against individual games (and/or an

aggregate) from a tagged second subset. Similarly, just some features from the aggregate data (such as for example those corresponding to an alignment chart, and/or features relating to the tags) may be used. In either case, this enables any predictive feature of trophies from other games played by the the user to contribute to a prediction of play behaviour within the tagged set of games.

In any of the above cases, the result is a machine learning model that, for a given input set of games played by a player, can predict what predetermined indicators of play behaviour of a player may be credited to the player for a newer game, and/or a game having similar descriptive tags and/or genre (depending on the subsets selected).

As will be explained in more detail later, a game repository server may then compare these predicted indicators of play behaviour to the trophy lists for candidate new games, in order to find the closest match, or a predetermined number of close matches. In a refinement of this approach, an aggregate measure of the trophies actually awarded to other players of a respective candidate game (which may be tracked by the game repository server) may be compared with the prediction to find a closest match. The corpus of other players may itself be selected according to the demographics of the player themselves (e.g. age, gender, nationality and the like). Alternatively or in addition, the corpus of players may be selected as being those who own a predetermined threshold number of the same games as the player, so as to improve the likelihood that they represent a similar playing style/ gaming taste.

It will be appreciated that the above functionality of the game repository server may be performed locally, for example when a player has a library of games, but has only played a limited percentage of them, which as noted previously is often the case. In this scenario the candidate new games can include games that the player already owns, and/or games that the player does not yet own.

In a second method, alternatively or in addition inputs similar to those described for the first method may be provided to a machine learning system. Hence for example indicators for individual games represented in the global scheme, optionally with aggregate indicators, are input to the machine learning system.

In this case, the target output for the machine learning system is a normalised period of time played by the player for the input individual game.

The player's own time playing a game is typically recorded by the system and also reported to a game repository server. Meanwhile the game repository server may compile statistics on play duration across a corpus of players, including average play time.

Statistical outliers may be dropped from the learning scheme. Hence games that have only been played by the player for less than N minutes may not be used for training, and similarly play times of less than M minutes within the corpus may not contribute to the statistics. The main cause of such short play times are that a user may install a game and then play it for a few minutes and/or past an introductory stage to ensure that it works to their satisfaction, but then leave it to play properly at a later date.

The player's time spent playing a game is typically a proxy indication of how much they enjoy it, or engage with it. This time may be normalised with reference to a mean time spent playing by the corpus of users. Hence, generally, if the user's time is less than the average, then they did not enjoy the game, whilst if the user's time is more than the average then they did enjoy the game.

Alternatively or in addition to using a mean duration of time spent by a corpus of players on the respective videogame, an expected duration of time to spend on the videogame may be provided by the videogame developer.

In addition, playtimes indicative of a strong positive or strong negative opinion may be determined based on user reviews (for example a mark out of five) accessible by the game repository server and the associated playtimes of those users. Hence for example potentially five Gaussian distributions for play times associated with for each mark out of five may be determined, and based on these, the probability of someone with the user's time scoring each of these marks out of five may be calculated, and this set of values may provided as the target for training machine learning on the particular game. For different scoring metrics, different options may be possible, such as a predicted percentage score or the like. In this way the opinions of a corpus of players and the user's own time spent with a game may be combined in the training target. Over training on multiple games as inputs, any correspondence between input representations and likely engagement / scoring of a game can be learned. Alternatively or in addition, as a training target the player's play time may be normalised with respect to a subset of a predetermined number of players having the most similar distribution of trophies to the player, as these can be expected to be the most similar players, and might be expected to have a similar

play time; any lack of correlation between playtime and trophies may thus be detected based on the variability of output on this target value.

Once trained, the trophies for a candidate new game can be input to the trained model, which will output a normalised prediction of play time spent and/or probability of a given mark out of five etc., indicating the user's likely enjoyment of the game. Again in a refinement of this technique, the distribution of trophies actually awarded to a corpus of players may be input to the trained model, or in a further refinement, the distribution of trophies actually awarded to a corpus of players who have provided a high rating for the game may be input to the trained model, so as to provide a more realistic proxy for a positive user experience of the game, and/or to a corpus of players with a similar set of played games in their library to those of the current player.

Games that score well are thus likely to be enjoyed by the player for whom the model was trained.

It will be appreciated that the target outputs of the second scheme can be concatenated with those of the first method to provide a combined machine learning scheme.

In a third method, alternatively or in addition inputs similar to those described for the first two methods may be provided to a machine learning system. Hence for example indicators for individual games represented in the global scheme, optionally with aggregate indicators, are input to the machine learning system.

In this case, the target value is a representation of engagement with a game. It will be appreciated that the amount of time played, as in the second method, is also a representation of engagement with a game; however it can only provide a representation for games that have been played. In the third method, the degree of engagement corresponds to a degree of interest.

Interest in games may be ranked in roughly the following order:

- Games actually played
- Games installed by not yet played
- Games purchased but not yet installed
- Games on a watch list or wish list
- Games for which a trailer or other detail has been intentionally viewed by the player
- Games clicked on for additional information
- Games presented to the user on the basis of any suggestion scheme
- Other games

Some categories in the above list may be missing or omitted, depending on the games platform used.

The predetermined indicators of play behaviour of a player for played games may be input and trained as high-ranked games, for example corresponding to a high output value. Then trophy
5 lists for other categories of games (optionally limited to aggregate actually awarded trophies for a corpus of players, as noted previously) may be input and trained as games of appropriate rank (e.g. of decreasing value).

Again, statistical outliers may be omitted. Hence for example only indicators of positive engagement may be used as the basis for training, e.g. games at least on a user's watch list and
10 above in rank, or games that the user has deliberately chosen to watch the trailer of, and above.

Subsequently new games may be tested with respect to the trained model to predict the user's level of engagement with them, and the highest scoring, or a predetermined number of the highest scoring, may be selected as a search result.

Again, the third method may be combined with the second, for example to provide different
15 levels of engagement for played games (as a function of normalised play time) and extend this to levels of engagement for as-yet unplayed games.

Similarly the third method can be combined with the first method (optionally also with the second), for example to use currently played games in the first subset to predict the trophy distributions of games having a high interest (installed, purchased, on watchlist etc) in a second
20 subset, to provide a prediction of the trophy distribution of games of interest to the user.

Hence more generally the third method comprises generating a model of playing preferences by training a machine learning system, using the obtained predetermined indicators of play behaviour for some or all of the player's videogames, to predict player engagement with a respective videogame in a list of new videogames, provided to the machine learning system
25 using some or all predetermined indicators of play behaviour associated with the videogame.

As noted above, because the user has not played the new videogames, these can be presented to the machine learning system by predetermined indicators of play behaviour associated with the videogame that are weighted according to the frequency with which they have been respectively credited to a corpus of players of the new videogame. This can be done for example using a
30 normalised histogram, as discussed previously.

In this regard it is possible that a single game may cater to several play styles. In this case, optionally the trophy distribution for a new game may encompass two different distributions corresponding to different play styles. As noted above, therefore, optionally the distribution of trophies may be for a corpus of players owning a predetermined threshold number of the same games as the player, so as to improve the likelihood that they represent a similar playing style.

Variants for any of the above described training methods include, for example, some or all of the obtained predetermined indicators of play behaviour being weighted according to a weighting scheme specific to the associated videogame (for example, a weighting scheme supplied by the developer or publisher of the game). Hence, in a similar manner to that described above for a degree of correspondence, the degree to which a trophy or other measure corresponds to one or more features of a global input scheme may be represented by one or more weights applied to an input layer of a neural network, or as an input bias to some other machine learning system. Furthermore, weights may potentially be negative, indicating a negative correlation or correspondence between a trophy and a feature of the global input scheme, rather than a mere lack of a positive correlation.

It will be appreciated that this approach may also be applied to the methods described previously, for example by replacing a single byte value (0-255) with a signed byte (0 to ± 128), or any other scheme to indicate a degree of positive or negative correspondence.

The notion of positive and negative weightings (or alternatively some other representation) may be used to signify predetermined indicators of play behaviour that correspond to some or all trophies not credited to the user by a game. In other words, the failure to be credited with some trophies may be as significant an indicator of player preferences and the success in being credited with other trophies – though not all trophies are of equal significance.

Hence for example a game developer or publisher could identify certain key trophies for which a failure to win the trophy is significant in terms of an aversion to a certain playing style or content preference. More generally, all trophies could have positive and/or negative weightings or correspondence values according to how emblematic or indicative they are of certain playstyles or tastes (positive) or how strongly their avoidance indicates a certain playstyle or taste (negative). To a first approximation, a single set of correspondence or weighting values may be provided, and if the trophy is awarded, the value is applied positively, and if the trophy is not awarded, the value is applied negatively.

Another variant makes use of hidden trophies; in this variant, additional trophies are provided by developers / publishers to facilitate use of one or more of the above described methods, but these are flagged to not be listed like conventional trophies, and do not contribute to a player's trophy collection. These trophies are thus provided simply to assist with characterising the user's play preferences/style/achievements and the like during game play, to better train the machine learning system. The developer or publisher can thus use the trophy system freely without concerns about providing too many trophies, or appearing to award trophies that are counter to the ethos of a game or appear to reflect boring activities (that may nevertheless be useful for characterising a style of play).

10 Whichever method or combination of methods is used, including potentially other training schemes (such as the user of player satisfaction surveys, asking the user to rate their satisfaction with different aspect of a game, and over time build a model correlating trophies to aspects of enjoyment), then in the third step s230 the scheme may select a new game for the player as a result of the above search through a plurality of candidate new games.

15 As noted previously, a 'new game' may be one that is new or comparatively new to the user in the sense that they have not yet played the game, or only played it for a threshold number of minutes (for example, equal to the total number of N minutes described previously herein, below which it is assumed that the user was simply establishing that the game worked).

20 Hence in a new game may be one that is already installed on the user's videogame device, or one that the user has already acquired but not yet installed. Alternatively or in addition, the new game may be one available from the game repository server that the user has not yet acquired.

25 It will be appreciated that the above techniques utilise an in-depth analysis of play behaviour of a player within existing games, either by direct analysis of the game state, or by using an existing trophy system as a proxy indicator, in order to search for other games that may provide a good match to the player's preferences. This provides a superior search function to one based on a preference survey or similar questionnaire presented to the player, as a player may not fully recall all their favourite modes of play, or may not have time to provide a sufficiently full feedback. It is also superior to a search function based on the player's existing game library per se, as this alone cannot reflect how the player chooses to enjoy playing these games.

30 It will be appreciated that the above methods may be carried out on conventional hardware, such as the Sony PlayStation 4®, optionally in conjunction with a game repository server, suitably

adapted as applicable by software instruction or by the inclusion or substitution of dedicated hardware.

Thus the required adaptation to existing parts of a conventional equivalent device may be implemented in the form of a computer program product comprising processor implementable instructions stored on a non-transitory machine-readable medium such as a floppy disk, optical disk, hard disk, PROM, RAM, flash memory or any combination of these or other storage media, or realised in hardware as an ASIC (application specific integrated circuit) or an FPGA (field programmable gate array) or other configurable circuit suitable to use in adapting the conventional equivalent device. Separately, such a computer program may be transmitted via data signals on a network such as an Ethernet, a wireless network, the Internet, or any combination of these or other networks.

In one configuration, the Sony PlayStation 4 ® uploads predetermined indicators of play behaviour of a player, for example in the form of credit trophies, to the game repository server, which administers a trophy database or other tracking scheme for a given player across multiple games. The game repository server then trains a machine learning system according to one or more of the above described methods in order to search for a new game for that player. In another configuration, the functions implemented by the game repository server above are implemented locally by the Sony PlayStation 4, such that the PlayStation 4 effectively operates as the game repository server for the purposes of the present invention. In this case, the new games may be limited to those installed on the PlayStation but not yet played, or the PlayStation may run global representations of games available to it on-line through its trained machine learning system, for example during idle time. In a variation on this configuration, statistics relating to a corpus of players that may be used as inputs or targets for a machine learning scheme are provided by the game repository server on request from the Sony PlayStation 4.

Hence referring again to Figure 1, in an embodiment of the present invention the videogame search apparatus (such as a Sony PlayStation 4®, game repository server, or a combination thereof, as illustrative examples), comprises a storage unit (such as HDD 37 and/or RAM 22 in conjunction with the CPU 20A) adapted (for example by suitable software instructions) to store a plurality of different predetermined indicators of play behaviour of a player, being a subset of possible predetermined indicators of play behaviour, as described previously herein, detected during play of one or more different games.

The apparatus also comprises a modelling processor (for example CPU 20A) adapted (for example by suitable software instructions) to generate a model of playing preferences of the player based on the obtained predetermined indicators of play behaviour, as described previously herein.

- 5 The apparatus also comprises a search processor (again for example CPU 20A) adapted (for example by suitable software instructions) to use the generated model to select a new videogame from a plurality of new videogames, based upon some or all of the respective possible predetermined indicators of play behaviour associated with each new videogame, as described previously herein.
- 10 It will be appreciated that the above apparatus may be further adapted (for example by suitable software instruction) to implement other aspects of the techniques described herein, including but not limited to the predetermined indicators of play behaviour for a game corresponding to trophies credited to the user by that game, and the modelling processor being adapted to train a machine learning system, using the obtained predetermined indicators of play behaviour for
- 15 some or all of the player's videogames, to predict player engagement with a respective videogame in a list of new videogames, characterised to the machine learning system using some or all predetermined indicators of play behaviour associated with the videogame.

CLAIMS

1. A method of videogame search, comprising the steps of:
obtaining a plurality of different predetermined indicators of play behaviour of a player,
being a subset of possible predetermined indicators of play behaviour, detected during play of
5 one or more different videogames;
generating a model of playing preferences of the player based on the obtained
predetermined indicators of play behaviour; and
using the generated model to select a new videogame from a plurality of new
videogames, based upon some or all of the respective possible predetermined indicators of play
10 behaviour associated with each new videogame.
2. The method of claim 1, in which the predetermined indicators of play behaviour for a
videogame correspond to trophies credited to the player by that videogame.
3. The method of claim 2, in which the trophies of a specific videogame are mapped to a
global set of predetermined indicators of play behaviour.
- 15 4. The method of any one of the preceding claims, in which the step of generating a model
of playing preferences of the player comprises the step of:
training a machine learning system, using the obtained predetermined indicators of play
behaviour for first subset of the player's videogames, to predict possible predetermined
indicators of play behaviour in a second subset of the player's videogames.
- 20 5. The method according to claim 4, in which at least a majority of the videogames in the
first subset of videogames was purchased by the player earlier than the videogames in the second
subset of videogames.
6. The method of any one of claims 1-3, in which the step of generating a model of playing
preferences of the player comprises the step of:
25 training a machine learning system, using the obtained predetermined indicators of play
behaviour for some or all of the player's videogames, to predict a normalised duration of time
spent by the player on a respective videogame.
7. The method according to claim 6, in which the normalised duration of time corresponds
to a ratio of the actual duration of time spent by the player on a respective videogame to an
30 expected duration of time, the expected duration of time being based on one or more selected
from the list consisting of:

- i. a mean duration of time spent by a corpus of players on the respective videogame; and
- ii. an expected duration of time to spend on the videogame, provided by the videogame developer.

5 8. The method according to anyone of the preceding claims, in which the step of generating a model of playing preferences of the player comprises the step of:

training machine learning system, using the obtained predetermined indicators of play behaviour for some or all of the player's videogames, to predict player engagement with a respective videogame in a list of new videogames, characterised to the machine learning system
10 using some or all predetermined indicators of play behaviour associated with the videogame.

9. The method of claim 8, in which the new videogame is characterised to the machine learning system by predetermined indicators of play behaviour associated with the videogame that are weighted according to the frequency with which they have been respectively credited to a corpus of players of the new videogame.

15 10. The method according to any one of the preceding claims, in which some or all of the obtained predetermined indicators of play behaviour are weighted according to a weighting scheme specific to the associated videogame.

11. The method according to any one of the preceding claims, in which the predetermined indicators of play behaviour additionally corresponds to some or all trophies not credited to the
20 user by a game.

12. A computer readable medium having computer executable instructions adapted to cause a computer system to perform the method of any one of the previous claims.

13. A videogame search apparatus, comprising:

a storage unit adapted to store a plurality of different predetermined indicators of play
25 behaviour of a player, being a subset of possible predetermined indicators of play behaviour, detected during play of one or more different games;

a modelling processor adapted to generate a model of playing preferences of the player based on the obtained predetermined indicators of play behaviour; and

a search processor adapted to use the generated model to select a new videogame from a
30 plurality of new videogames, based upon some or all of the respective possible predetermined indicators of play behaviour associated with each new videogame.

14. The videogame search apparatus of claim 13, in which the predetermined indicators of play behaviour for a game correspond to trophies credited to the user by that game.

15. The videogame search apparatus of claim 13 or 14,
in which the modelling processor is adapted to train a machine learning system, using the
5 obtained predetermined indicators of play behaviour for some or all of the player's
videogames, to predict player engagement with a respective videogame in a list of new
videogames, characterised to the machine learning system using some or all
predetermined indicators of play behaviour associated with the videogame.



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Claims searched: 1 - 15

Date of search: 24 August 2018

Patents Act 1977: Search Report under Section 17

Documents considered to be relevant:

Category	Relevant to claims	Identity of document and passage or figure of particular relevance
X	1 - 15	US2015/099589 A1 (SMITH) See paragraphs 25, 26, 73 and figures
X	1 - 15	US2009/197681 A1 (KRISHNAMOORTHY et al.) See paragraphs 25, 34, 45 and figures
X	1 - 15	WO2014/107786 A1 (SPIELO INT CANADA ULC) See paragraph 21, 92, 93 and figures
X	1 - 15	US2014/274355 A1 (GEORGE et al.) See paragraphs 64, 74 and figures
X	1 - 15	US2007/072678 A1 (DAGRES) See paragraphs 143, 146 and figures

Categories:

X	Document indicating lack of novelty or inventive step	A	Document indicating technological background and/or state of the art.
Y	Document indicating lack of inventive step if combined with one or more other documents of same category.	P	Document published on or after the declared priority date but before the filing date of this invention.
&	Member of the same patent family	E	Patent document published on or after, but with priority date earlier than, the filing date of this application.

Field of Search:

Search of GB, EP, WO & US patent documents classified in the following areas of the UKC^X :

Worldwide search of patent documents classified in the following areas of the IPC

A63F; G06Q

The following online and other databases have been used in the preparation of this search report

EPODOC, WPI



International Classification:

Subclass	Subgroup	Valid From
A63F	0013/79	01/01/2014
A63F	0013/30	01/01/2014
A63F	0013/85	01/01/2014
G06Q	0030/02	01/01/2012