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Table with 5 columns: APPLICATION NO., FILING DATE, FIRST NAMED INVENTOR, ATTORNEY DOCKET NO., CONFIRMATION NO. Includes application details for Sartaki Sinha ROY and examiner ELCHANTI, TAREK.

Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Notice of the Office communication was sent electronically on above-indicated "Notification Date" to the following e-mail address(es):

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Notice of Pre-AIA or AIA Status

The present application, filed on or after March 16, 2013, is being examined under the first inventor to file provisions of the AIA.

DETAILED ACTION

1. This office action is responsive to amendment filed on 01/04/2021. Claims 1-2 are amended. Claims 1-2 are pending examination.

Claim Rejections - 35 USC § 101

2. 35 U.S.C. 101 reads as follows:

Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

Claims 1-2 are rejected under 35 U.S.C. 101 because the claimed invention is directed to a judicial exception (i.e., a law of nature, a natural phenomenon, or an **abstract idea**) *without significantly more*.

Claim(s) 1 is/are drawn to a non-transitory computer readable medium (i.e., a machine/manufacture). As such, claim 1 is/are drawn to one of the statutory categories of invention.

Claims 1-2 are directed to predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time. Specifically, the claims recite perform data analysis, perform feature engineering on the identified variables, train a random forest model, and predict ad spend, which is grouped within the Methods Of Organizing Human Activity and is similar to the concept of (*commercial or legal interactions including agreements in the form of contracts, legal obligations, advertising, marketing or sales activities or behaviors business relations*) grouping of abstract ideas in **prong one of step 2A** of the *Alice/Mayo* test (See 2019 Revised Patent Subject Matter Eligibility Guidance, 84 Fed. Reg. 50, 52, 54 (January 7, 2019)). Accordingly, the claims recite an abstract idea (See pages 7, 10, *Alice Corporation Pty. Ltd. v. CLS Bank International, et al.*, US Supreme Court, No. 13-298, June 19,

2014; 2019 Revised Patent Subject Matter Eligibility Guidance, 84 Fed. Reg. 50, 53-54 (January 7, 2019)).

This judicial exception is not integrated into a practical application because, when analyzed under **prong two of step 2A** of the *Alice/Mayo* test (See 2019 Revised Patent Subject Matter Eligibility Guidance, 84 Fed. Reg. 50, 54-55 (January 7, 2019)), the additional element(s) of the claim(s) such as network, a computer readable medium, and a computing device merely use(s) a computer as a tool to perform an abstract idea and/or generally link(s) the use of a judicial exception to a particular technological environment. Specifically, the network, a computer readable medium, and a computing device perform(s) the steps or functions of perform data analysis, perform feature engineering on the identified variables, train a random forest model, and predict ad spend. The use of a processor/computer as a tool to implement the abstract idea and/or generally linking the use of the abstract idea to a particular technological environment does not integrate the abstract idea into a practical application because it requires no more than a computer performing functions that correspond to acts required to carry out the abstract idea. The additional elements do not involve improvements to the functioning of a computer, or to any other technology or technical field (MPEP 2106.05(a)), the claims do not apply or use the abstract idea to effect a particular treatment or prophylaxis for a disease or medical condition (Vanda Memo), the claims do not apply the abstract idea with, or by use of, a particular machine (MPEP 2106.05(b)), the claims do not effect a transformation or reduction of a particular article to a different state or thing (MPEP 2106.05(c)), and the claims do not apply or use the abstract idea in some other meaningful way beyond generally linking the use of the abstract idea to a particular technological environment, such that the claim as a whole is more than a drafting effort designed to monopolize the exception (MPEP 2106.05(e) and Vanda Memo). Therefore, the claims do not, for example, purport to improve the functioning of a computer. Nor do they effect an improvement in any other technology or technical field. Accordingly, the additional elements do not impose any meaningful limits on practicing the abstract idea, and the claims are directed to an abstract idea.

The claim(s) does/do not include additional elements that are sufficient to amount to significantly more than the judicial exception because, when analyzed under **step 2B** of the *Alice/Mayo* test (See 2019 Revised Patent Subject Matter Eligibility Guidance, 84 Fed. Reg. 50, 52, 56 (January 7, 2019)), the

additional element(s) of using a network, a computer readable medium, and a computing device to perform the steps amounts to no more than using a computer or processor to automate and/or implement the abstract idea of predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time. As discussed above, taking the claim elements separately, the network, a computer readable medium, and a computing device perform(s) the steps or functions of perform data analysis, perform feature engineering on the identified variables, train a random forest model, and predict ad spend. These functions correspond to the actions required to perform the abstract idea. Viewed as a whole, the combination of elements recited in the claims merely recite the concept of predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time. Therefore, the use of these additional elements does no more than employ the computer as a tool to automate and/or implement the abstract idea. The use of a computer or processor to merely automate and/or implement the abstract idea cannot provide significantly more than the abstract idea itself (MPEP 2106.05(I)(A)(f) & (h)). Therefore, the claim is not patent eligible.

Dependent claim 2 further describe the abstract idea of predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time. The dependent claims do not include additional elements that integrate the abstract idea into a practical application or that provide significantly more than the abstract idea. Therefore, the dependent claims are also not patent eligible.

Claim Rejections - 35 USC § 103

3. In the event the determination of the status of the application as subject to AIA 35 U.S.C. 102 and 103 (or as subject to pre-AIA 35 U.S.C. 102 and 103) is incorrect, any correction of the statutory basis for the rejection will not be considered a new ground of rejection if the prior art relied upon, and the rationale supporting the rejection, would be the same under either status.

The following is a quotation of 35 U.S.C. 103 which forms the basis for all obviousness rejections set forth in this Office action:

A patent for a claimed invention may not be obtained, notwithstanding that the claimed invention is not identically disclosed as set forth in section 102 of this title, if the differences between the claimed invention and the prior art are such that the claimed invention as a whole would have been obvious before the effective filing date of the claimed invention to a person

having ordinary skill in the art to which the claimed invention pertains. Patentability shall not be negated by the manner in which the invention was made.

Claim(s) 1-2 is/are rejected under 35 U.S.C. 103 as being unpatentable over Chittilappilly et al., (U.S. Patent Application Publication No. 20160210661) in view of Minor et al., (U.S. Patent Application Publication No. 20150161662) in view of Volovich et al., (U.S. Patent Application Publication No. 20150089523).

As to Claim 1, Chittilappilly teaches a computer program product for

(i) known ad spend for a subset of media programs, and (abstract: determine a set of channel spend allocation values for a plurality of media channels based on a predictive model),

(a) perform data analysis on the media program data to identify one or more variables (0079: The example dataset of touchpoint attribute chart 3B00 correlates the various touchpoints with a plurality of attributes 332 associated with respective touchpoints), or combinations of variables that correlate with ad spend; (0079: As discussed herein, a touchpoint (e.g., touchpoints 157) can be any occurrence where a user interacts with any aspect of a media campaign (e.g., display ad, keyword search, TV ad, etc.).

Recording the various stimulation and response touchpoints associated with a marketing campaign can occur over a time period (e.g., see time series of user level activity 334), which stimulation and response touchpoints or records therefrom can enable certain key performance indicators for the campaign to be determined. Yet, some touchpoints are more readily observed than other touchpoints. Specifically, touchpoints in non-digital media channels might be not be observable at a user level and/or an individual transaction level such that summary and/or aggregate responses in non-digital channels are provided. In comparison, touchpoints in digital media channels can be captured in real-time at a user level (e.g., using Internet technology). The attributes of such touchpoints in digital media channels can be structured as depicted in the touchpoint attribute chart 3B00. Specifically, the touchpoint attribute chart 3B00 shows a plurality of touchpoints (e.g., touchpoint 330.sub.1, touchpoint 330.sub.2, touchpoint 330.sub.3, touchpoint 330.sub.4, touchpoint 330.sub.5, and touchpoint 330.sub.6) that might be collected and stored (e.g., in response data store 525) for various analyses (e.g., at measurement server 110 and apportionment server 111). The example dataset of touchpoint attribute chart 3B00 correlates the various touchpoints with a plurality of attributes 332 associated with respective touchpoints),

(b) perform feature engineering on the identified one or more variables, or the combinations of variables to identify a subset of one or more variables, or combinations of variables that provide the greatest explanatory value; (0079: As discussed herein, a touchpoint (e.g., touchpoints 157) can be any occurrence where a user interacts with any aspect of a media campaign (e.g., display ad, keyword search, TV ad, etc.). Recording the various stimulation and response touchpoints associated with a marketing campaign can occur over a time period (e.g., see time series of user level activity 334), which stimulation and response touchpoints or records therefrom can enable certain key performance indicators for the campaign to be determined. Yet, some touchpoints are more readily observed than other touchpoints. Specifically, touchpoints in non-digital media channels might be not be observable at a user level and/or an individual transaction level such that summary and/or aggregate responses in non-digital channels are provided. In comparison, touchpoints in digital media channels can be captured in real-time at a user level (e.g., using Internet technology). The attributes of such touchpoints in digital media channels can be structured as depicted in the touchpoint attribute chart 3B00. Specifically, the touchpoint attribute chart 3B00 shows a plurality of touchpoints (e.g., touchpoint 330.sub.1, touchpoint 330.sub.2, touchpoint 330.sub.3, touchpoint 330.sub.4, touchpoint 330.sub.5, and touchpoint 330.sub.6) that might be collected and stored (e.g., in response data store 525) for various analyses (e.g., at measurement server 110 and apportionment server 111). The example dataset of touchpoint attribute chart 3B00 correlates the various touchpoints with a plurality of attributes 332 associated with respective touchpoints).

Chittilappilly does not teach predicting ad spend for a specific media program aired or streamed on a specific network at a specific date and time using a database of media program data that includes

(c) train a random forest model to predict ad spend using the identified subset of one or more variables, or the combinations of variables, the random forest model including a random forest having a plurality of individual decision trees; and

(d) predict ad spend for a specific media program that is aired or streamed on a specific network at a specific date and time, and which has an unknown ad spend, using the random forest model,

wherein the predicted ad spend is an average of ad spend predicted from the individual decision trees of the random forest.

However Minor teaches predicting ad spend for a specific media program aired or streamed on a specific network at a specific date and time using a database of media program data that includes (0034: the model builder then generates a number of random forest ensemble solutions for predicting their performance. These predictions of GDN performance include how much this group of campaigns can spend for a given quality of result, such as number of clicks versus CPC, or number of conversions versus CPA. Similarly, for the GSN set of campaigns a number of different random forest ensemble solutions for predicting their performance is generated from the first separated data set),

(c) train a random forest model to predict ad spend using the identified subset of one or more variables, or the combinations of variables, the random forest model including a random forest having a plurality of individual decision trees; and (0032: In an operation 310, predictive models 205 are built using the first separated data set. Predictive models 205 are a set of models which predict the outcome (e.g., impressions, clicks, conversions. CPC, CPA, etc.) of a given budget allocation for the purchase of a given online advertisement. Such models can include or use genetic algorithms, machine learning algorithms, Bayesian models, spline models, random forest trees, etc., all as known in the art),

(d) predict ad spend for a specific media program that is aired or streamed on a specific network at a specific date and time, and which has an unknown ad spend, using the random forest model, wherein the predicted ad spend is an average of ad spend predicted from the individual decision trees of the random forest; (0058: As an example, data normalizer 215 normalizes data based on weighting values received from a user of the system. For example, a user determines that a click on average is worth one amount to them for one type of advertisement (e.g., that a click on average for mobile advertising on a search is worth \$0.80 to them) and worth another amount to them for another type of advertisement (e.g., that a click on average for desktop advertising on a search is worth \$1.00 to them). According to this example, data normalizer 215 normalizes the data by dividing each purchased advertisement of the given type by its user-provided valuation. In other words, if the data indicates that a purchased mobile advertisement on a search cost \$0.90, then the resulting normalized data would be 1.125 ($\$0.90/\0.80). Likewise, if the data indicates that a purchased desktop advertisement on a search cost \$0.90, then the resulting

normalized data would be 0.90 (\$0.90/\$1.00). This normalization provides a relative weighting of the data based on the user's determination of value. The normalized data is then made available to the other modules within master system 105, either directly or by storing them in data store 210), (0032: In an operation 310, predictive models 205 are built using the first separated data set. Predictive models 205 are a set of models which predict the outcome (e.g., impressions, clicks, conversions. CPC, CPA, etc.) of a given budget allocation for the purchase of a given online advertisement. Such models can include or use genetic algorithms, machine learning algorithms, Bayesian models, spline models, random forest trees, etc., all as known in the art), (abstract: a master computing system directs slave computing systems in the purchasing of advertising within one or more online advertising channels by building a set of models for predicting the outcome of advertising purchases based on data received from the advertising channels, evaluating those models to determine which one(s) to use, allocating an advertiser's budget across the slave systems and channels for a given time period, and adjusting those allocations during the time period based on performance results received from the slave systems. In turn, the slave systems attempt to purchase advertisements within their channels based on their allocation and adjustments and report performance results back to the master system), and (0006: predictive models using a first of the three separate data sets; choosing, by the master computing device, which of the predictive models to use by comparing results from running the predictive models using a second of the three separate data sets and eliminating those predictive models that indicate overfit when run using a third of the three separate data sets; predicting, by the master computing device, using the chosen predictive models, results of advertisements purchased in the multiple channels; allocating, by the master computing device, an advertising budget for a given time period for each of the multiple online advertising channels based on the predicted results: communicating the budget allocations across a network from the master computing device to one or more slave computing devices responsible for purchasing online advertisements within the channels). It would have been obvious to one of ordinary skill in the art at the time of the invention to modify Chittilappilly to include predict ad spend for a specific media program that is aired or streamed on a specific network at a specific date and time, and which has an unknown ad spend, using the random forest model, wherein the predicted ad spend is an average of ad spend predicted from the individual decision trees of the random forest of Minor. Motivation to do so comes from

the knowledge well known in the art that predict ad spend for a specific media program that is aired or streamed on a specific network at a specific date and time, and which has an unknown ad spend, using the random forest model, wherein the predicted ad spend is an average of ad spend predicted from the individual decision trees of the random forest would help provide a more accurate content which the user would be interested in and that would promote an increase in the sales and would therefore make the method/system more profitable and accurate.

Chittilappilly does not teach (ii) viewership data for each of the media programs, including total viewership and viewership ratings, wherein each of the media programs is identified by its respective network, and date and time of airing or streaming, the computer program product comprising a computer readable medium tangibly embodying non-transitory computer-executable program instructions thereon that, when executed, cause one or more computing devices in a machine learning platform to.

However Volovich teaches (ii) viewership data for each of the media programs, including total viewership and viewership ratings, wherein each of the media programs is identified by its respective network, and date and time of airing or streaming, the computer program product comprising a computer readable medium tangibly embodying non-transitory computer-executable program instructions thereon that, when executed, cause one or more computing devices in a machine learning platform to: (0020: information in the account profile 144 is used for querying the viewership data in response to a client request or minimizing the bias associated with the viewership data collected by one provider when projecting the TV viewership rating from the collected viewership data. In some cases, the account information database 132 includes the TV viewership data 142 that represents the television viewing activity of the household 180 associated with each account. For example, the TV viewing activity can include information on every program viewed by the household, including, for each program, a name and description of the program, the channel that played the program, the date/time of the viewing, etc. In other implementations, the TV viewing activity saved in the database 132 includes only programs that are viewed for at least a threshold amount of time (e.g., 1 minute or 5 minutes) as well as the start time of a program and the end time of the program. In some implementations, the viewing activity tracked includes only premium content. The TV viewership data 142 may include either the raw data sample collected from a household, such as the date and time when the data sample was collected and information about the

TV program being broadcasted in the household when the data sample was collected, or the pre-processed data sample, such as the broadcasting duration of the TV program in the household. As shown in FIG. 1, the database 132 may include the TV viewership data collected from multiple TV broadcasters (or TV metering data providers) 102. A data pre-processing procedure may be applied to the data from different sources if their formats are different from the one used by the database 132. The terms like "viewership data" and "metering data" are used interchangeably throughout this application). It would have been obvious to one of ordinary skill in the art at the time of the invention to modify Chittilappilly to include viewership data for each of the media programs, including total viewership and viewership ratings, wherein each of the media programs is identified by its respective network, and date and time of airing or streaming, the computer program product comprising a computer readable medium tangibly embodying non-transitory computer-executable program instructions thereon that, when executed, cause one or more computing devices of Volovich. Motivation to do so comes from the knowledge well known in the art that viewership data for each of the media programs, including total viewership and viewership ratings, wherein each of the media programs is identified by its respective network, and date and time of airing or streaming, the computer program product comprising a computer readable medium tangibly embodying non-transitory computer-executable program instructions thereon that, when executed, cause one or more computing devices would help provide a more accurate content which the user would be interested in and that would promote an increase in the sales and would therefore make the method/system more profitable and accurate.

As to claim 2, Chittilappilly, Minor, and Volovich teach the computer program product of claim 1.

Chittilappilly further teaches wherein the total viewership is captured using unique IP addresses of devices that viewed respective media programs; (0119: The interaction event data record 972 can further comprise data (e.g., user identifier, computing device identifiers, timestamps, IP addresses, etc.) related to the users and/or the users' actions).

4. The prior art made of record and not relied upon is considered pertinent to applicant's disclosure. The NPL "Random Forest and Ensemble Methods for YouTube Brand Lift Forecasting" describes "Google's YouTube Brand Lift Study (or BLS) is a tool for quantifying the impact of a YouTube video campaign's effectiveness in generating brand awareness, brand awareness, ad recall, consideration, favorability, purchase intent, or brand interest. In this article, I'll walk through the business use cases and challenges for the BLS study. While I won't be sharing any results from our team's BLS forecasts, I will deep-dive into why the ensemble model nature of Random Forests are an ideal fit for the special business requirements of working with BLS data".

Response to Arguments

5. Applicant's arguments filed 01/04/2021 have been fully considered but they are not persuasive.

A. Applicant argues that Chittilappilly does not teach identify one or more variables, or combinations of variables that correlate with ad spend.

Examiner respectfully disagrees. Chittilappilly teaches the above limitation as following:

identify one or more variables (0079: The example dataset of touchpoint attribute chart 3B00 correlates the various touchpoints with a plurality of attributes 332 associated with respective touchpoints)

"Examiner interpretation: touchpoints can be variables and its identifying touchpoints",

or combinations of variables that correlate with ad spend; (0079: As discussed herein, a touchpoint (e.g., touchpoints 157) can be any occurrence where a user interacts with any aspect of a media campaign (e.g., display ad, keyword search, TV ad, etc.) ***"Examiner interpretation: its identifying touchpoints***

where the user is clicking on content which can be advertisements or media advertisement to determine media campaign which can be how much a user interacted with the media content".

Recording the various stimulation and response touchpoints associated with a marketing campaign can occur over a time period (e.g., see time series of user level activity 334), which stimulation and response touchpoints or records therefrom can enable certain key performance indicators for the campaign to be determined. Yet, some touchpoints are more readily observed than other touchpoints. Specifically, touchpoints in non-digital media channels might be not be observable at a user level and/or an individual transaction level such that summary and/or aggregate responses in non-digital channels are provided. In

comparison, touchpoints in digital media channels can be captured in real-time at a user level (e.g., using Internet technology). The attributes of such touchpoints in digital media channels can be structured as depicted in the touchpoint attribute chart 3B00. Specifically, the touchpoint attribute chart 3B00 shows a plurality of touchpoints (e.g., touchpoint 330.sub.1, touchpoint 330.sub.2, touchpoint 330.sub.3, touchpoint 330.sub.4, touchpoint 330.sub.5, and touchpoint 330.sub.6) that might be collected and stored (e.g., in response data store 525) for various analyses (e.g., at measurement server 110 and apportionment server 111). The example dataset of touchpoint attribute chart 3B00 correlates the various touchpoints with a plurality of attributes 332 associated with respective touchpoints).

B. Applicant argues that Minor does not teach identify one or more variables, or combinations of variables that correlate with ad spend.

Examiner respectfully disagrees. Minor teaches the above limitation as following:

predicting ad spend for a specific media program aired or streamed on a specific network at a specific date and time using a database of media program data that includes (0034: the model builder then generates a number of random forest ensemble solutions for predicting their performance. These predictions of GDN performance include how much this group of campaigns can spend for a given quality of result, such as number of clicks versus CPC, or number of conversions versus CPA. Similarly, for the GSN set of campaigns a number of different random forest ensemble solutions for predicting their performance is generated from the first separated data set). In para. 0034 it is predicting ad spend by predictions of GDN performance include how much this group of campaigns can spend for a given quality of result.

Therefore, Applicant's argument is not persuasive. Examiner further notes that citations by Examiner are representative of the teachings in the cited arts and are applied to the specific limitations within the individual claim, other passages and figures may apply as well and Applicant is to consider fully the entire references as potentially teaching all or part of the claimed invention, as well as the context of the passage as taught by the prior arts or disclosed by the Examiner.

C. Applicant argues that the claims are not directed to a judicial exception under Step 2A Prong One.

As for Step 2A Prong One, of the Abstract idea is directed towards the abstract idea of predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time which is grouped within the Methods Of Organizing Human Activity and is similar to the concept of *(commercial or legal interactions including agreements in the form of contracts, legal obligations, advertising, marketing or sales activities or behaviors business relations)* grouping of abstract ideas in **prong one of step 2A** of the *Alice/Mayo* test (See 2019 Revised Patent Subject Matter Eligibility Guidance, 84 Fed. Reg. 50, 52, 54 (January 7, 2019)). Accordingly, the claims recite an abstract idea (See pages 7, 10, *Alice Corporation Pty. Ltd. v. CLS Bank International, et al.*, US Supreme Court, No. 13-298, June 19, 2014; 2019 Revised Patent Subject Matter Eligibility Guidance, 84 Fed. Reg. 50, 53-54 (January 7, 2019)).

D. Applicant argues that the claims are not directed to a judicial exception under Step 2A Prong Two.

As for Step 2A Prong Two, the claim limitations do not include additional elements in the claim that apply, rely on, or use the judicial exception in a manner that imposes a meaningful limit on the judicial exception, and the claim is not more than a drafting effort designed to monopolize the judicial exception and the claim limitation simply describe the abstract idea. The limitation directed to predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time does not add technical improvement to the abstract idea. The recitations to “network, a computer readable medium, and a computing device” perform(s) the steps or functions of perform data analysis, perform feature engineering on the identified variables, train a random forest model, and predict ad spend. The use of a processor/computer as a tool to implement the abstract idea and/or generally linking the use of the abstract idea to a particular technological environment does not integrate the abstract idea into a practical application because it requires no more than a computer performing functions that correspond to acts required to carry out the abstract idea. The additional elements do not involve improvements to the functioning of a computer, or to any other technology or technical field (MPEP 2106.05(a)), the claims do

not apply or use the abstract idea to effect a particular treatment or prophylaxis for a disease or medical condition (Vanda Memo), the claims do not apply the abstract idea with, or by use of, a particular machine (MPEP 2106.05(b)), the claims do not effect a transformation or reduction of a particular article to a different state or thing (MPEP 2106.05(c)), and the claims do not apply or use the abstract idea in some other meaningful way beyond generally linking the use of the abstract idea to a particular technological environment, such that the claim as a whole is more than a drafting effort designed to monopolize the exception (MPEP 2106.05(e) and Vanda Memo). Therefore, the claims do not, for example, purport to improve the functioning of a computer. Nor do they effect an improvement in any other technology or technical field. Accordingly, the additional elements do not impose any meaningful limits on practicing the abstract idea, and the claims are directed to an abstract idea.

E. Applicant argues that the claims are not directed to a judicial exception under **Step 2B**.

As for Step 2B, The claim(s) does/do not include additional elements that are sufficient to amount to significantly more than the judicial exception because, when analyzed under **step 2B** of the *Alice/Mayo* test (*See* 2019 Revised Patent Subject Matter Eligibility Guidance, 84 Fed. Reg. 50, 52, 56 (January 7, 2019)), the limitation directed to predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time does not add significantly more to the abstract idea.

Furthermore, using well-known computer functions to execute an abstract idea does not constitute significantly more. The recitations to “network, a computer readable medium, and a computing device” are generically recited computer structure. These functions correspond to the actions required to perform the abstract idea. Viewed as a whole, the combination of elements recited in the claims merely recite the concept of predicting ad spend for a specific media program aired or streamed on a specific network a specific date and time. Therefore, the use of these additional elements does no more than employ the computer as a tool to automate and/or implement the abstract idea. The use of a computer or processor to merely automate and/or implement the abstract idea cannot provide significantly more than the abstract idea itself (MPEP 2106.05(I)(A)(f) & (h)). Therefore, the claim is not patent eligible.

THIS ACTION IS MADE FINAL. Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the mailing date of this final action.

Conclusion

Any inquiry concerning this communication or earlier communications from the examiner should be directed to TAREK ELCHANTI whose telephone number is (571) 272-9638. The examiner can normally be reached on Flex Mon - Thur 7-7:00 and Fri 7-4:00.

Examiner interviews are available via telephone, in-person, and video conferencing using a USPTO supplied web-based collaboration tool. To schedule an interview, applicant is encouraged to use the USPTO Automated Interview Request (AIR) at <http://www.uspto.gov/interviewpractice>.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Abhishek Vyas can be reached on (571) 270-1836. The fax phone number for the organization where this application or proceeding is assigned is (571) 273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see <http://pair-direct.uspto.gov>. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free). If you would like assistance from a USPTO Customer Service Representative or access to the automated information system, call 800-786-9199 (IN USA OR CANADA) or 571-272-1000.

/TAREK ELCHANTI/
Primary Examiner, Art Unit 3621

REMARKS

Claim 1 is pending. Claim 1 is amended as discussed below. Claim 2 is canceled.

No new matter was added. The amendments to claim 1 regarding the newly added clause “wherein ad spend is an amount of money spent on advertising for a product or service” is fully supported by at least page 1, lines 6-7 of the present application. The amendment to claim 1 adding the clause “wherein the total viewership is captured using unique IP addresses of devices that viewed respective media programs” is fully supported by original claim 2, which is now canceled.

Statement of Substance of Examiner Interview

Applicants wish to thank Examiner Elchanti for extending the courtesy of a telephone interview with Applicants’ undersigned representative on March 24, 2021. During the interview, the contents of a previously filed “Amendment After Final...” (1st Amendment) was discussed, but no agreement was reached regarding the patentability of claim 1 presented in that amendment. Entry of the 1st Amendment was previously denied in an Advisory Action mailed March 23, 2021.

However, during the interview, agreement was reached that all outstanding rejections will be withdrawn, and the application would be in condition for allowance, if claim 1 was amended to incorporate the features of dependent claim 2. The Examiner attempted to make this amendment via an Examiner’s Amendment, but since the Advisory Action was previously mailed, the USPTO computer system would not accept entry of an Examiner’s Amendment. Accordingly, agreement was reached that Applicants would formally file a “2nd Amendment After Final...” (non-AFCP 2.0) to make this claim amendment, and then entry of this second amendment can be made, thereby allowing a Notice of Allowance to be processed.

Entry of Rule 116 Response

Entry of this response is requested because this response does not raise any new issues that would require further consideration and/or search since no new claim limitations are

proposed. No new matter is raised by this response. Furthermore, entry is requested because the Examiner agreed that the application would be in condition for allowance upon the submission of this amendment, as noted in the interview summary above.

Lastly, it is requested that the response be entered even if the application is not allowed because this response will place the application in better form for appeal by materially simplifying the issues.

If the application is not in proper form for allowance, Applicants request that the Examiner telephone the undersigned to discuss any further outstanding issues.

Conclusion

Insofar as the Examiner's rejections were fully addressed, the instant application is in condition for allowance. Withdrawal of the Final Rejection, entry of this paper, and issuance of a Notice of Allowability of all pending claims is therefore earnestly solicited.

Respectfully submitted,

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Amendments to and Listing of the Claims

This listing of claims will replace all prior versions, and listings, of claims in the application:

1. (Currently Amended) A computer program product for predicting ad spend for a specific media program aired or streamed on a specific network at a specific date and time using a database of media program data that includes (i) known ad spend for a subset of media programs, and (ii) viewership data for each of the media programs, including total viewership and viewership ratings, wherein each of the media programs is identified by its respective network, and date and time of airing or streaming, and wherein ad spend is an amount of money spent on advertising for a product or service, the computer program product comprising a computer readable medium tangibly embodying non-transitory computer-executable program instructions thereon that, when executed, cause one or more computing devices in a machine learning platform to:

(a) perform data analysis on the media program data to identify one or more variables, or combinations of variables, that correlate with ad spend, the ad spend being the amount of money spent on advertising for a product or service;

(b) perform feature engineering on the identified one or more variables, or the combinations of variables to identify a subset of one or more variables, or combinations of variables, that provide the greatest explanatory value;

(c) train a random forest model to predict ad spend using the identified subset of one or more variables, or the combinations of variables, the random forest model including a random forest having a plurality of individual decision trees; and

(d) predict ad spend for a specific media program that is aired or streamed on a specific network at a specific date and time, and which has an unknown ad spend, using the trained random forest model, wherein the predicted ad spend is an average of ad spend predicted from the individual decision trees of the random forest,

wherein the total viewership is captured using unique IP addresses of devices that viewed respective media programs.

2. (Canceled)