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Gallusser et al.

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(54) **SCORING AND RECOMMENDING A MEDIA FILE**

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(52) **U.S. Cl.**
CPC ***G06Q 30/0201*** (2013.01)

(58) **Field of Classification Search**
CPC G06Q 30/0201
See application file for complete search history.

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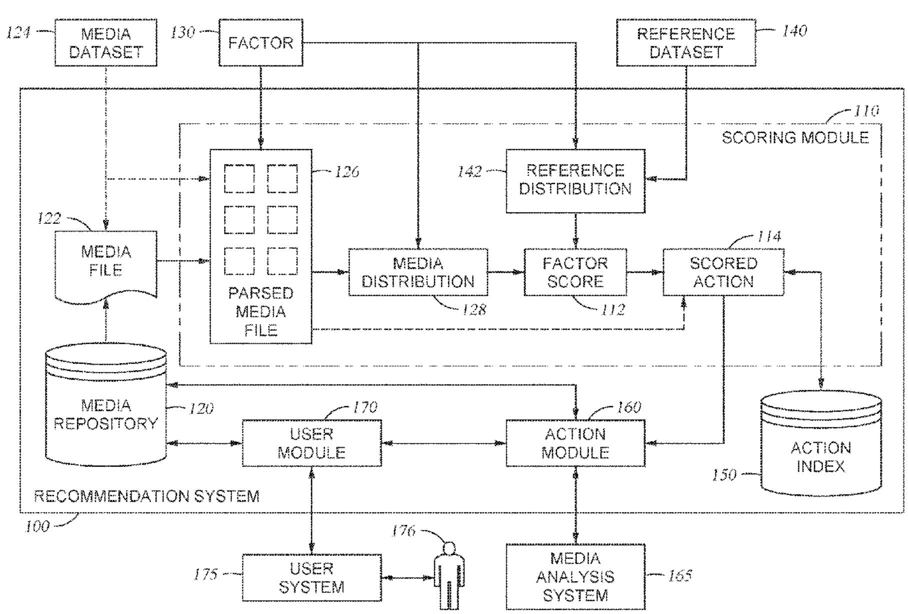
(57) **ABSTRACT**

Embodiments provide for parsing a media file using a factor of interest, determining a factor score for the media file, and performing a scored action based on the factor score to provide a media content recommendation to a user/consumer or to content providers. The scored action may include sorting and filtering a media repository, including the media file, which in turn reduces an amount of data needed for a system to provide an objective recommendation to a user, as well as reducing the time and data processing required to provide a recommendation to the user.

18 Claims, 12 Drawing Sheets



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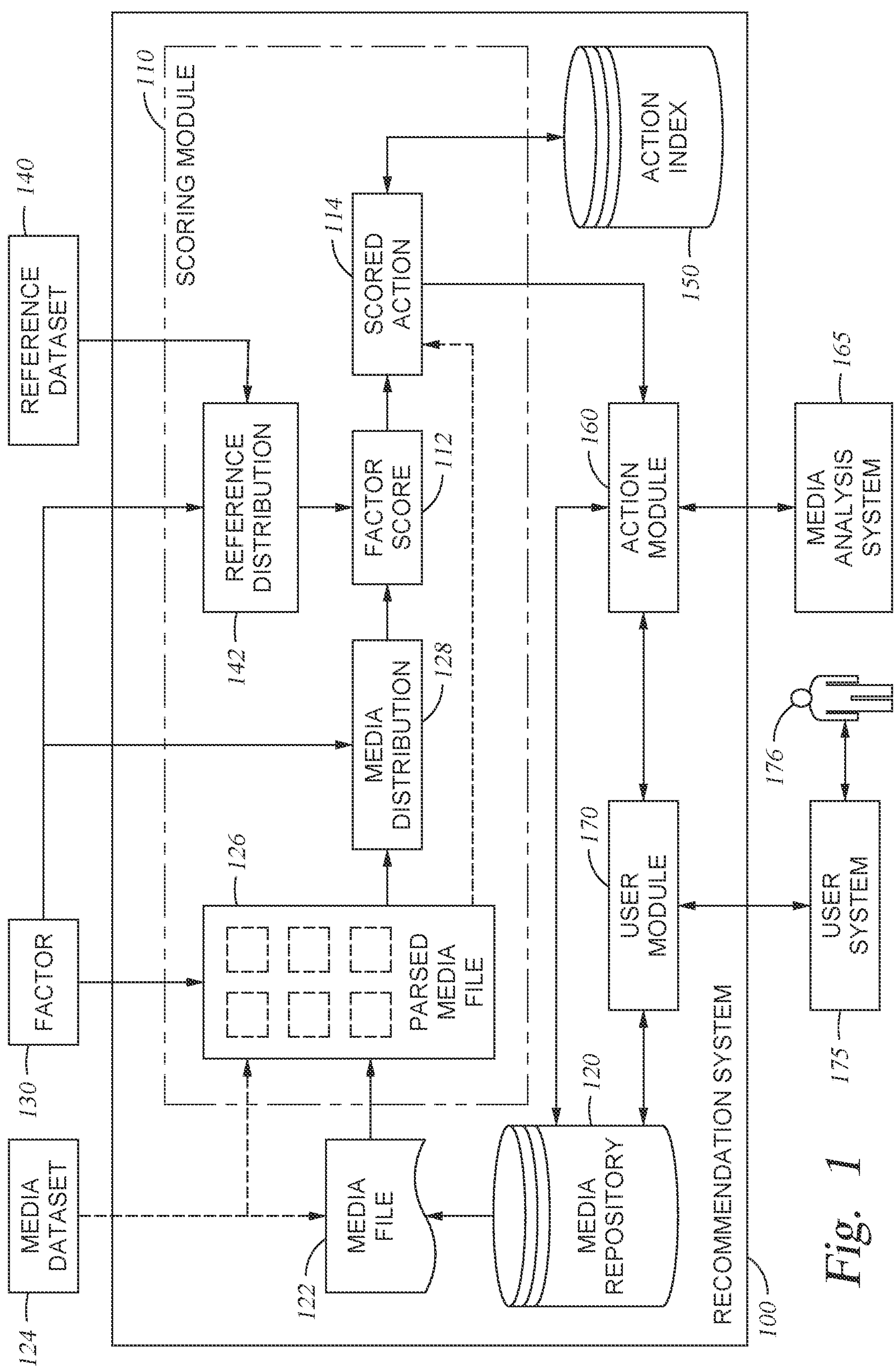

MEDIA DATASET
124
FACTOR
130
REFERENCE DATASET
140
SCORING MODULE
110
PARSED MEDIA FILE
126
MEDIA DISTRIBUTION
128
REFERENCE DISTRIBUTION
142
FACTOR SCORE
112
SCORED ACTION
114
ACTION INDEX
150
MEDIA FILE
122
MEDIA REPOSITORY
120
USER MODULE
170
ACTION MODULE
160
RECOMMENDATION SYSTEM
100
USER SYSTEM
175
176
MEDIA ANALYSIS SYSTEM
165

Fig. 1

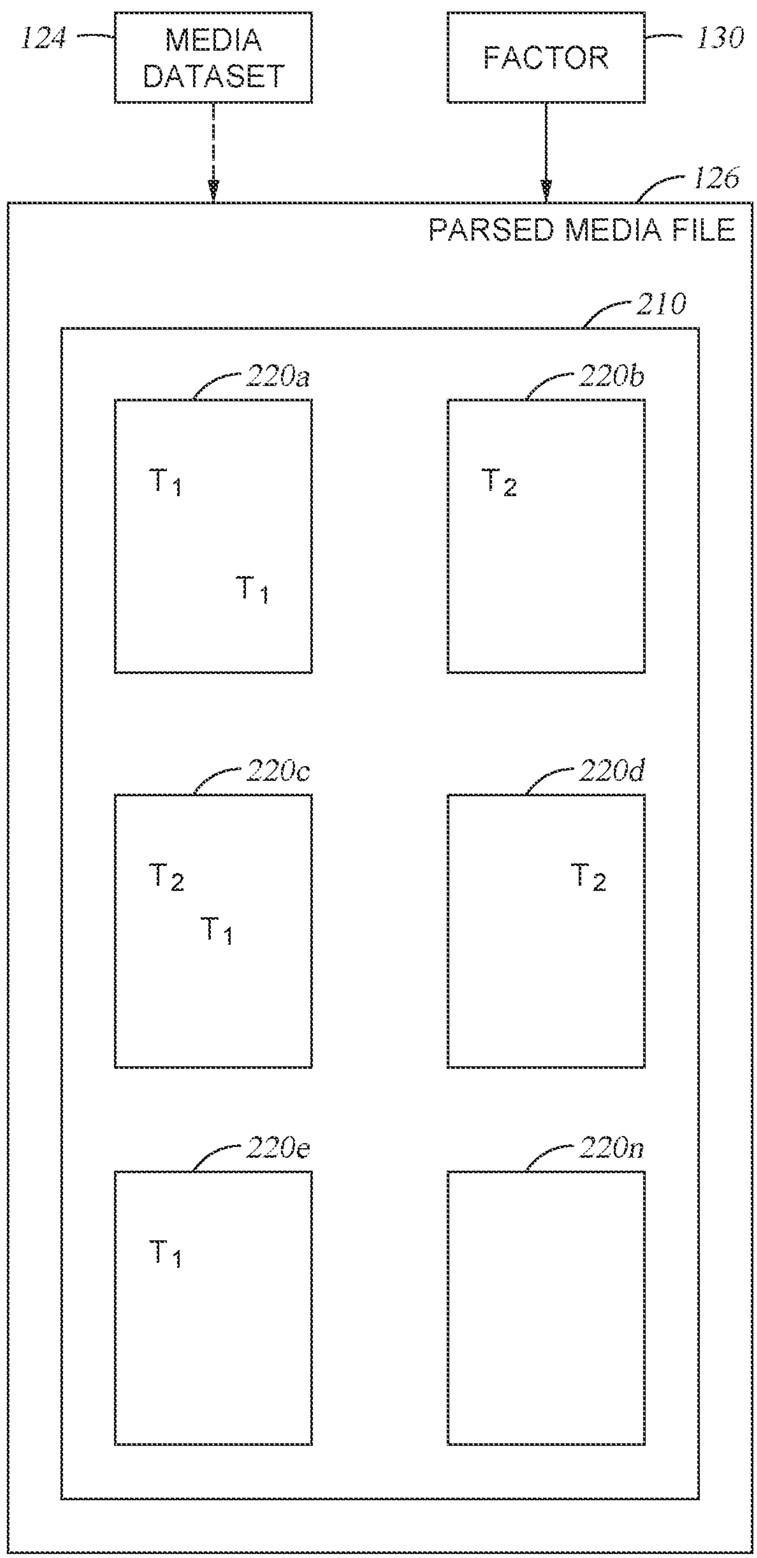
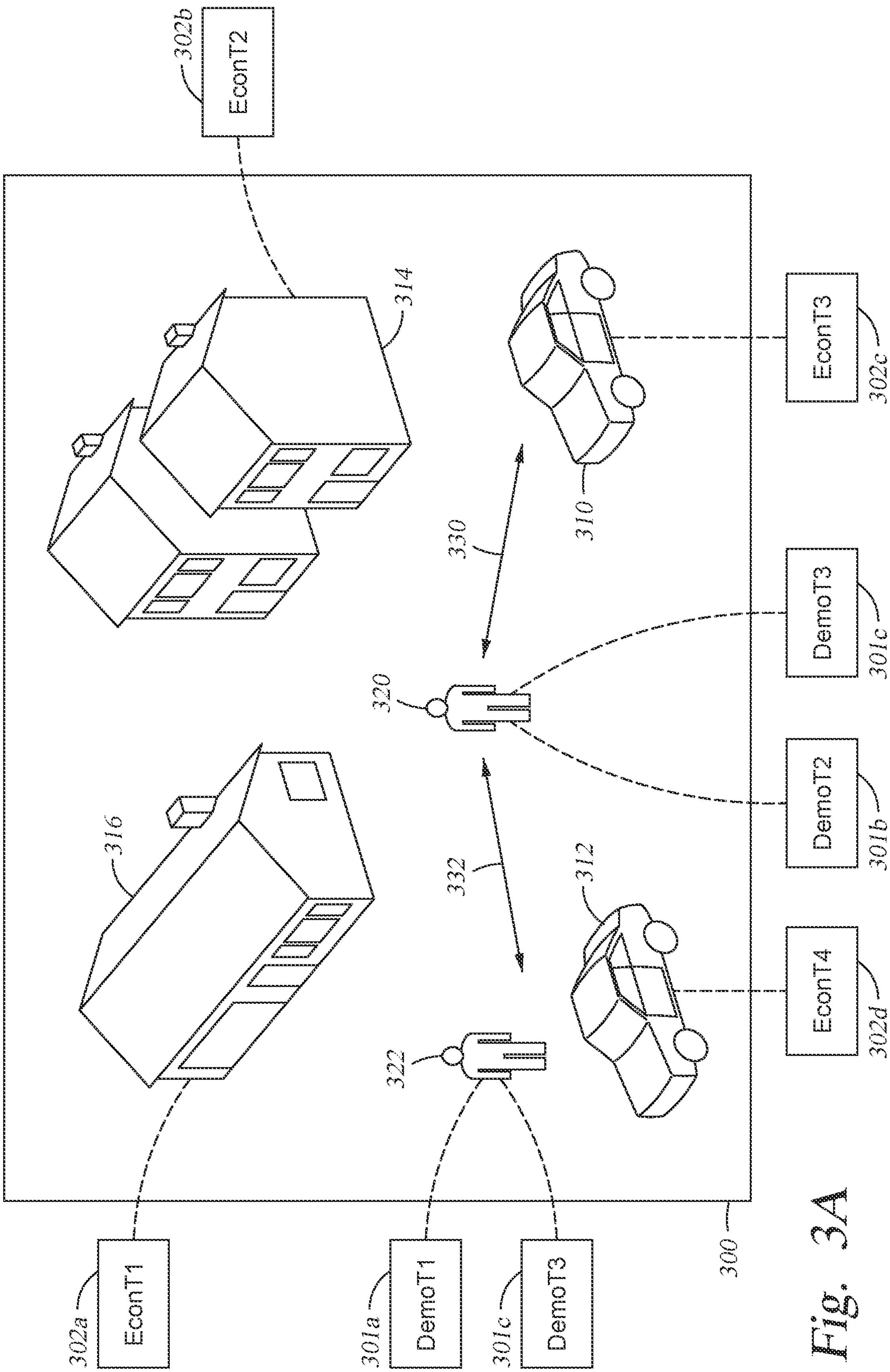

124
MEDIA DATASET
FACTOR
130
126
PARSED MEDIA FILE
210
220a
T1
T1
220b
T2
220c
T2
T1
220d
T2
220e
T1
220n

Fig. 2



EconT2
302b
314
316
320
330
332
310
312
322
EconT3
302c
DemoT3
301c
DemoT2
301b
EconT4
302d
EconT1
302a
DemoT1
301a
DemoT3
301c
300

Fig. 3A

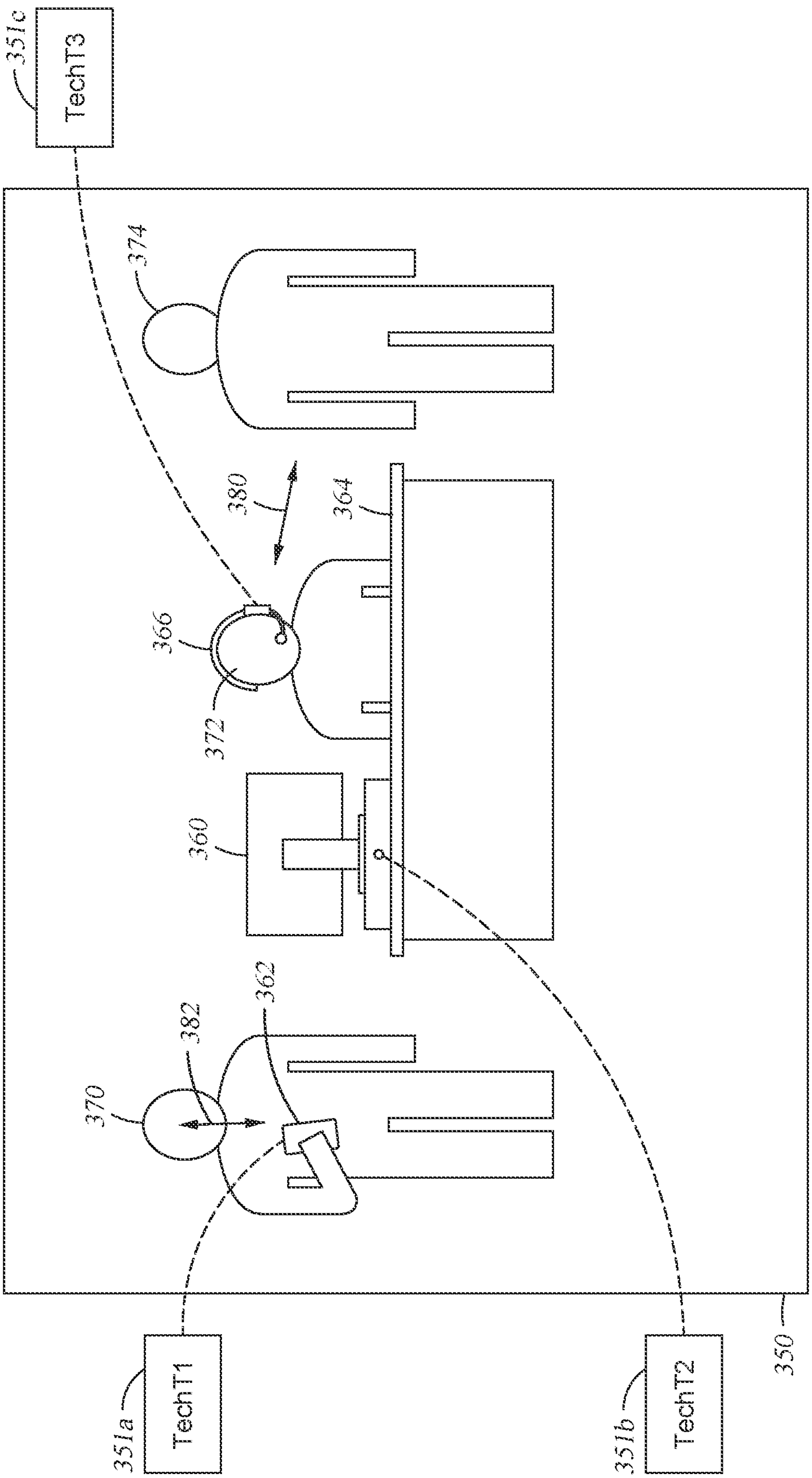

351c
TechT3
374
380
364
366
372
360
382
362
370
351a
TechT1
351b
TechT2
350

Fig. 3B

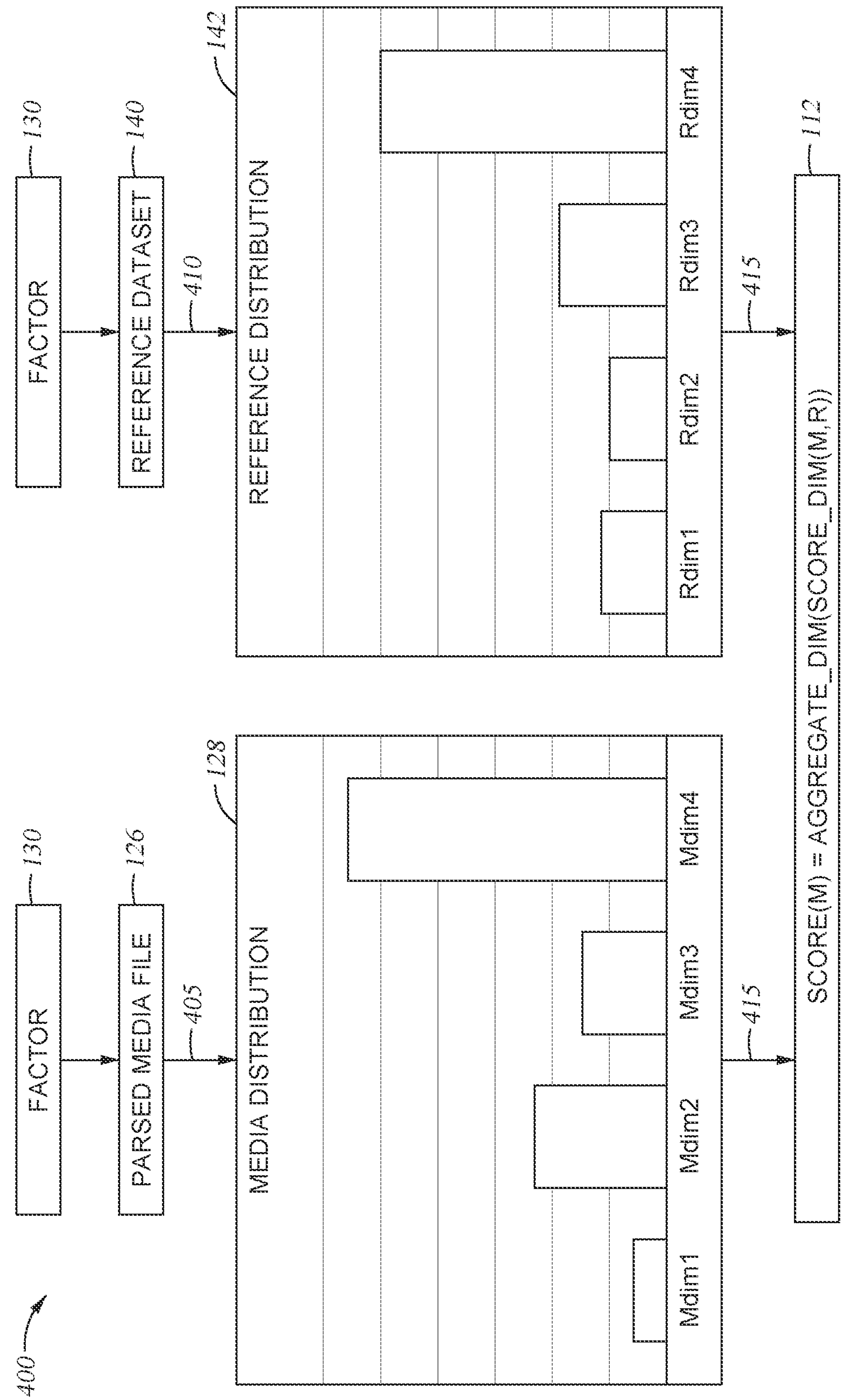

400
130
FACTOR
126
PARSED MEDIA FILE
405
128
MEDIA DISTRIBUTION
Mdim1
Mdim2
Mdim3
Mdim4
130
FACTOR
140
REFERENCE DATASET
410
142
REFERENCE DISTRIBUTION
Rdim1
Rdim2
Rdim3
Rdim4
415
415
112
SCORE(M) = AGGREGATE_DIM(SCORE_DIM(M,R))

Fig. 4A

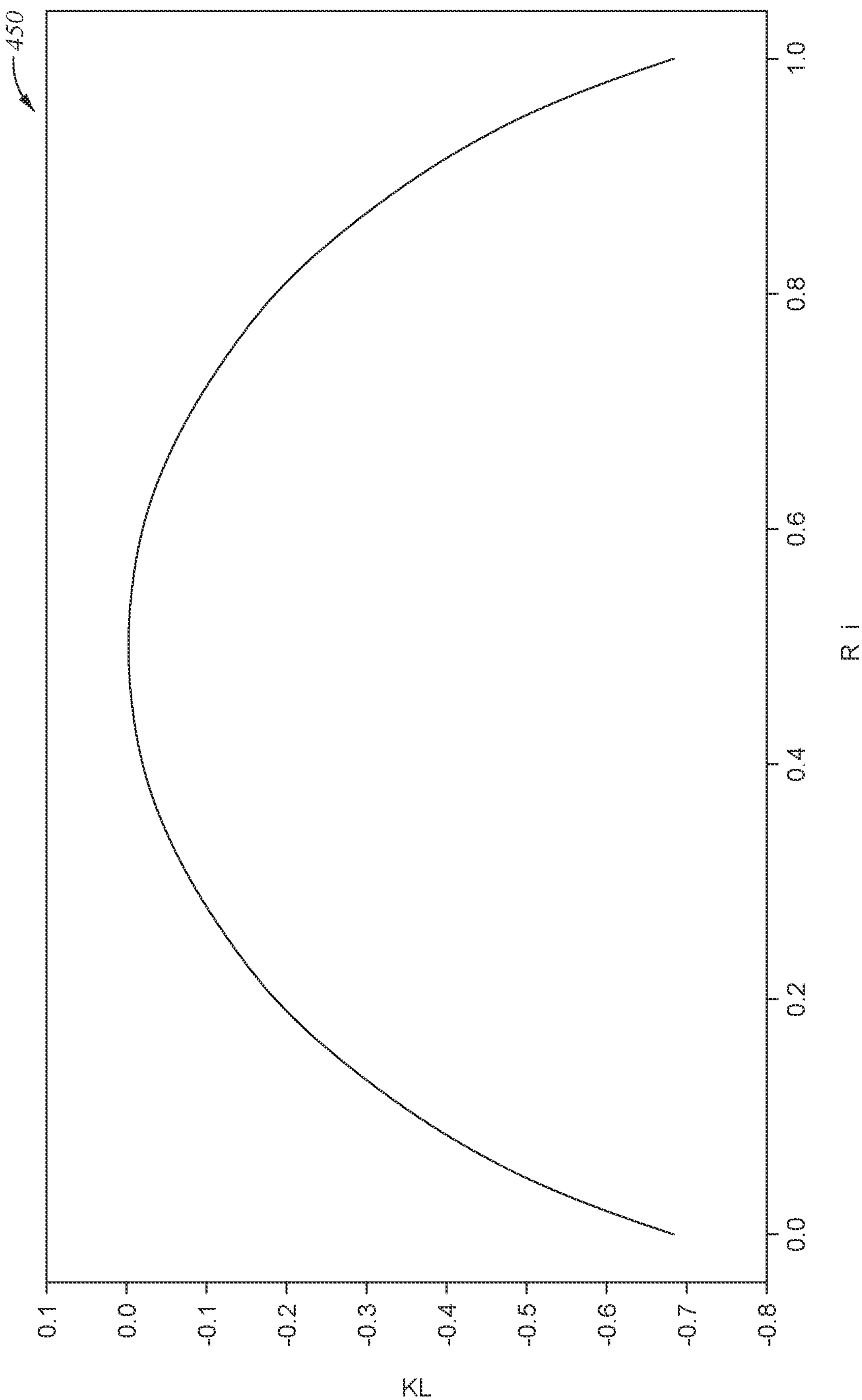


Fig. 4B

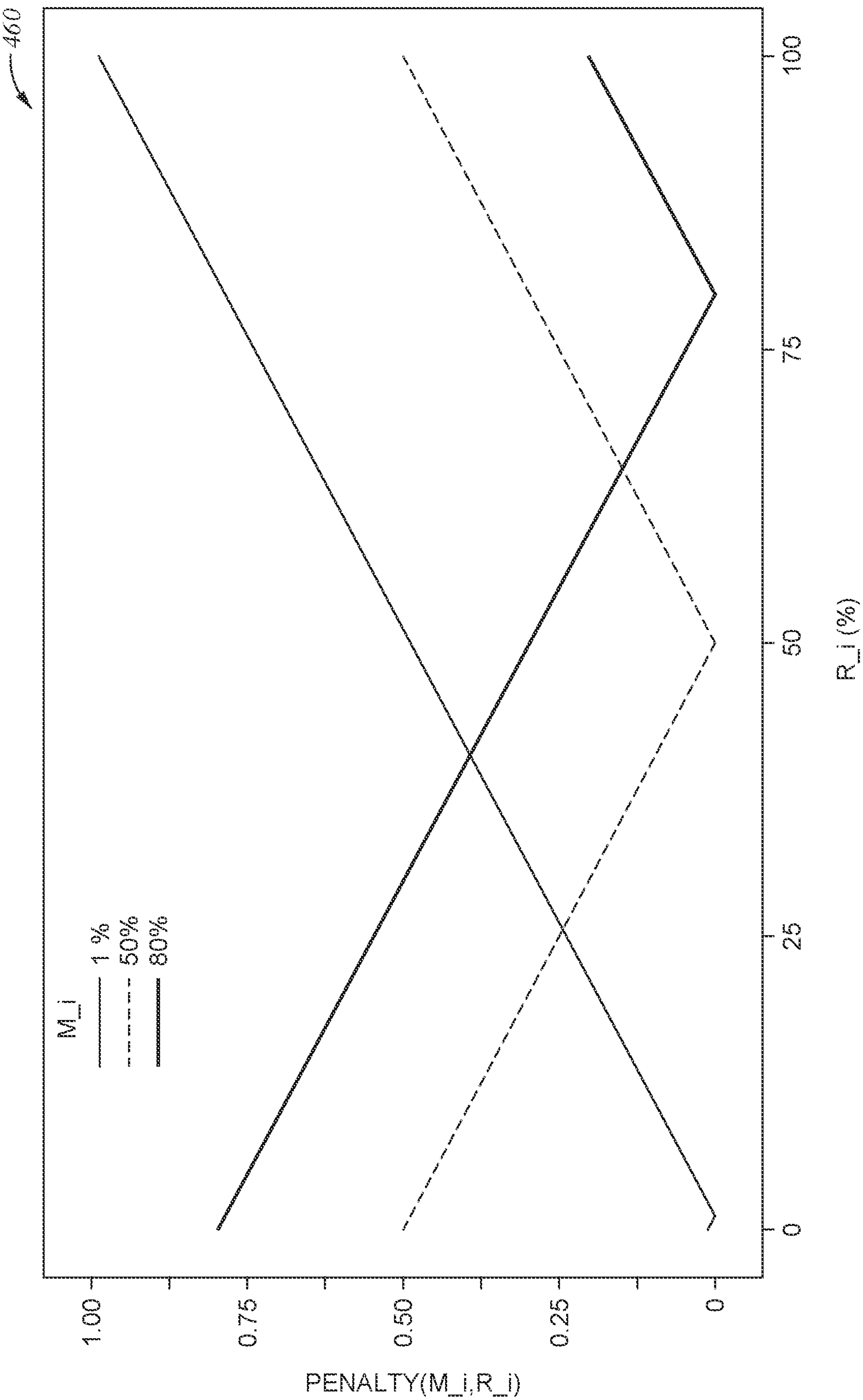


Fig. 4C

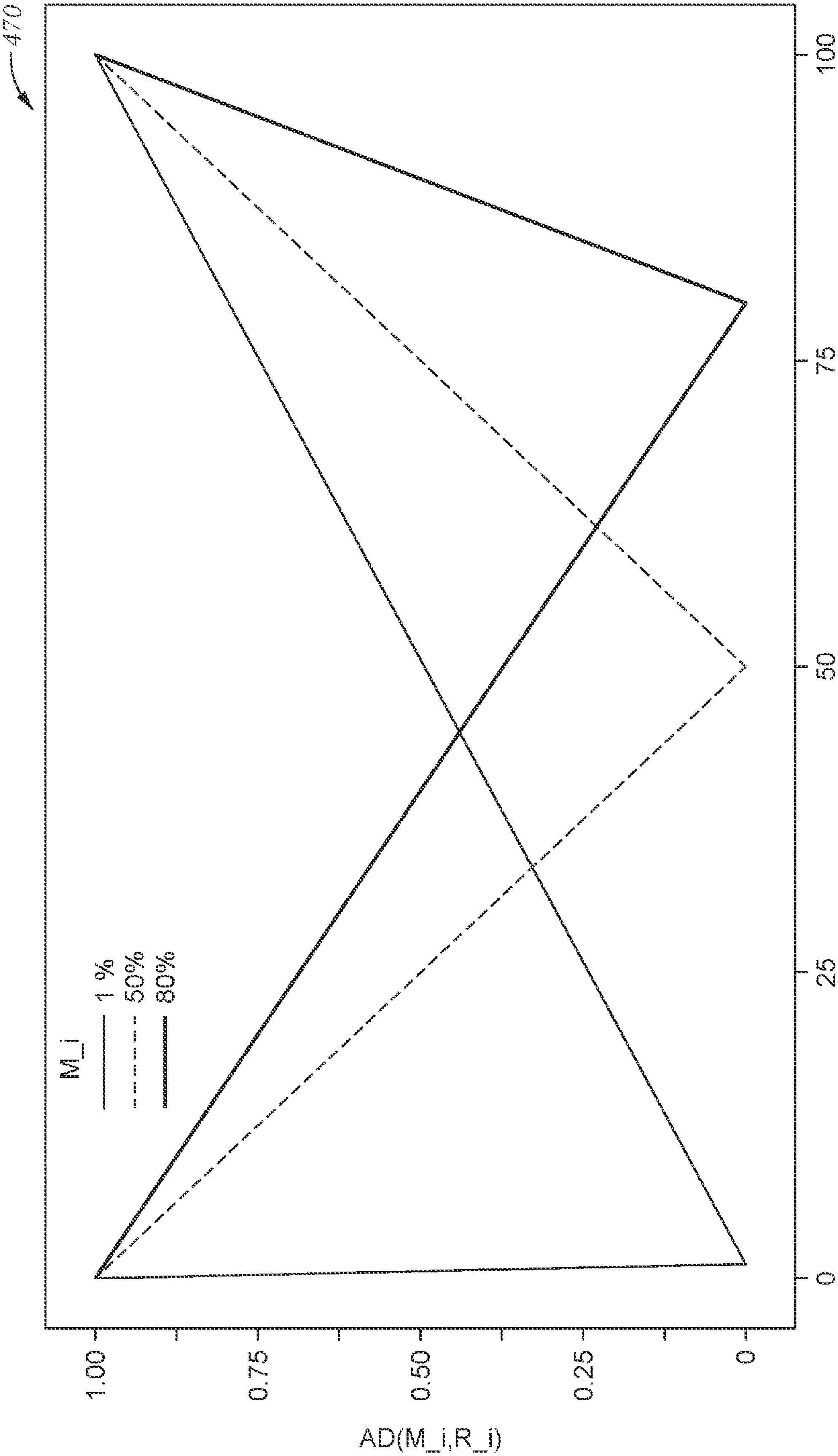


Fig. 4D

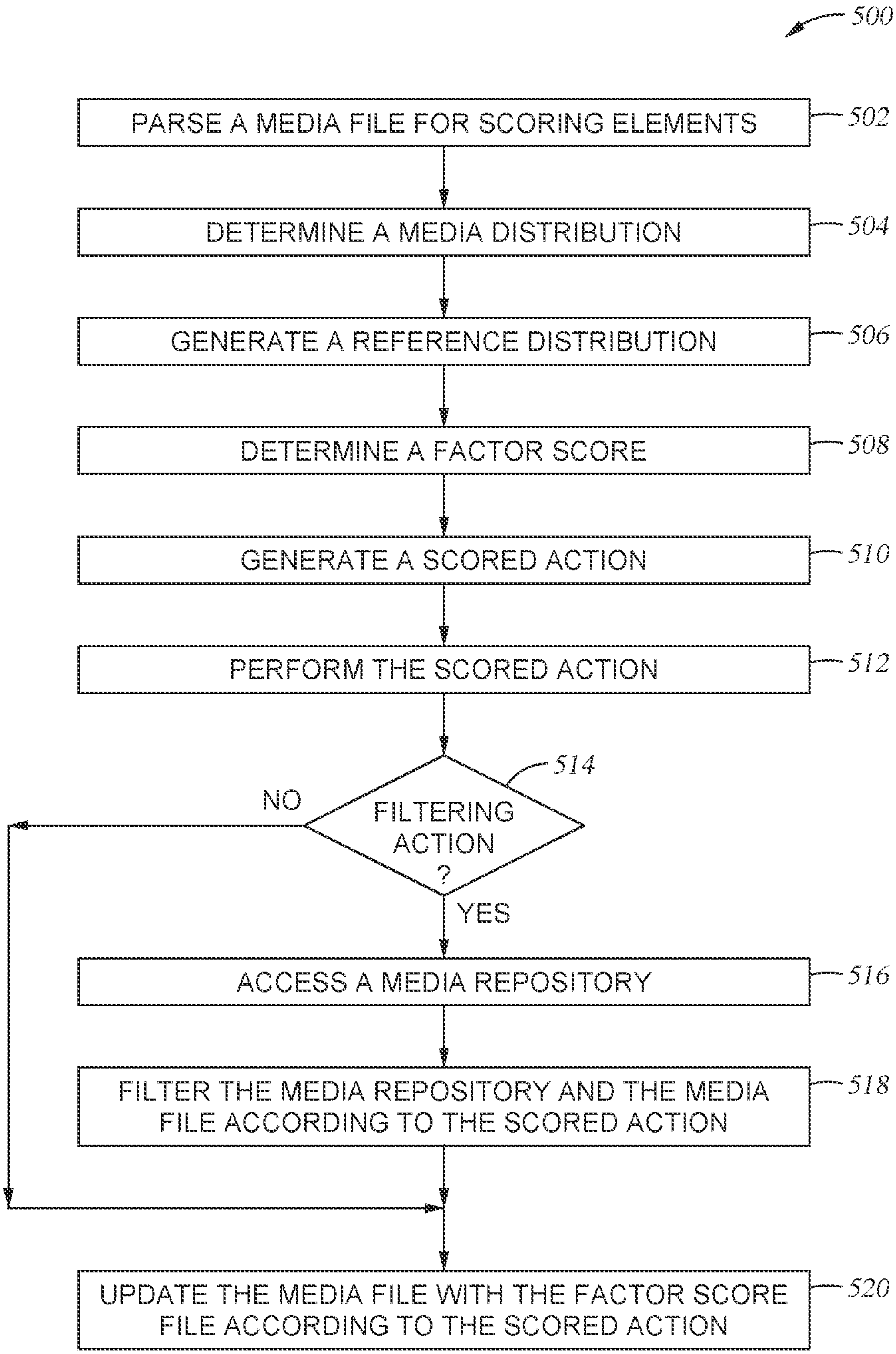

500
PARSE A MEDIA FILE FOR SCORING ELEMENTS
502
DETERMINE A MEDIA DISTRIBUTION
504
GENERATE A REFERENCE DISTRIBUTION
506
DETERMINE A FACTOR SCORE
508
GENERATE A SCORED ACTION
510
PERFORM THE SCORED ACTION
512
FILTERING ACTION ?
514
NO
YES
ACCESS A MEDIA REPOSITORY
516
FILTER THE MEDIA REPOSITORY AND THE MEDIA FILE ACCORDING TO THE SCORED ACTION
518
UPDATE THE MEDIA FILE WITH THE FACTOR SCORE FILE ACCORDING TO THE SCORED ACTION
520

Fig. 5

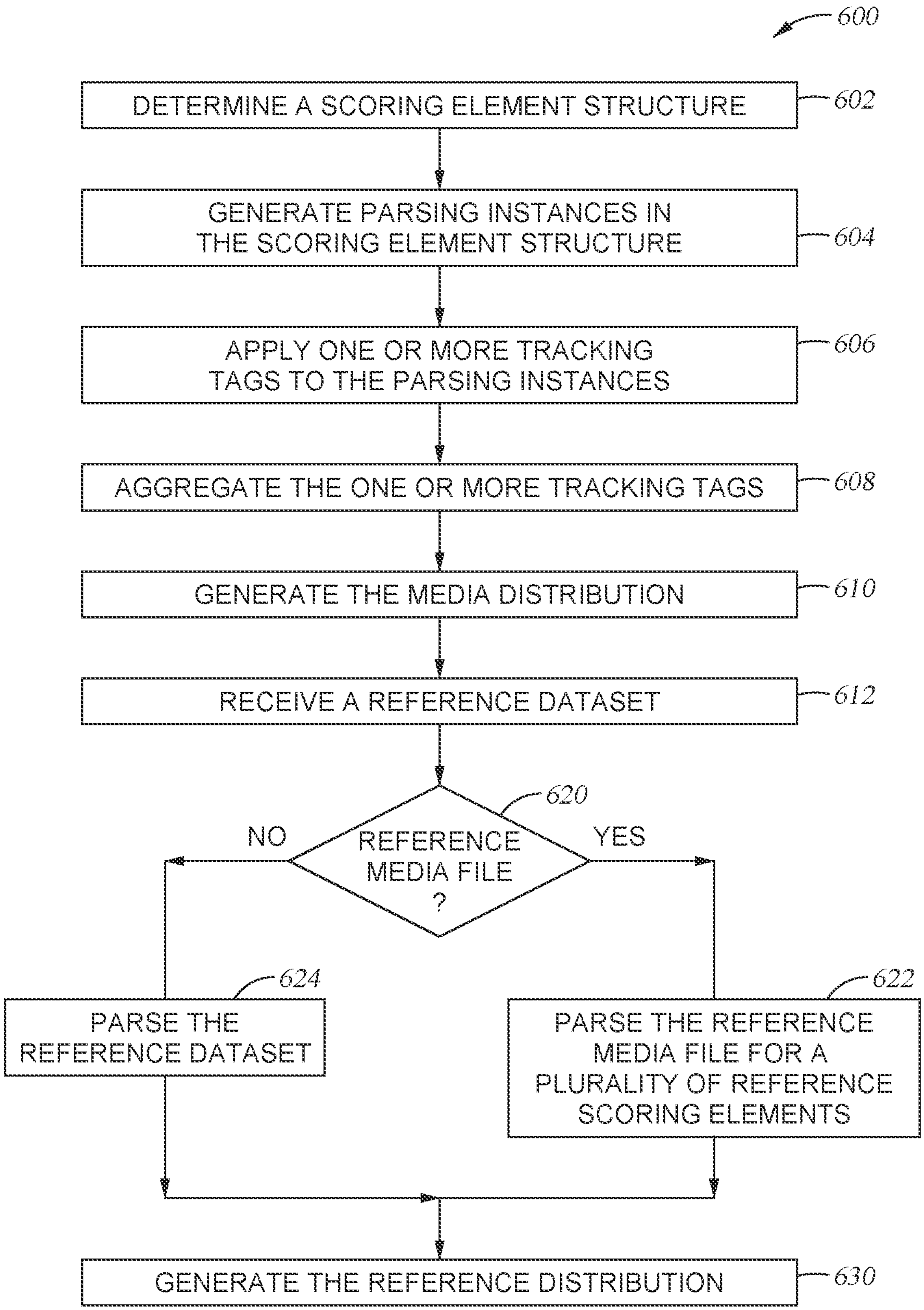

600
DETERMINE A SCORING ELEMENT STRUCTURE
602
GENERATE PARSING INSTANCES IN THE SCORING ELEMENT STRUCTURE
604
APPLY ONE OR MORE TRACKING TAGS TO THE PARSING INSTANCES
606
AGGREGATE THE ONE OR MORE TRACKING TAGS
608
GENERATE THE MEDIA DISTRIBUTION
610
RECEIVE A REFERENCE DATASET
612
REFERENCE MEDIA FILE ?
620
NO
YES
PARSE THE REFERENCE DATASET
624
PARSE THE REFERENCE MEDIA FILE FOR A PLURALITY OF REFERENCE SCORING ELEMENTS
622
GENERATE THE REFERENCE DISTRIBUTION
630

Fig. 6

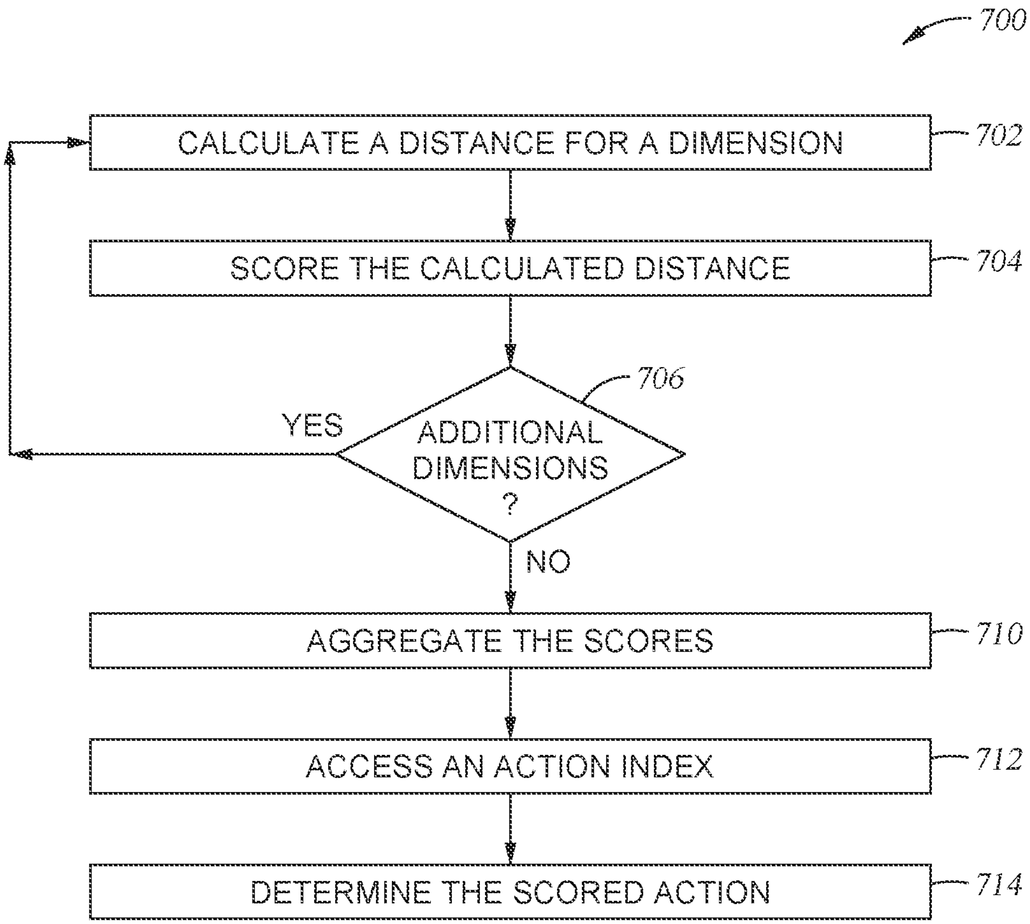

700
CALCULATE A DISTANCE FOR A DIMENSION
702
SCORE THE CALCULATED DISTANCE
704
706
YES
ADDITIONAL DIMENSIONS ?
NO
AGGREGATE THE SCORES
710
ACCESS AN ACTION INDEX
712
DETERMINE THE SCORED ACTION
714

Fig. 7

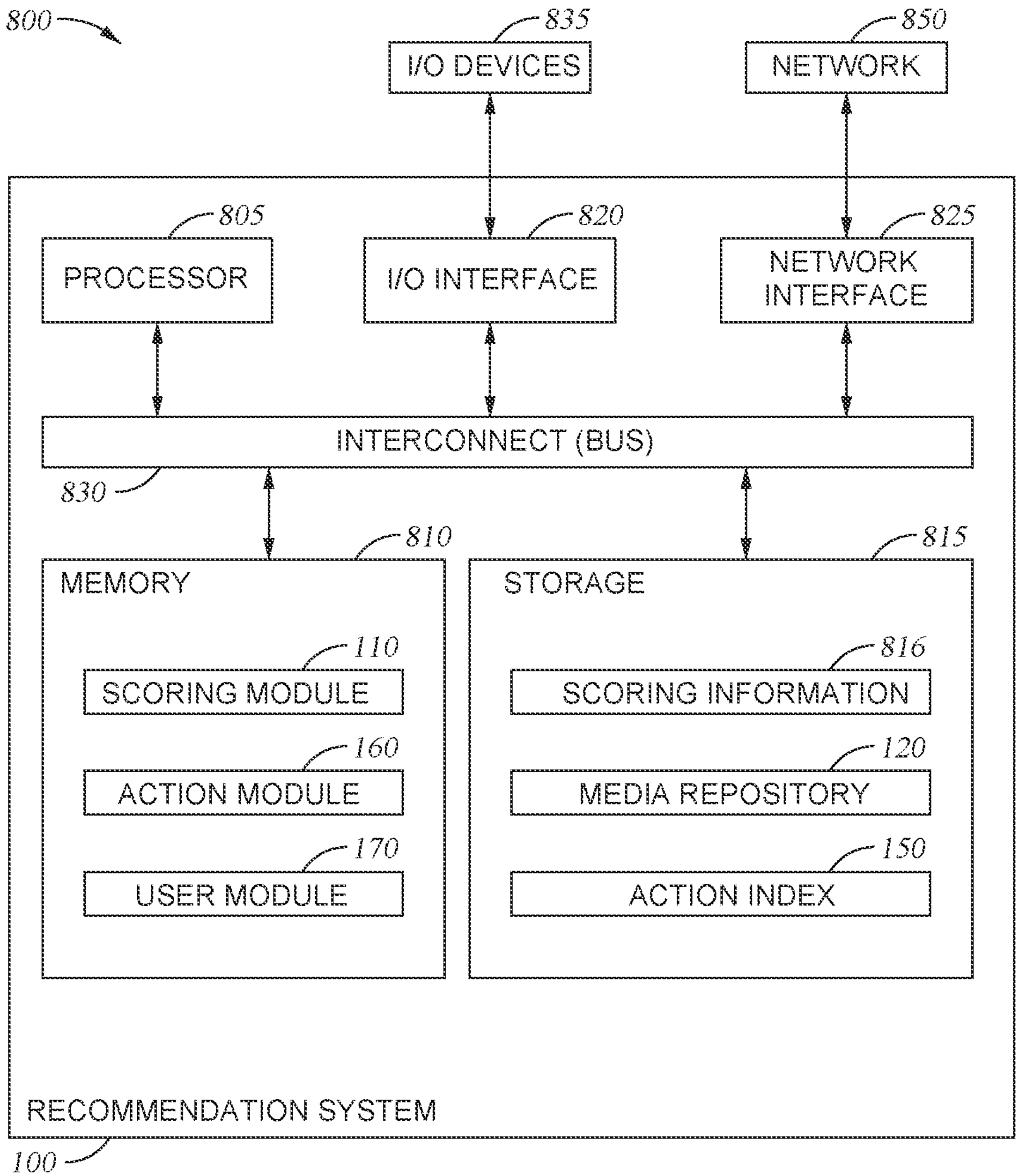

800
835
I/O DEVICES
850
NETWORK
805
PROCESSOR
820
I/O INTERFACE
825
NETWORK INTERFACE
INTERCONNECT (BUS)
830
810
MEMORY
110
SCORING MODULE
160
ACTION MODULE
170
USER MODULE
815
STORAGE
816
SCORING INFORMATION
120
MEDIA REPOSITORY
150
ACTION INDEX
RECOMMENDATION SYSTEM
100

Fig. 8

SCORING AND RECOMMENDING A MEDIA FILE

BACKGROUND

The entertainment industry is increasingly moving towards providing media content directly to individual consumers via streaming services and other direct to consumer methods. As a part of this transition, the amount of digital content available to consumers is also rapidly increasing. This digital content includes content created for mass market appeal, where the content is intended for consumption across large populations, such as an entire country or consumers around the world. Other digital content includes content created for more niche market subsets of consumers, where the content may be readily enjoyed by some consumers, but less enjoyed by others.

Entertainment companies and other media content creators increasingly own and generate large amounts of media content across many different genres and media formats. The general goal of these companies and creators is to provide the media content to consumers for media consumption (e.g., viewing, listening, reading, etc.). As the media content landscape grows and the amount of digital content increases, the owners, creators, producers, reviewers, etc. (herein stakeholders) of the media content desire to understand what content currently exists in various media libraries, what current media content consumers want to consume, and what media content should be created to match consumer expectations for the future

Content creators, providers, and consumers all desire for more efficient ways to both understand what content is available in the market for consumption, as well as what content should be made in the future. Methods for recommending content to individual consumers as well as for understanding what additional content should be made or otherwise provided currently relies on large amounts of data collection and analysis. This data collection tracks individual and group consumer usage of the media content and uses that data to provide additional content to the consumer. Less intrusive and more objective methods for evaluating and recommending media content remains a challenge.

While some media content providers have sophisticated systems for providing user's recommended content, these systems largely rely on large scale and intrusive data collection for both individual users and aggregate users across a given platform. For example, a user's habits for an individual movie in a media content library may indicate that the user enjoys watching the individual movie and similar movies. These previous methods use that data for the user to recommend other nominally similar media content based on other user's watching habits. For example, User A views titles A, B, and C and when User B views title A, the previous methods recommend titles B and C to User B (based on User A's history). However, these current recommendation methods rely on observing user behavior and are limited in the insights that can be gained for media content.

BRIEF DESCRIPTION OF THE DRAWINGS

So that the manner in which the above recited aspects are attained and can be understood in detail, a more particular description of embodiments described herein, briefly summarized above, may be had by reference to the appended drawings.

It is to be noted, however, that the appended drawings illustrate typical embodiments and are therefore not to be considered limiting; other equally effective embodiments are contemplated.

FIG. **1** depicts a recommendation system for scoring a media file, according to embodiments described herein.

FIG. **2** illustrates a parsed media file, according to embodiments described herein.

FIGS. **3**A-B illustrate parsing instances, according to embodiments described herein.

FIG. **4**A is a system flow diagram for determining a factor score, according to embodiments described herein.

FIGS. **4**B-D are example graphs for determining distance values, according to embodiments described herein.

FIG. **5** is flowchart of a method for scoring a media file, according to embodiments described herein.

FIG. **6** is flowchart of a method for parsing a media file, according to embodiments described herein.

FIG. **7** is flowchart of a method for determining a scored action, according to embodiments described herein.

FIG. **8** is a block diagram depicting a recommendation system, according to some embodiments disclosed herein

DETAILED DESCRIPTION

The system of the present disclosure allows media content owners and providers to gain insight into how well their media libraries represent a diversity of populations along a variety of characteristics and metrics. For example, an individual movie, or a group of movies taken as a collection, may over-represent or under-represent various demographic groups (as compared to a general or target population). Similarly, media content may present various other experiences across economic, technological, and sociological spectrums.

Understanding what the media content provides or presents to a consumer allows for more nuanced and targeted recommendations for users, as well as providing insight to content creators on what new media content or changes to existing media content should be made to address gaps in representation. Filling these gaps of representation in media content can improve a general reputation for the media content and the media content providers/creators. This can also encourage engagement with the media content and increase consumption of the media content as well as profit for the media content providers/creators.

In order to address these concerns and provide nuanced insight into media content, the systems and methods described herein provide for parsing a media file using a factor of interest, determining a factor score for the media file, and performing a scored action based on the factor score to provide a media content recommendation to a user/consumer or to content providers. The scored action may include sorting and filtering a media repository, including the media file, which in turn reduces an amount of data needed for a system to provide an objective recommendation to a user, as well as reducing the time and data processing required to provide a recommendation to the user.

FIG. **1** depicts a recommendation system, system **100**, for scoring a media file, according to embodiments described herein. The system **100** scores a media file **122** and provides for improved sorting and filtering of a media repository **120**. The system **100** may also provide recommendations related to the media file **122** to external systems, such as a user system **175** and a media analysis system **165**, as discussed herein.

In some examples, the media file **122** may contain any combination of digital media including video media, audio media, text based media, etc. For example, the media file **122** may be a video content file stored in the media repository **120**, where the media repository **120** is a video content library or catalogue of video titles generally accessible by a user **176** via the user system **175** and a user module **170**. In this example, the video content file includes any of a movie, an episode of a television show/feature, a music video, short form video, and other video content.

The user module **170** may filter, select, and otherwise recommend media selections from the media repository **120** for the user **176** to consume. For example, the user module **170** selects video content from the media repository **120** for the user **176** to view (e.g. via a display associated with the user system **175**). In some examples, the user **176** may seek access to a media file **122** in the media repository **120** such as via a search function via the user module **170** and the media repository **120**. The user module **170** and the media repository **120** utilize the search function to directly filter or select the desired media file and provide the media file **122** to the user **176** via the user system **175**. For example, when the user **176** has a specific movie they desire to watch, the system **100** permits the user **176** to directly access and view the specific movie. While the user **176** may continue direct access to the system **100**, the stakeholders in the system **100** often want to encourage engagement between the user **176** and the system **100**. The engagement can be increased when the user **176** is informed about other media in the media repository **120** that may be of interest to the user **176**.

For example, the system **100** may recommend additional media files in the media repository **120** that the user **176** may find interesting or worth consuming, and in turn, continue to access the system **100**. In some examples, the media repository **120** includes a large catalogue of media files, where some media files (e.g. video content) are relevant to the user **176** (e.g., the user desires to view the content or would likely enjoy viewing the content) and other media files are less relevant or less interesting to the user **176**. Relying on the user **176** to manually sort through the media repository **120** for relevant media may fatigue the user **176** and reduce engagement with the system **100**. Moreover, collecting search and interaction data related to the user's interactions with the system **100** can raise data privacy concerns as well as necessitate some baseline user engagement with the system in order to collect at least some interaction data.

In order for the system **100** and the user module **170** to efficiently provide relevant media files (e.g., video content) to the user **176**, the media files (such as the media file **122**) in the media repository **120** are scored and filtered according to various factors of interest, discussed herein, where the filtered media repository provides filtered media to the user upon access by the user. While various examples discussed herein are related to video content files, as discussed above the media file **122** may be any type of media or other data file which contains scorable information. For example, the media file **122** may include any combination of a still image, a digital book, an audio recording, or other type of media content. The system **100** parses and scores each of these various types of media to provide a recommendation to the user **176** and the media analysis system **165**.

In some examples, a scoring module **110** of the system **100** obtains or accesses the media file **122** from the media repository **120**. The scoring module **110** parses the media file **122** into the parsed media file **126** for tagging and further scoring. The scoring module **110** may use a media dataset **124** and a factor of interest **130** to parse the media file **126** into scoring elements, as discussed in greater detail in relation to FIG. **2**.

The media dataset **124** may include data relevant to the media file **122**. For example, for a video content file, such as a movie, the media dataset **124** may include a script, actor credits for the movie, as well as demographic and other relevant information for each actor, etc. If the actor information contains personally-identifiable or other sensitive information, it must be gathered, handled, secured, and used in strict compliance with all data and privacy laws and best practices of the relevant jurisdiction. In some examples, the media dataset **124** may be included as a part of the media file **122** (e.g., data, metadata, etc.). For example, previously applied tags or other similar information data may be included as part of the media file **122**, where the previously applied tags contain information relevant to the factor of interest. For example, previously applied tags for a video content file may include tags for media genre, demographic and other representational characteristics of lead actor(s), characteristics of supporting actor(s) (demographic and other representational characteristics, as well as relevance to plot, screen time, etc.).

The media dataset **124** may also include data accessible via an external network, such as the Internet, where the system **100** accesses the information from public or private databases via the external network, as the scoring module **110** parses the media file **122**. For example, the media dataset **124** may include data collected by the system **100** from external databases that include actor information for a movie including demographic information for the actor, past roles, etc.

In some examples, the scoring module **110** also uses the factor of interest **130** to parse the media file **122**. The factor of interest may include any combination of factors and dimensions relevant to a user **176** or to the stakeholders of the system **100**. For example, the factor of interest **130** may include association with one or more groups. Furthermore, each factor of interest includes dimensions or values of the factor.

Additionally, the factor of interest may include any combination of representational interests which may or may not be represented in the media file **122**. Representational interests may include demographic interests which include, but are not limited to race, age, ethnicity, education level, employment status, income, gender, sex, additional biological traits, disability status, height, body type, additional sociological traits, and other demographic measures which can be used to describe people. Other representational interests included in a factor of interest may include economic interests, technological interests, brand representation, product placement, story themes, set locations, and other example interests that may be represented in media files. Collection, handling, use, and documentation of such information should be done on purely voluntary basis, with consent clearly obtained and documented and processes used to ensure that all such information is secured and only used in strict compliance with all data and privacy laws and best practices of the relevant jurisdiction.

The scoring module **110** provides a factor score based on the data in the media file **122** (as compared to the reference dataset **140** described herein). For example, the factor score ultimately considers how often characters meeting a certain factor criteria are on screen in a movie, how often characters meeting the criteria speak in the dialogue, how the characters are represented in the movie (e.g., positive characterization vs negative characterization), among other factors.

These factors and the various dimensions associated with the factor are used determine what types of scoring elements are needed in the parsed media file **126** and to score the media file **122** as discussed herein in more detail in relation to FIGS. **2-7**. The factor of interest **130** may also include limiting factors or dimensions individually selected by a user **176**.

In general, the media file **122** is also parsed to apply tracking tags to the various instances of the parsed media file **126** which relate to a respective dimension/value of the factor of interest **130**. For example, whenever a dimension of the factor of interest **130** is detected or associated with a portion of the media file **122**, the scoring module **110** applies a tracking tag for the dimension. The scoring module **110** aggregates the applied tracking tags for the parsed media file **126** and generates a media distribution **128** for the media file **122**. The media distribution may include any type of distribution function or representation which represents the factor of interest and the related dimensions in the media file **122**. For example, the media distribution **128** may include a discrete distribution of the tracking tags applied to the parsed media file **126**.

The scoring module **110** also generates a target or reference distribution, such as a reference distribution **142** using reference dataset **140**. In some examples, the reference dataset **140** may include publicly accessible demographic data such as census data, population survey data, governmental records, etc. and must be must be gathered, handled, secured, and used in strict compliance with all confidentiality restrictions, data and privacy laws, and best practices of the relevant jurisdiction. The reference dataset **140** may also include limited or private datasets which include information and data related to the scoring of media files. The reference dataset **140** may also include a target dataset for the media file **122** as selected by the operator of the system **100**. For example, the scoring module **110** scores the media file **122** against a target or goal dataset (e.g., scored against a goal representation). In some examples, the reference dataset **140** may be pre-trimmed where the data in the dataset is specifically selected for scoring the media file **122** using the factor of interest (e.g. data is directly related to the dimensions of the factors of interest).

While referred to herein as a single dataset, the reference dataset **140** may include multiple datasets from across multiple sources. For example, the reference dataset **140** may include reference media, where the scoring module **110** scores the media file **122** against the reference media file or reference media library (e.g., the media file **122** is scored against every other media file in a media library or media libraries). In some examples, scoring the media file against a reference dataset **140** that includes demographic information for a population may provide advantageous insight into how the media file **122** represents the population, but may not represent other populations or a global population. Reference dataset **140** may have different subsets representing different markets, or there may be more than one reference dataset **140** representing different markets. A media file may score high with respect to one market and low with respect to another market. Scoring the media file **122** against a media catalog (e.g., the media repository **120** or other collection of media content) provides for insight into how the media file **122** scores against currently available media content.

In another example, the scoring module **110** parses or otherwise processes the reference dataset **140** using the factor of interest **130** to extract and tabulate data related to the dimensions. The scoring module **110** also uses the extracted relevant data and the factor of interest **130** to generate a reference distribution **142**. The reference distribution **142** may include any type of distribution function or representation which represents the factor of interest and the related dimensions in the reference dataset **140**. In some examples, the reference distribution **142** is a same form of distribution as the media distribution **128** (e.g., both are discrete distributions).

The scoring module **110** uses the media distribution **128** and the reference distribution **142** to determine a factor score **112** for the media file **122**. The factor score **112** indicates how well the media file **122** matches or otherwise relates to the reference dataset **140** based on the factor of interest **130**. In some examples, the factor score **112** is within a range from (0)-(100) where (0) indicates no relation, similarity, or match between the media file **122** and the reference dataset **140** and (100) indicates a perfect or near perfect match between the media file **122** and the reference dataset **140**.

Additionally, the factor score **112** may be calculated by the scoring module **110** using normalized and aggregated versions of the media distribution **128** and the reference distribution **142**. The scoring module **110** may also use distance calculations between the media distribution **128** and the reference distribution **142** in order to determine the factor score **112**. The generation of the media distribution **128** and the reference distribution **142** and calculation of the factor score **112** are discussed in greater detail herein in relation to FIGS. **4**A-D.

The scoring module **110** uses the factor score **112** to generate a scored action **114**. In some examples, the scoring module **110** accesses or otherwise interacts with an action index **150** to generate the scored action **114**. The scored action **114** includes actions for the system **100** to perform related to the media file **122**. The action index may include stored discrete actions (e.g., provide a scored media file with a high score to a user, sort a scored media file with a low score to a bottom of a recommendation queue, etc.) where the scoring module **110** selects one of the stored discrete actions as the scored action **114** for the media file **122**. The action index may also include various steps for generating an action based on the factor of interest **130**, the media file **122**, the media repository **120**, the user **176**, etc. For example, the scoring module **110** may select various sub-actions from the action index **150** to form the scored action **114**.

In some examples, the system **100** stores the factor score **112** and the scored action **114** with a direct correlation to the media file **122** (e.g., as metadata for the media file **122**). In some examples, the action module **160** executes, implements, or otherwise performs the scored action **114**. For example, the action module **160** in conjunction with user module **170** filters the media repository **120** to sort or filter the repository in order to provide relevant media files to the user **176**. For example, the action module **160** sorts the media file **122** and the media repository **120** to cause the media file **122** to be recommended to the user **176**, hidden from the user **176**, etc.

In some examples, the system **100** repeats the process of scoring the media file for each media file in the media repository **120** in order to score each media file according to the factor of interest **130** and the reference dataset **140**. The user module **170** and the user **176** may then efficiently access the media repository where relevant, recommended media files are easily accessible by and provided to the user **176**.

In some examples, the scored action **114** also includes suggestions, notes, or directives for the stakeholders or operator of the recommendation system. For example, when the media file **122** includes a low score for the factor of interest **130**, the scored action **114** may include a low score alert for the media analysis system **165**. The action module **160** provides the alert to the media analysis system **165** in order to inform the operator that the media file **122** has a low score for the factor of interest **130**. The operator may then use the low score to alter the system **100**, the media repository **120**, the media file **122**, etc. in order to raise the score for the media file **122** or an aggregate score for the media repository **120** overall.

In any example described above in relation to FIG. **1**, the scoring of the media file **122** is directly related to the content presented in the media file. That is, the content that the user **176** is consuming or would ultimately consume (e.g., view, hear, read, etc.) via the user system **175**. As discussed above, in order to score the media content and the media file **122** properly, the scoring module **110** parses the media file **122** into the parsed media file **126** as discussed in relation to FIGS. **2**, **3**A, and **3**B.

FIG. **2** illustrates a parsed media file, according to embodiments described herein. The scoring module **110**, discussed in FIG. **1**, uses the media dataset **124** and the factor of interest **130** to parse the media file **122**, shown in FIG. **1**, into the parsed media file **126**. In some examples, the scoring module **110** determines a scoring element structure **210** for the media file, where one or more parsing instances, including parsing instances **220***a*-**220***n* are stored. The scoring element structure and the one or more parsing instances **220***a*-**220***n* form a plurality of scoring elements for the media file **122**.

For example, for a video content file, the scoring element structure **210** may include a container to collect the various relevant parts or scoring elements of a video content file, including the parsing instances **220***a-n*. The parsing instance **220***a* may include data related to the rendered images in the video file (e.g., what a user sees when viewing or watching the file). The scoring module **110** may populate the parsing instance **220***a* using video/image processing and other processes to include the data related to rendered images. The parsing instance **220***b* may include information related to words spoken in the video content file. The scoring module **110** may populate the parsing instance **220***b* from any of closed caption data from the media file **122**, script data for the media file **122** (received from the media dataset **124**), and speech recognition processes to derive the actual words communicated in the video content of the media file **122**. The parsing instance **220***c* may include data related to sounds other than scripted words or speech, such as soundtrack, background noise, etc. from the media file **122**. The other parsing instances **220***d*-**220***n* may include other related data for parsing, classifying, and tagging the media file **122**.

In some examples, the types of parsing instances are determined by the scoring module **110** based on the factor of interest **130**. In one example, where the factor of interest **130** relates to demographics, the scoring module **110** scores the media file **122** based on the representation of the demographic dimensions in the media file, thus the parsing instances for video content may include parsing instances for rendered images and spoken words to capture representation of the demographic dimensions.

In another example, the factor of interest **130** relates to auditory dimensions (e.g., type of music or sounds), where the scoring module **110** scores the media file based on a certain type or category of music included in the video content of the media file **122**. In this case, rendered images may not be necessary for determining the factor score, thus the scoring module **110** does not process the video content for rendered images.

In some examples, the parsing instances **220***a*-**220***n* may be interrelated. For example, rendered images in parsing instance **220***a* may be related to words spoken in parsing instance **220***b* as well as the background or soundtrack playing during the video content stored in the parsing instance **220***c*. This example may be seen in video content where a character with demographic characteristics may be shown in the rendered images of a scene, but has no dialogue or interaction with other characters. Thus, while represented in the rendered images, the character may not be fully represented in the video content since there is no engagement with the character beyond being in the background of the presented video content. These interrelations may then be used to adjust the applied tags and to calculate/update the factor described herein. These interrelations may be stored in the parsing instances themselves or as part of a separate parsing instance (e.g., the parsing instance **220***e*).

In some examples, the scoring module **110** applies tags to the parsing instances to represent the dimensions of the factor of interest **130** represented in the parsing instance. In some examples, the scoring module **110** utilizes a variety of processing methods including Machine Learning (ML) algorithms. The ML algorithms and other methods may include methods for video processing, image recognition, object identification, natural language processing, and other processes performed by the scoring module **110** to efficiently process the media file **126** and applies tags to the parsing instances.

In an example where the factor of interest **130** is a binary representation, the scoring module **110** applies a first tag T_1 to the parsing instances **220***a*, **220***c*, and **220***e* when a first dimension is present in the respective parsing instances. For example, the scoring module **110** detects a character of a certain type is depicted in the rendered images of the parsing instance **220***a* (using image recognition processes, accessing media dataset **124**, etc.) and applies the first tag T_1 to the parsing instance **220***a*. The scoring module **110** detects the background music or soundtrack in the parsing instance **220***c* is composed, orchestrated, or performed by a musician having a similar characteristic (using sound recognition processes, accessing media dataset **124**, etc.) and applies the first tag T1 to the parsing instance **220***c*. Furthermore, the scoring module detects a favorable or positive interaction for a character in the interactions of parsing instance **220***e* (using natural language processing for spoken words in the media file **122**, ML gesture processing for rendered images, etc.), and applies the first tag T_1 to the parsing instance **220***e*.

In some examples, the scoring module **110** also applies a second tag (T**2**) for a second dimension of the binary representation to parsing instances **220***b*, **220***c*, and **220***d*. For example, the scoring module **110** detects a character of a certain type speaking in words spoken in parsing instance **220***b* and applies the second tag T**2** to the parsing instance **220***b* as well as the instances **220***c* and **220***d* based on other detection processes related to the various parsing instances. In some examples, a parsing instance includes or represents several instances of the dimensions, where the scoring module **110** applies a tag multiple times to the parsing instance. For example, the parsing instance **220***a* includes the first dimension (e.g., two characters with the first characteristic) such that the scoring module **110** applies the first tag T_1 to the parsing instance at least twice. Parsing instances and related tags are described in more detail in relation to FIGS. **3**A-**3**B.

FIGS. 3A-B illustrate parsing instances, according to embodiments described herein. For example, FIG. 3A includes a parsing instance **300** which depicts at least one scene of video content. In some examples, the parsing instance **300** includes images rendered in the video content of the media file **122**. For example, the parsing instance **300** includes objects **310**, **312**, **316**, and **314** as well as person **322** and person **320**. The parsing instance **300** also depicts interactions occurring in the video content. For example, the person **322** and the person **320** have an interaction **332** during the scene associated with the parsing instance **300**. Additionally, the person **320** may also interact with the object **310** (e.g., a car) during the video content.

For the parsing instance **300**, a factor of interest may include a demographic factor of interest with several demographic dimensions. As described in relation to FIG. **2**, as the system processes the parsing instance **300** and the scoring module **110** applies tags related to the demographic dimensions using various ML learning and additional video processing methods.

For example, the scoring module **110** applies a first tag for the demographic dimension (DemoT**1** **301***a*) of a person to the parsing instance **300** when either the person **322** or the person **320** match the demographic dimension. In some examples, the scoring module **110** also determines whether the persons **320** or **322** match or represent a characteristic such as DemoT**1** **301***a* by video processing/image identification, information related to the characters/person (e.g., a character description for the persons **320** and **322**) in the media file **122**, information related to the actor/actress portraying the persons contained in the media dataset **124**, etc. In an example where the person **322** matches the demographic DemoT**1** **301***a*, the scoring module **110** applies the DemoT**1** **301***a* to the parsing instance **300**.

Additionally, the person **322** may represent a different dimension than the person **320**, such that the scoring module **110** applies a second tag DemoT**2** **301***b* to parsing instance **300** to represent the different demographic dimension/characteristic.

In some examples, tags related to the first tag and the second tag may also be used to analyze and tag the interaction **332** (e.g., using text recognition and natural language processing for the dialogue, image processing to access physical aspects of the interaction, etc.). For example, additional tags DemoT**1** **301***a* or DemoT**2** **301***b* may be applied based on the dialogue in the interaction **332** or other measures that quantify which of the person **320** and **322** is represented by the interaction **332**.

In some examples, the factor of interest **130** may also include an additional factor with additional dimensions. For example, the factor of interest may include an additional demographic of age group. In this example, a third tag DemoT**2** **301***b* may also be applied for both the person **320** and the person **322** when a third demographic dimension related to the factor of interest is shared by both persons **320** and **322**. For example, the scoring module **110** detects, using the media dataset **124**, image recognition, etc., that the persons **320** and **322** are a same or similar age (e.g., both 20 years old, both young adults, etc.) and applies the tag DemoT**3** **301***c* to the parsing instances. In this example, the multiple factors and the respective dimensions may be utilized in the generation of the factor score described herein.

For the tags **301***a*-**301***c*, the factor of interest is related to demographic or other attributes of the characters depicted in the parsing instance **300**. In some examples, the scoring module **110** may also apply tags to represent economic or other characteristics of things other than people depicted in the parsing instance **300**, such as when the factor of interest **130** is related to economic or other factors.

For example, the scoring module **110** applies a first economic tag (EconT**1** **302***a*) when the object **316** is a single family home (representing a first economic dimension) and applies a second economic tag (EconT**2** **302***b*) when the object **314** is a multi-family home (representing a second economic dimension). Similarly, the scoring module **110** applies a third economic tag (EconT**3** **302***c*) and a fourth economic tag (EconT**4** **302***d*) to the parsing instance **300** to track the objects **310** and **312** respectively, where the objects **310** and **312** are cars representing different makes and model as well as age of the car etc. In some examples, the scoring module **110** uses image recognition as well as ML algorithms to detect a represented socio-economic class or status in the parsing instance **300**, where the economic tags represent varying social classes (e.g., lower, middle, and upper classes, etc.).

Furthermore, in some examples the factor of interest may include several different factors of interest, including different types of factors of interest, combined to form a combined factor of interest and a combined factor score. For example, the demographic tags and the economic tags in the parsing instance **300** are aggregated and processed into a single media distribution. In another example, dimensions associated with just one factor are aggregated and processing into a media distribution, as described in greater detail herein in relation to at least FIG. **4**A.

As described herein, the applied tags, related distributions, and factor scores for the demographic and economic concerns represented in the tags in parsing instance **300**, provide objective insight into various sociological factors that may ultimately affect a user viewing the media file **122**. However, the system **100** and the scoring module **110** also provides objective insights into additional factors of interest beyond demographic, economic, or sociological factors of concern.

For example, FIG. **3**B includes a parsing instance **350** which depicts at least one scene of video content. In this example, the factor of concern may include interaction or product use/placement concerns, such as interactions and use of technology or other products. For example, persons **370**, **372**, and **374** may interact with objects **360**, **362**, **364**, and **366**. The objects **362**, **360**, and **366** may include technological or electronic devices where the scoring module **110** applies technological tags (TechT**1** **351***a*, TechT**2** **351***b*, TechT**3** **351***c*) to the parsing instance **350** when the objects are present in the parsing instances **350**. The applied tags may also be updated based on interactions with the objects, such as interaction **382** between the person **370** and the object **362**. The scoring module **110** may also update the technological tags based on an interaction **380** between the persons **374** and **372** if the object **366** or the object **360** are used or mentioned during the interaction **380**.

Like the respective tags in the parsing instance **300** of FIG. **3**A, the tags applied to the parsing instance **350** may be aggregated and compared to a reference dataset. This comparison may provide insight into technological uptake depicted in the media file **122** (e.g., the types of technology used and depicted). The tags in the parsing instance may also be used to analyze and determine additional dimensions, such as product placement (e.g., brands represented in the media file **122**), among other scorable dimensions.

In both the parsing instance **300** in FIG. **3**A and the parsing instance **350** in FIG. **3**B, the scoring module **110** may use the applied tags, both in individual form (i.e. tags for one set of dimensions) as well as aggregated form (i.e. plurality of tags for one dimension or several dimensions) to determine a scored action directly. For example, referring back to FIG. **1** the scoring module **110** may utilize the parsed media file **126** directly to determine a scored action. For example, when the user **176** prefers to view media files that have a high representation of a certain factor of interest the number of tags for the certain factor of interest in the parsed media file (regardless of the comparison to the reference dataset) may indicate that the user **176** is interested in viewing the media file **122**, where the system **100** recommends or otherwise provides the media file **122** to the user **176** via the user module **170** (as discussed herein).

With continued reference to FIG. **1**, in some examples, a direct relation of the factor of interest **130** to the user **176** may not be clear to the system **100**. For example, the user **176** may be a new user where past viewing behaviors and viewing preferences are not known to the system **100**. Additionally, an operator of the system **100** may decline to collect usage and other data for the user **176** in order to provide data privacy to the user **176**. Other examples, where the system **100** may not have a clear process to recommend a media file includes where the media file **122** is a new file (e.g., a new movie or T.V. show in a content library) or where the media repository **120** is a new media repository (e.g., a new or recently added content library). In each of these examples, the system **100** may require additional context for providing a recommendation to the user **176** and the media analysis system **165**. In turn, the scoring module **110** generates the factor score **112** using the media distribution **128** and the reference distribution **142** as described in more detail in relation to FIGS. **4**A-D.

FIG. **4**A illustrates a system flow **400** to determine a factor score, according to embodiments described herein. In some examples, the scoring module **110** uses the parsed media file **126** and the factor of interest **130** to generate the media distribution **128** at the step **405**. The media distribution **128** may include a discrete distribution of each dimension in the factor of interest **130**. For example, for each instance of the tags applied to a parsed media file (such as the parsed media file **126** as discussed in relation to FIGS. **2**-**3**B) the media distribution **128** includes an aggregate distribution of the dimension. For example, the factor of interest **130** may include multiple factors of interest, where individual factors make up the dimensions of the factor of interest. In this example, the scoring module **110** processes the media file **122** and applies tags based on the detected dimensions in the media file **122** using any combination of image recognition, ML algorithms, character information, actor information, etc. as described in the parsing of the media file **122** in relation to FIGS. **1**-**3**B. The aggregation of the tags for the for each dimension is shown in Table 1:

TABLE 1

Dimension	Media Distribution	Reference Distribution
Dim 1	6%	11%
Dim2	23%	10%
Dim3	15%	19%
Dim4	56%	60%

In the example shown in Table 1, each dimension (Dim**1**-Dim**4**) is a different category or classification detected and tagged by the scoring module **110** in the media file **122** (using the processes discussed in relation to FIGS. **1**-**3**B). The media distribution **128** shown in FIG. **4**A includes the four dimensions for the factor of interest (shown as M_{dim1}-M_{dim4}) where the resulting distribution represents the amount of times a respective tag (and corresponding dimension) was observed in the parsed media file **126**, aggregated against a total number of tags for the factor of interest. For example, a first dimension represented by Dim**1** is represented by 6% overall in the media file **122**. This percentage includes an aggregation of the tags for characters depicted in rendered images, dialogue spoken, among other factor discussed in relation to the parsing instances **220***a*-*n* in FIG. **2**. A second, third, and fourth dimension are represented by the dimension Dim**2**-**4** respectively in Table 1.

In some examples, for a given number of dimensions (N), the media distribution may be represented by Equation 1.

$$M\{M_{dim1}, M_{dim2}, \ldots M_{dimN}\} \qquad \text{Equation 1:}$$

The reference distribution **142**, shown in FIG. **4**A, includes four dimensions (shown as R_{dim1} through R_{dim4}) where the resulting distribution represents the amount of times a respective dimension was observed in the reference dataset. In some examples, for a given number of dimensions (N), the reference distribution **142** may be represented by Equation 2.

The scoring module **110** also uses the reference dataset **140** and the factor of interest **130** to generate the reference distribution **142** at the step **410**. In some examples, the reference distribution **142** may include a discrete distribution of each dimension in the factor of interest derived from the reference dataset **140**. For example, for each instance of the dimension applied to the parsed media file (as discussed in relation to FIGS. **2**-**3**B) the reference distribution includes an aggregate distribution of the corresponding dimension(s) from the reference dataset.

Referring back to Table 1, each dimension (Dim**1** through Dim**4**) is a different category or classification where the scoring module **110** extracts or tabulates a representation of the racial categories from the reference dataset **140**. The reference distribution **142** shown in FIG. **4**A includes the four dimensions for the factor of interest (shown as R_{dim1} through R_{dim4}) where the resulting distribution represents the amount of times the respective dimension was observed in the reference dataset **140** aggregated against a total number dimensions for the factor of interest. For example, a first dimension represented by Dim**1** is represented by 11% overall in the reference dataset **140**. This may include the representation of the first dimension in a given population represented by the reference dataset **140**. The second, third, and fourth dimension are represented by the dimensions Dim**2**-**4** respectively in Table 1.

$$R\{R_{dim1}, R_{dim2}, \ldots R_{dimN}\} \qquad \text{Equation 2:}$$

In some examples, the reference dataset may include demographic information or other information where the dimensions are pre-classified or sorted together (e.g., the reference dataset includes census information including classification for various demographic dimensions). In this example, the scoring module **110** populates the distribution with the data from the reference dataset **140**. In another example, the reference dataset **140** may need further processing such as processing raw population data other demographic data, etc. to determine and tabulate the values for each dimension. The scoring module **110** processes the reference dataset **140** to identify, calculate, or aggregate the values for the various dimensions for tracking for the reference distribution **142**. Additionally, the reference dataset **140** may include a media library or catalogue, such as the media repository **120** shown in FIG. **1**, where the scoring module **110** processes the entire catalogue to provide comparative or relative scores to the media files in the catalogue as discussed in further detail herein.

Upon generation of the media distribution **128** and the reference distribution **142**, the scoring module **110** calculates the factor score **112** for the media file **122** in step **415**. In some examples, the factor score **112** represents a similarity between the media distribution **128** and the reference distribution **142**. In some examples, the step **415** includes processing and normalizing steps where the scoring module **110** continues processing the media distribution **128** and the reference distribution **142** in order to calculate the factor score **112** and better represent the similarity or lack of similarity between the distributions. In some examples, the scoring module **110** also computes multiple scores across each dimension (e.g., for each of Dim**1**-**4** in Table 1) or factor of interest and then aggregates the individual scores into a single factor score, the factor score **112**.

In some examples, the scoring module **110** computes a distance between two discrete distributions. For example, for each dimension, the scoring module **110** computes the score between the media distribution **128** and the reference distribution **142**. In some examples, the distributions are discrete (e.g., each distribution targets a single factor of interest, where the factor of interest has multiple dimensions for tracking). In this example, the distance between the distributions is expressed in Equation 3.

$$D(M,R) \quad \text{Equation 3:}$$

$$D(M,R)=D(R,M) \quad \text{Equation 4:}$$

In some examples, distance metrics such as the distance metric shown in Equation 3 are symmetrical as shown in Equation 4, where the distance between each distribution is symmetrical regardless of the order of operation in performing the distance calculations. However, for the computation of the distance for the factor score **112**, the distance metrics are bounded by the scoring module **110**, in order to provide a bounded score. In some examples, a bounded score provides an easily interpretable and usable score for both the system **100** and any users which may view the score. For example, the system **100** utilizes a bounded score to perform quality checks and analysis of the scoring processes described herein in order to determine that the methods are performing correctly. In order to provide the bounded distance metrics, the scoring module **110** normalizes the distance calculations, making the distance no longer symmetrical as shown in Equations 5 and 6.

$$DN(M,R)=D(M,R)/\max(m,D(m,R)) \quad \text{Equation 5:}$$

$$DN(M,R)\neq DN(R,M) \quad \text{Equation 6:}$$

The normalized distance DN is bounded between value of 0 and 1, but as shown in Equation 6, the normalized distances are not symmetrical between the alternate distance computations. In some examples, the usage of the DN requires careful computation and following a precise order of arguments/calculations by the scoring module **110** in order to provide an accurate factor score. Furthermore, several varying distance functions may be utilized in order to calculate the distance.

For example, the distance may be calculated using a Kullback-Leibler (KL) Divergence. The KL Divergence is standard non-symmetrical solution for computing the distance between two distributions adapted for use in generating the factor score **112**. The KL Divergence in the context of the calculation of the factor score may be calculated as shown in Equation 7 (where the dimensions are represented by "i" notation for simplicity in presenting the equations). In some examples, the KL divergence includes relatively flat values for distances. For example, as shown in divergence graph **450** in FIG. **4**B, when a reference distribution includes a dimension for a 50% representation of a character of type A and the media distribution includes a 66% representation of type A characters, the KL divergence between two distributions may be relatively flat relative to a KL divergence for 100% (or 0%) type A representation in the media file and 50% type A representation in the media file. For example, KL (50, 50) is 0, KL (66, 50) is −0.05, and KL (100, 50), KL (0, 50) is −0.69. The additional distance calculations herein provide for more varied distances.

$$D(M,R)=KL(M,R)=\text{sum}_i(M_i*\log(M_i/R_i)) \quad \text{Equation 7:}$$

Another example distance calculation includes utilizing symmetrical absolute difference calculations. In this calculation, for each dimension a penalty value is computed as shown in Equation 8. For example, as shown in distance graph **460** in FIG. **4**C for a dimension value for R_i of 1%, the penalty value for various potential M_i's of 1%, 50% and 100% are 0, 0.49, and 0.99 respectively. In another example, for a dimension value for R_i of 50%, the penalty value for various potential M_i's of 1%, 50% and 100% are 0.5, 0, and 0.5 respectively. In another example, for a dimension value for R_i of 80%, the penalty value for various potential M_i's of 1%, 50% and 100% are 0.8, 0.3, and 0.2 respectively. The distance between the distributions is then computed as the sum across all dimensions as shown in Equation 9. A normalization factor is also determined as shown in Equation 10 and applied to the distance function to calculate a normalized distance function in Equation 11. In some examples, the value of X in Equation 11 is "0" for every dimension except for the dimension "j" calculated in equation 10, where the value of X is "1."

$$\text{penalty}(M_i,R_i)=\text{abs}(M_i-R_i). \quad \text{Equation 8:}$$

$$D(M,R)=\text{sum}_i(\text{abs}(M_i-R_i)) \quad \text{Equation 9:}$$

$$j=\text{argmin}(R) \quad \text{Equation 10:}$$

$$DN(M,R)=\text{sum}_i(\text{abs}(M_i-R_i))/\text{sum}_i(\text{abs}(X_i-R_i)) \quad \text{Equation 11:}$$

For example, referring back to the values presented in Table 1, the symmetrical absolute difference calculations may include the values shown in Tables 2 and 3. In this example, the total absolute difference as calculated in Equation 9 is 0.26, shown in Table 2. Using Dim**2** in Equation 10 where j=2 and calculating the total absolute difference using Equation 11=0.14.

TABLE 2

Dimension	Media Distribution (M)	Reference Distribution (R)	Absolute Difference (Eq. 8)
Dim1	0.06	0.11	0.05
Dim2	0.23	0.1	0.13
Dim3	0.15	0.19	0.04
Dim4	0.56	0.6	0.04
Total	1	1	0.26

TABLE 3

Dimension	Lowest case distribution (X)	Reference Distribution (R)	Absolute difference
Dim1	0	0.11	0.11
Dim2	1	0.1	0.9
Dim3	0	0.19	0.19
Dim4	0	0.6	0.6
Total	1	1	1.8

Another example distance calculation includes utilizing asymmetrical absolute difference calculations. In this example, for each dimension, a linear penalty is computed, as shown in Equation 12, with a minimal value at a reference point, and maximal value on either side of the spectrum (0% and 100%) as shown in distance graph **470** in FIG. **4**D with example AD values for M_i's of 1%, 50%, and 80%. The distance between the distributions is computed as the sum across all levels as shown in Equation 13. The normalization factor is obtained when all weight is placed on the level with smallest value as shown in Equation 10, where the normalized distance is calculated using Equation 14. In some examples, the value of X in Equation 15 is "0" for every dimension except for the dimension "j" calculated in equation 10, where the value of is "1."

$$AD(M_i,R_i).=\text{penalty}(M_i,R_i)=\max(R_i-M_i)/R_i,(M_i-R_i)/(1-R_i)) \quad \text{Equation 12:}$$

$$D(M,R)=\text{sum}_i(AD(M_i,R_i)) \quad \text{Equation 13:}$$

$$DN(M,R)=\text{sum}_i(AD(M_i,R_i))/\text{sum}_i(AD(X_i,R_i))) \quad \text{Equation 14:}$$

In some examples, the above methods for distance calculations can also be further refined using weighted values related to parameters specific to the various dimensions and factors of interest. In any example, once the calculated distance between the media distribution **128** and the reference distribution **142** is used to generate the factor score **112** as shown in Equations 15-17. In Equation 15, the scoring module **110** computes distance across each dimension in the media file **122** (e.g., using any of the methods described above). For example, the scoring module computes a distance for each dimension Dim**1** through Dim**4** shown in Table 1. The scoring module **110** computes a score across each dimension of the media file using Equation 16, where the scores are scaled from "0" to "100", with "100" being the highest score (i.e. distance of 0) and "0" being a bounded lowest score (e.g., indicating a large distance between the dimensions in the respective distributions). The scoring module **110** also aggregates the dimension-specific scores into a single score, such as the factor score **112**, using the Equation 17. For example, using the values calculated above in Tables 2 and 3, the Score (M, R) using equation 16 is 86, where the factor score **112** is further calculated using the aggregate of the dimension scores in Equation 16.

$$DN(M,R) \quad \text{Equation 15:}$$

$$\text{Score}_{dim}(M,R)=100^*(1-DN(M,R)) \quad \text{Equation 16:}$$

$$\text{Score}(M)=\text{Aggregate}_{dim}(\text{Score}_{dim}(M,R)) \quad \text{Equation 17:}$$

As discussed above, the reference dataset **140** may be a specific dataset for a given region related to a user or population of users. However, content providers may also want to score media files against a catalogue or library of media files instead of external data. In some examples, the scoring module **110** iteratively scores the media file **122** against each catalogue media file and an aggregate score for a media library. This scoring allows content providers to insight into creating new content which differs from everything that has been created in the past in the media catalogue/library. In this example, the scoring module **110** utilizes Equations 18-20 and processes through each media file in a media library (e.g., the media repository **120**).

$$\text{Score}_{k\ dim}(M,C_k)=100^*(1-DN_k(M,C_k))) \quad \text{Equation 18:}$$

$$\text{Score}_k(M,C_k)=\text{Aggregate}_{dim}(\text{Score}_{k\ dim}(M,C_k)) \quad \text{Equation 19:}$$

$$\text{Score}(M)=\text{Aggregate}_k(\text{Score}_k(M,C_k)) \quad \text{Equation 20:}$$

For example, the selected media library is set as C_k. The scoring module **110** computes a new title's or media file's distance across each dimension and scores the media file against the selected media library, C_k, shown in Equation 18. The scoring module **110** aggregates the dimension-specific scores into a single score for that media file **122** using Equation 19 and aggregates a score for a single file, such as the media file **122**, using Equation 20. This process is iteratively repeated for each media file in a media file library or repository to continue updating individual and aggregate scores media files in the library.

The scoring module **110** utilizes any of the various distance calculations to determine/calculate the factor score **112**. The calculated factor score **112** is then used by the scoring module **110** to generate a scored action, where the system **100** performs the scored action as described above in relation to FIG. **1**.

FIG. **5** is flowchart of a method **500** for scoring a media file, according to embodiments described herein. The methods described in relation to FIGS. **5**-**7** are performed by the system **100** as shown in the FIG. **1** (including the scoring module **110**). A block diagram of system **100** is also described in relation to FIG. **8**. For ease of discussion, reference will be made to FIGS. **1**-**4**D throughout the discussion of the methods of FIGS. **5**-**7**. Method **500** begins at block **502** where the system **100** parses a media file for a plurality of scoring elements using a factor of interest. In some examples, the system **100** parses the media file **122** for the plurality of scoring elements, which may include a scoring element structure and various parsing instances as discussed in relation to FIGS. **1**-**3**B. Parsing the media file may also include using the factor of interest to determine a format for the scoring element structure such as the structure or format of the parsing instances, (e.g., the parsing instances **220***a*-**220***n*). Furthermore, the system **100** may utilize the media dataset **124** to process and form the parsing instances **220***a*-**220***n*.

In some examples, parsing the media file also includes applying one or more tags to the parsing instances in order to track various dimensions of the factor of interest within the parsing instances (and the media file in general). The parsing and tagging of the media file **122** is discussed in additional detail in relation to the method in FIG. **6**.

At block **504**, the system **100** determines a media distribution for the media file based on dimensions a presence of the factor of interest in the plurality of scoring elements. For example, the system **100** determines or generates the media distribution **128** described in FIGS. **1** and **4** using the parsed media file **126** (including various parsing instances and applied tags). At block **506**, the system **100** generates a reference distribution for the factor of interest based on a presence of the dimensions of the factor of interest in a reference dataset. For example, the system **100** determines or generates the reference distribution **142** described in

FIGS. **1** and **4** using the reference dataset **140** (including various data related to the factor of interest).

At block **508**, the system **100** determines a factor score for the factor of interest in the media file based on the first distribution and the reference distribution. For example, the system **100** calculates a distance between the media distribution **128** and the reference distribution **142** using any of the methods discussed in relation to FIG. **4**A, where the calculated distance is used to determine the factor score for the media file.

At block **510**, the system **100** generates a scored action for the media file using the factor score. In some examples, the system **100** utilizes the factor of interest **130**, the action index **150**, and the factor score **112** to generate or select the scored action **114**. As discussed herein the scored action **114** may include any of or a combination of any of: a recommendation action for a user, a filtering content action for a user, a recommendation to a content producer/creator, recommendation for additional content creation, a content warning alert for the media file, recommendation for content score to be provided to a user, recommendation to generate an additional score for the media file for another factor of interest or reference data, etc.

At block **512**, the system **100** performs the scored action. In some examples, the scored action may include providing a recommendation or alert to a user or system stakeholder where the system **100** provides the alert to the user system **175** or the media analysis system **165**. The system **100** may also perform the various other types of scored actions including the steps described in blocks **514**-**516**.

At block **514**, the system **100** determines whether the scored action includes a media filtering action. When the scored action includes a filtering action, method **700** proceeds to block **516**, where the system **100** accesses a media repository including the media file and filters the media repository and the media file according to the scored action at block **518**. For example, the system **100** filters, updates, reorders, etc. the media repository **120** and the media file **122** based on the scored action **114** and the factor score **112**.

In both examples, where the scored action is a filtering action and when the scoring action is not a filtering action, the system **100** updates the media file with the factor score at block **520**. For example, the system **100** stores the factor score as metadata for the media file **122**, stores the factor score in factor score database for the media repository **120**, or otherwise stores the factor score **112** with a correlation to the media file **122** for future use or reference.

FIG. **6** is flowchart of a method **600** for parsing a media file, according to embodiments described herein. Method **600** begins at block **602**, where the system **100** determines a scoring element structure for the media file based on the factor of interest and a media type of the media file. For example, the scoring element structure **210**, described in FIG. **2**, may include a container to collect the various relevant parts or scoring elements of a video content file, including the parsing instances.

At block **604**, the system **100** generates at least one parsing instance in the scoring element structure from the media file. In some examples, the types of parsing instances are determined by the scoring module **110** based on the factor of interest **130**. In one example, where the factor of interest **130** is related to demographic diversity, the media file **122** is scored based on the representation of the demographic dimensions in the media file, thus the parsing instances for video content may include parsing instances for rendered images and spoken words to capture representation of the demographic dimensions. In another example, the factor of interest **130** relates to other media dimensions, where the media file is scored based on other various other factors. In this case, rendered images may not be necessary for determining the factor score, thus the scoring module **110** does not process the video content for rendered images. In any example, the parsing instances are generated and populated in the scoring element structure in a format that allows for the system **100** to apply tags to the parsing instance structures.

At block **606**, the system **100** applies one or more tracking tags to the at least one parsing instance, where the factor of interest includes one or more dimensions. In some examples, the one or more tracking tags track the presence of the one or more dimensions in the parsing structure instances. For example, as shown in FIGS. **3**A and **3**B, the system **100** applies tags the parsing instances upon detection of the one or more dimensions in the parsing instances.

At block **608**, the system **100** aggregates the one or more tracking tags for the at least one parsing instance. For example, the system **100** aggregates a number of tags across the various dimensions for the factor of interest for each parsing instance in the parsed media file **126**. At block **610**, the system **100** generates the media distribution using the aggregated one or more tracking tags demonstrating the presence of the one or more dimensions in the media file. For example, the system **100** generates the media distribution **128** as described in relation to FIGS. **1**, **2**, and **4**A.

At block **612**, the system **100** receives a reference dataset, where the reference dataset includes data representing factors of interest and the one or more dimensions. For example, the system **100** accesses or receives the reference dataset **140** shown in FIGS. **1** and **4**A. At block **620**, the system **100** determines when the reference dataset is a reference media file or library. For example, when the reference dataset is a media library or catalogue such as the media repository **120**, the method **600** proceeds to block **622**.

At block **622**, the system **100** parses the reference media file for a plurality of reference scoring elements. For example, the system **100** proceeds through a process for iteratively processing and scoring each of the media files in the media repository **120** as described in relation to FIG. **4**A (e.g., using Equations 18-20). The system **100** may further aggregate and reprocess the media repository **120** until all media files, including the media file **122**, are scored against an aggregate score for the media repository **120**.

In an example, where the dataset is not a media library or catalogue, the method **600** proceeds to block **624**, where the system **100** parses the reference dataset to tabulate a presence of the one or more dimensions in the reference dataset. In this example, the system **100** parses or extracts the data from the reference dataset **140**. In another example, the reference dataset **140** may need further processing such as processing raw population data other demographic data, etc. to determine/tabulate the values for each dimension. The system **100** processes the reference dataset **140** to identify, calculate, or aggregate the values for the various dimensions for tracking for the reference distribution **142**. At block **630**, the system **100** generates the reference distribution using the presence of the one or more dimensions in the reference dataset. For example, the system **100**, using data parsed in block **622** or the block **624**, generates the distribution **142** as described in relation to FIG. **4**A.

FIG. **7** is flowchart of a method **700** for determining a scored action, according to embodiments described herein. Method **700** begins at block **702**, where the system **100** calculates a distance across from the media distribution to the reference distribution for each of the one or more dimensions. For example, for each dimension the in the media distribution **128** and the reference distribution **142**, the system **100** calculates a distance using methods and equations discussed in relation to FIG. **4**A. The system **100** also scores the distance for each of the one or more dimensions at block **704**.

At block **706**, the system **100** determines whether additional dimensions remain to be scored. For example, when the factor of interest includes multiple factors or the dimensions of the factor of interests include several discrete dimensions, the system **100** determines when additional dimensions require distance calculations and proceeds back to **702** to calculate a distance for a next dimension. At block **710**, the system **100** aggregates the scores to generate the factor score for the media file. For example, the system **100** aggregates the scores for each dimension for each factor or factors of interest.

At block **712** and block **714**, the system **100** accesses an action index for one or more action candidates and determines, from the factor of interest and an action request, the scored action from the action candidates. For example, the system **100** may select or generate a scored action from various action candidates including preselected actions or sub-action routines stored in the action index as described in relation to FIG. **1**. Upon determining the scored action, the system **100** performs the scored action as described in relation to FIGS. **1** and **5** to advantageously update the media repository **120** and provide various alerts and recommendations to the user **176** and the media analysis system **165**.

FIG. **8** is a block diagram depicting the recommendation system, the system **100**, in an arrangement **800** configured to parse and score media files using a factor of interest, according to some embodiments disclosed herein. Although depicted as a physical device, in embodiments, the system **100** may be implemented as a virtual device or service, or across a number of devices (e.g., in a cloud environment). As illustrated, the system **100** includes a Processor **805**, Memory **810**, Storage **815**, I/O Interface **820**, and a Network Interface **825**. The components are connected by one or more Interconnects **830**. In the illustrated embodiment, the Processor **805** retrieves and executes programming instructions stored in Memory **810**, as well as stores and retrieves application data residing in Storage **815**. The Processor **805** is generally representative of a single CPU, a GPU, a CPU and a GPU, multiple CPUs, multiple GPUs, a single CPU or GPU having multiple processing cores, and the like. The Memory **810** is generally included to be representative of a random access memory. Storage **815** may be any combination of memory or storage components, including (but not limited to) disk drives, flash-based storage devices, and the like, and may include fixed storage devices, removable storage devices or a combination both, such as fixed disk drives, removable memory cards, caches, optical storage, network attached storage (NAS), or storage area networks (SAN).

In some embodiments, I/O Devices **835** (such as a mouse, a keyboard, a monitor, a touchscreen, etc.) are connected via the I/O Interface **820**. Further, via the Network Interface **825**, the System **100** can be communicatively coupled with one or more other devices and components (directly or indirectly), such as content servers, via one or more networks such as a network **850**.

In the illustrated embodiment, the Storage **815** includes a set of one or more models and other data such as scoring information **816**, media repository **120**, and action index **150**. Although depicted as residing in Storage **815**, the scoring information **816**, the media repository **120**, and action index **150** may reside in any suitable location. In embodiments, the scoring information **816**, media repository **120**, and action index **150** are generally used to generate distributions and compute factor scores as described herein. The scoring information **816** may include trained machine learning models, algorithms, sets of scoring rules, and the like.

As illustrated, the Memory **810** includes a scoring module **110**, action module **160**, and the user module **170**. Although depicted as software residing in Memory **810**, in embodiments, the functionality of the various modules may be implemented using hardware, software, or a combination of hardware and software. The scoring module **110**, action module **160**, and the user module **170** is generally configured to perform one or more embodiments disclosed herein. Although depicted as discrete components for conceptual clarity, in embodiments, the operations of the scoring module **110**, action module **160**, and the user module **170** may be combined or distributed across any number of components.

In the current disclosure, reference is made to various embodiments. However, it should be understood that the present disclosure is not limited to specific described embodiments. Instead, any combination of the following features and elements, whether related to different embodiments or not, is contemplated to implement and practice the teachings provided herein. Additionally, when elements of the embodiments are described in the form of "at least one of A and B," it will be understood that embodiments including element A exclusively, including element B exclusively, and including element A and B are each contemplated. Furthermore, although some embodiments may achieve advantages over other possible solutions or over the prior art, whether or not a particular advantage is achieved by a given embodiment is not limiting of the present disclosure. Thus, the aspects, features, embodiments and advantages disclosed herein are merely illustrative and are not considered elements or limitations of the appended claims except where explicitly recited in a claim(s). Likewise, reference to "the invention" shall not be construed as a generalization of any inventive subject matter disclosed herein and shall not be considered to be an element or limitation of the appended claims except where explicitly recited in a claim(s).

As will be appreciated by one skilled in the art, embodiments described herein may be embodied as a system, method or computer program product. Accordingly, embodiments may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a "circuit," "module" or "system." Furthermore, embodiments described herein may take the form of a computer program product embodied in one or more computer-readable storage medium(s) having computer-readable program code embodied thereon.

Program code embodied on a computer readable medium may be transmitted using any appropriate medium, including but not limited to wireless, wireline, optical fiber cable, RF, etc., or any suitable combination of the foregoing.

Computer program code for carrying out operations for embodiments of the present disclosure may be written in any combination of one or more programming languages, including an object oriented programming language such as Java, Smalltalk, C++ or the like and conventional procedural programming languages, such as the "C" programming language or similar programming languages. The program code may execute entirely on the user's computer, partly on the user's computer, as a stand-alone software package, partly on the user's computer and partly on a remote computer or entirely on the remote computer or server. In the latter scenario, the remote computer may be connected to the user's computer through any type of network, including a local area network (LAN) or a wide area network (WAN), or the connection may be made to an external computer (for example, through the Internet using an Internet Service Provider).

Aspects of the present disclosure are described herein with reference to flowchart illustrations or block diagrams of methods, apparatuses (systems), and computer program products according to embodiments of the present disclosure. It will be understood that each block of the flowchart illustrations or block diagrams, and combinations of blocks in the flowchart illustrations or block diagrams, can be implemented by computer program instructions. These computer program instructions may be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the block(s) of the flowchart illustrations or block diagrams.

These computer program instructions may also be stored in a computer readable medium that can direct a computer, other programmable data processing apparatus, or other device to function in a particular manner, such that the instructions stored in the computer readable medium produce an article of manufacture including instructions which implement the function/act specified in the block(s) of the flowchart illustrations or block diagrams.

The computer program instructions may also be loaded onto a computer, other programmable data processing apparatus, or other device to cause a series of operational steps to be performed on the computer, other programmable apparatus or other device to produce a computer implemented process such that the instructions which execute on the computer, other programmable data processing apparatus, or other device provide processes for implementing the functions/acts specified in the block(s) of the flowchart illustrations or block diagrams.

The flowchart illustrations and block diagrams in the Figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods, and computer program products according to various embodiments of the present disclosure. In this regard, each block in the flowchart illustrations or block diagrams may represent a module, segment, or portion of code, which comprises one or more executable instructions for implementing the specified logical function(s). It should also be noted that, in some alternative implementations, the functions noted in the block may occur out of the order noted in the Figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order or out of order, depending upon the functionality involved. It will also be noted that each block of the block diagrams or flowchart illustrations, and combinations of blocks in the block diagrams or flowchart illustrations, can be implemented by special purpose hardware-based systems that perform the specified functions or acts, or combinations of special purpose hardware and computer instructions.

While the foregoing is directed to embodiments of the present disclosure, other and further embodiments of the disclosure may be devised without departing from the basic scope thereof, and the scope thereof is determined by the claims that follow.

What is claimed is:

1. A method comprising:

parsing, by a recommendation computing system, a media file for a plurality of scoring elements using a factor of interest for a first user, wherein the recommendation computing system receives the media file from a content server communicatively coupled to the recommendation computing system through a network;

determining, by the recommendation computing system, a media distribution of one or more dimensions of the factor of interest for the first user for the media file based on a presence of the one or more dimensions of the factor of interest for the first user in the plurality of scoring elements;

generating, by the recommendation computing system, a reference distribution of the one or more dimensions of the factor of interest for the first user based on a presence of the one or more dimensions of the of the factor of interest for the first user in a reference dataset;

determining, by the recommendation computing system, a factor score for the factor of interest for the first user in the media file based on the media distribution and the reference distribution;

generating, by the recommendation computing system, a scored action for the media file using the factor score; and

performing, by the recommendation computing system, the scored action by at least filtering a media repository based on the scored action and the factor score by:

accessing the media repository comprising the media file, wherein the media repository is accessible by the first user through a user system that is communicatively coupled to the recommendation computing system through the network; and

filtering, by the recommendation computing system according to the scored action, the media repository to change an order of the media file in the media repository, wherein the media repository provides filtered media to the first user through the recommendation computing system, wherein the filtered media is displayed on a display of the user system upon access by the first user.

2. The method of claim 1, wherein parsing, by the recommendation computing system, the media file further comprises:

determining, by the recommendation computing system, a scoring element structure for the media file based on the factor of interest for the first user and a media type of the media file;

generating, by the recommendation computing system, at least one parsing instance in the scoring element structure from the media file; and

applying, by the recommendation computing system, one or more tracking tags to the at least one parsing instance, wherein the one or more tracking tags track the presence of the one or more dimensions in the scoring element structure.

3. The method of claim 2, wherein determining, by the recommendation computing system, the media distribution for the media file further comprises:

aggregating, by the recommendation computing system, the one or more tracking tags for the at least one parsing instance; and

generating, by the recommendation computing system, the media distribution using the aggregated one or more tracking tags demonstrating the presence of the one or more dimensions in the media file.

4. The method of claim **3**, wherein generating, by the recommendation computing system, the reference distribution for the factor of interest for the first user further comprises:

receiving, at the recommendation computing system, the reference dataset, wherein the reference dataset comprises data representing factors of interest and the one or more dimensions; and

parsing, by the recommendation computing system, the reference dataset to tabulate the presence of the one or more dimensions in the reference dataset; and

generating, by the recommendation computing system, the reference distribution using the presence of the one or more dimensions in the reference dataset.

5. The method of claim **4**, wherein determining, by the recommendation computing system, the factor score comprises:

calculating, by the recommendation computing system, a distance across from the media distribution to the reference distribution for each of the one or more dimensions;

scoring, by the recommendation computing system, the distance for each of the one or more dimensions; and

aggregating, by the recommendation computing system, the scores to generate the factor score for the media file.

6. The method of claim **1**, wherein generating, by the recommendation computing system, the scored action further comprises:

accessing, by the recommendation computing system, an action index for one or more action candidates; and

determining, by the recommendation computing system, from the factor of interest for the first user, the scored action from the action candidates.

7. A system, comprising:

a processor; and

a memory comprising instructions which, when executed on the processor, performs an operation, the operation comprising:

parsing, by a recommendation computing system, a media file for a plurality of scoring elements using a factor of interest for a first user, wherein the recommendation computing system receives the media file from a content server communicatively coupled to the recommendation computing system through a network;

determining, by the recommendation computing system, a media distribution of one or more dimensions of the factor of interest for the first user for the media file based on a presence of the one or more dimensions of the factor of interest for the first user in the plurality of scoring elements;

generating, by the recommendation computing system, a reference distribution of the one or more dimensions of the factor of interest for the first user based on a presence of the one or more dimensions of the of the factor of interest for the first user in a reference dataset;

determining, by the recommendation computing system, a factor score for the factor of interest for the first user in the media file based on the media distribution and the reference distribution;

generating, by the recommendation computing system, a scored action for the media file using the factor score; and

performing, by the recommendation computing system, the scored action by at least filtering a media repository based on the scored action and the factor score by:

accessing the media repository comprising the media file, wherein the media repository is accessible by the first user through a user system that is communicatively coupled to the recommendation computing system through the network; and

filtering, by the recommendation computing system according to the scored action, the media repository to change an order of the media file in the media repository, wherein the media repository provides filtered media to the first user through the recommendation computing system, wherein the filtered media is displayed on a display of the user system upon access by the first user.

8. The system of claim **7**, wherein parsing, by the recommendation computing system, the media file further comprises:

determining, by the recommendation computing system, a scoring element structure for the media file based on the factor of interest for the first user and a media type of the media file;

generating, by the recommendation computing system, at least one parsing instance in the scoring element structure from the media file; and

applying, by the recommendation computing system, one or more tracking tags to the at least one parsing instance, wherein the one or more tracking tags track the presence of the one or more dimensions in the scoring element structure.

9. The system of claim **8**, wherein determining, by the recommendation computing system, the media distribution for the media file further comprises:

aggregating, by the recommendation computing system, the one or more tracking tags for the at least one parsing instance; and

generating, by the recommendation computing system, the media distribution using the aggregated one or more tracking tags demonstrating the presence of the one or more dimensions in the media file.

10. The system of claim **9**, wherein generating, by the recommendation computing system, the reference distribution for the factor of interest for the first user further comprises:

receiving, at the recommendation computing system, the reference dataset, wherein the reference dataset comprises data representing factors of interest and the one or more dimensions; and

parsing, by the recommendation computing system, the reference dataset to tabulate the presence of the one or more dimensions in the reference dataset; and

generating, by the recommendation computing system, the reference distribution using the presence of the one or more dimensions in the reference dataset.

11. The system of claim **9**, wherein determining, by the recommendation computing system, the factor score comprises:

calculating, by the recommendation computing system, a distance across from the media distribution to the reference distribution for each of the one or more dimensions;

scoring, by the recommendation computing system, the distance for each of the one or more dimensions; and

aggregating, by the recommendation computing system, the scores to generate the factor score for the media file.

12. The system of claim **7**, wherein generating, by the recommendation computing system, the scored action further comprises:

accessing, by the recommendation computing system, an action index for one or more action candidates; and

determining, by the recommendation computing system, from the factor of interest for the first user, the scored action from the action candidates.

13. A non-transitory computer-readable storage medium comprising computer-readable program code embodied therewith, the computer-readable program code is configured to perform, when executed by a processor, an operation, the operation comprising:

parsing, by a recommendation computing system, a media file for a plurality of scoring elements using a factor of interest for a first user, wherein the recommendation computing system receives the media file from a content server communicatively coupled to the recommendation computing system through a network;

determining, by the recommendation computing system, a media distribution of one or more dimensions of the factor of interest for the first user for the media file based on a presence of the one or more dimensions of the factor of interest for the first user in the plurality of scoring elements;

generating, by the recommendation computing system, a reference distribution of the one or more dimensions of the factor of interest for the first user based on a presence of the one or more dimensions of the of the factor of interest for the first user in a reference dataset;

determining, by the recommendation computing system, a factor score for the factor of interest for the first user in the media file based on the media distribution and the reference distribution;

generating, by the recommendation computing system, a scored action for the media file using the factor score; and

performing, by the recommendation computing system, the scored action by at least filtering a media repository based on the scored action and the factor score by:

accessing the media repository comprising the media file, wherein the media repository is accessible by the first user through a user system that is communicatively coupled to the recommendation computing system through the network; and

filtering, by the recommendation computing system according to the scored action, the media repository to change an order of the media file in the media repository, wherein the media repository provides filtered media to the first user through the recommendation computing system, wherein the filtered media is displayed on a display of the user system upon access by the first user.

14. The computer-readable storage medium of claim **13**, wherein parsing, by the recommendation computing system, the media file further comprises:

determining, by the recommendation computing system, a scoring element structure for the media file based on the factor of interest for the first user and a media type of the media file;

generating, by the recommendation computing system, at least one parsing instance in the scoring element structure from the media file; and

applying, by the recommendation computing system, one or more tracking tags to the at least one parsing instance, wherein the one or more tracking tags track the presence of the one or more dimensions in the scoring element structure.

15. The computer-readable storage medium of claim **14**, wherein determining, by the recommendation computing system, the media distribution for the media file further comprises:

aggregating, by the recommendation computing system, the one or more tracking tags for the at least one parsing instance; and

generating, by the recommendation computing system, the media distribution using the aggregated one or more tracking tags demonstrating the presence of the one or more dimensions in the media file.

16. The computer-readable storage medium of claim **15**, wherein generating, by the recommendation computing system, the reference distribution for the factor of interest for the first user further comprises:

receiving, at the recommendation computing system, the reference dataset, wherein the reference dataset comprises data representing factors of interest and the one or more dimensions; and

parsing, by the recommendation computing system, the reference dataset to tabulate the presence of the one or more dimensions in the reference dataset; and

generating, by the recommendation computing system, the reference distribution using the presence of the one or more dimensions in the reference dataset.

17. The computer-readable storage medium of claim **16**, wherein determining, by the recommendation computing system, the factor score comprises:

calculating, by the recommendation computing system, a distance across from the media distribution to the reference distribution for each of the one or more dimensions;

scoring, by the recommendation computing system, the distance for each of the one or more dimensions; and

aggregating, by the recommendation computing system, the scores to generate the factor score for the media file.

18. The computer-readable storage medium of claim **13**, wherein generating, by the recommendation computing system, the scored action further comprises:

accessing, by the recommendation computing system, an action index for one or more action candidates; and

determining, by the recommendation computing system, from the factor of interest for the first user, the scored action from the action candidates.

* * * * *