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(54) **ADVANCED MODEL MANAGEMENT PLATFORM FOR OPTIMIZING AND SECURING AI SYSTEMS INCLUDING LARGE LANGUAGE MODELS**

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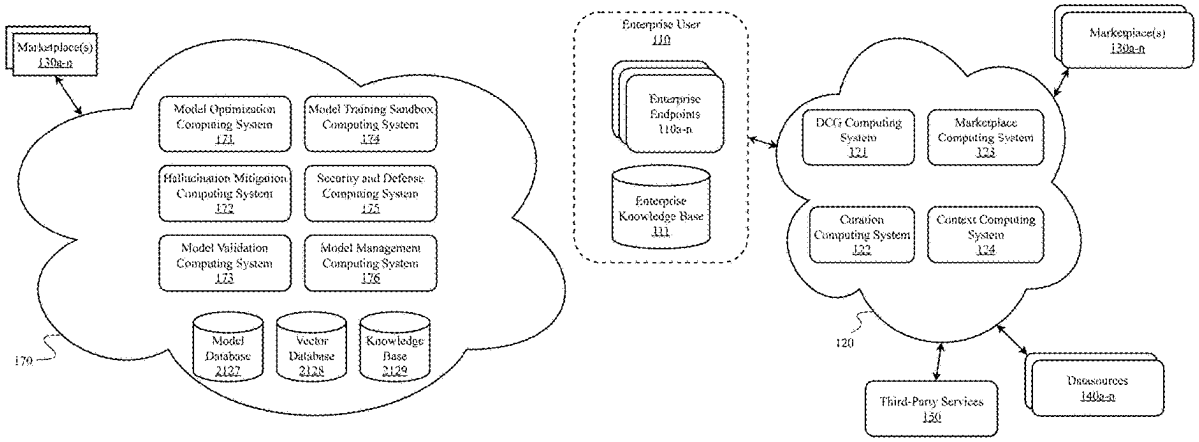
(52) **U.S. Cl.**
CPC ***G06N 3/094*** (2023.01); ***G06N 3/092*** (2023.01)

(57) **ABSTRACT**

An advanced model management platform for optimizing and securing generative artificial intelligence systems such as large language models (LLMs) and diffusion models. The platform incorporates various techniques to address the limitations of current generative AI systems, such as hallucination, lack of validation, security vulnerabilities, and inadequate model management. The system employs reinforcement learning algorithms for model optimization, retrieval augmented generation (RAG) for hallucination mitigation, domain-specific validation against expert knowledge, model distillation and similarity scoring for security, adversarial training for robustness, and attention mechanism search and model blending for advanced management and neuro symbolic AI routine combinations. By integrating these techniques, the platform significantly improves the performance, reliability, and security of generative AI across a wide range of tasks and domains leveraging the best elements of symbolic and connectionist techniques alongside automated planning and modeling simulation.



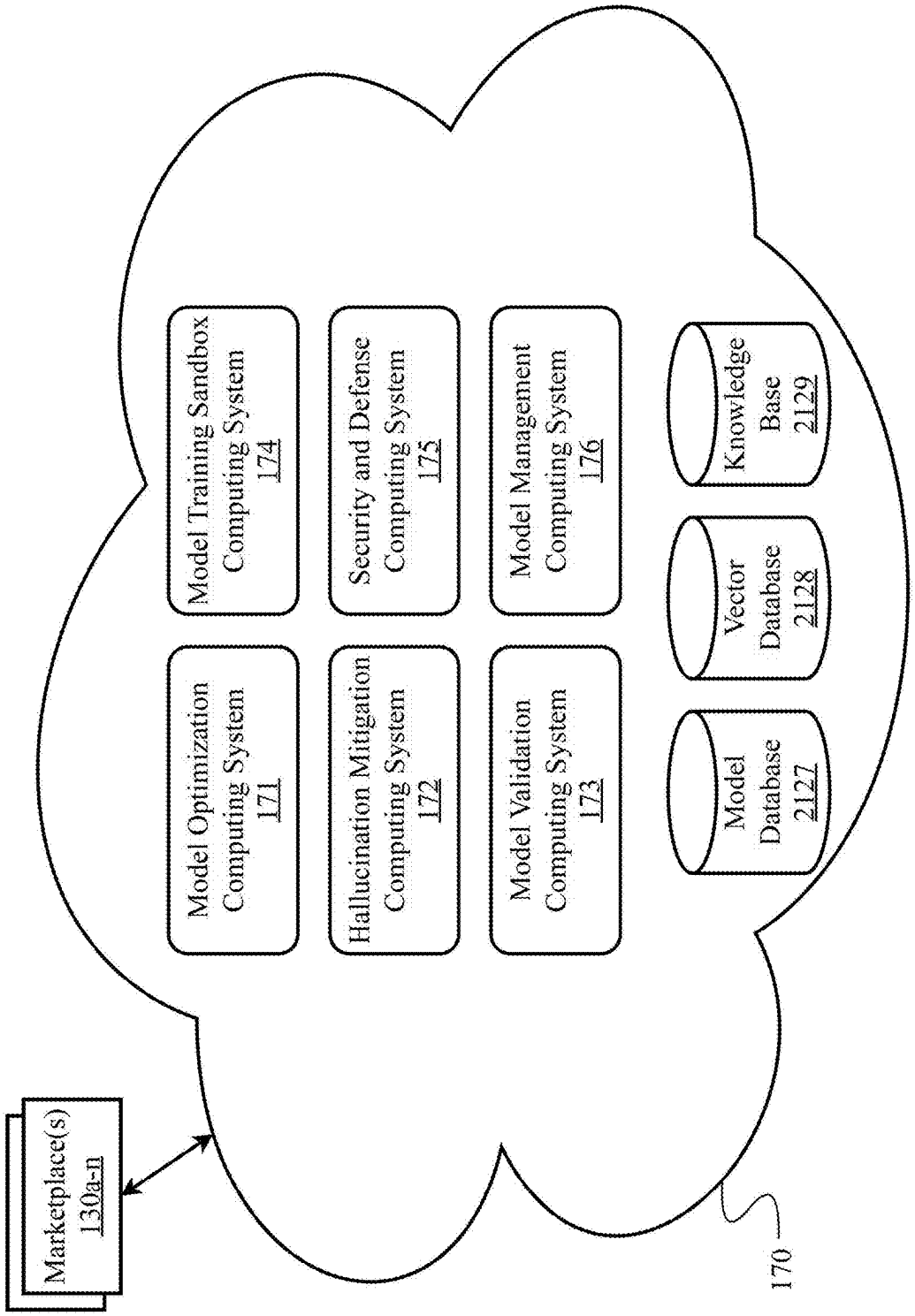

Marketplace(s)
130a-n
Model Optimization Computing System
171
Hallucination Mitigation Computing System
172
Model Validation Computing System
173
Model Training Sandbox Computing System
174
Security and Defense Computing System
175
Model Management Computing System
176
Model Database
2127
Vector Database
2128
Knowledge Base
2129
170

FIG. 1A

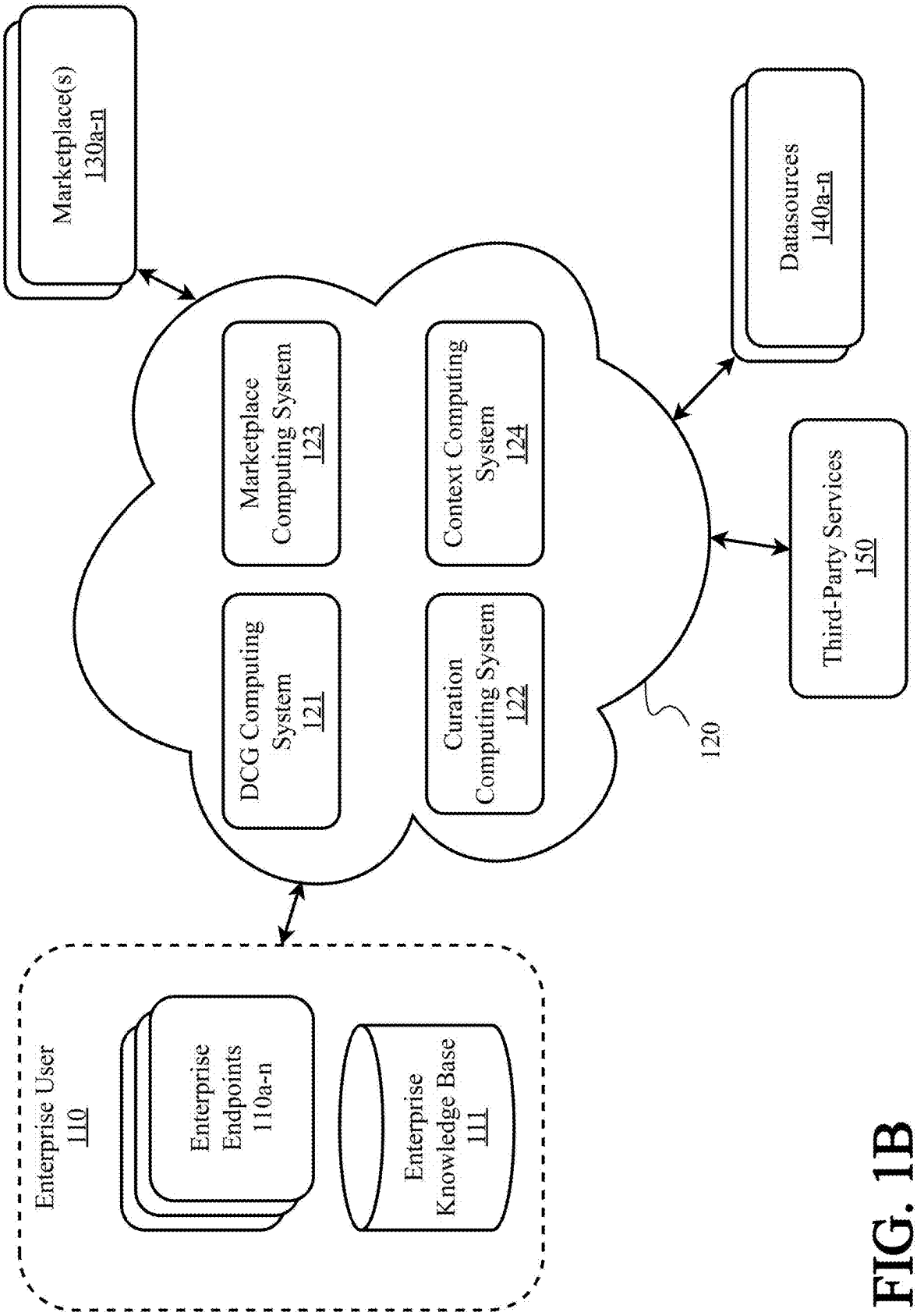

Marketplace(s)
130a-n
Marketplace Computing System
123
Context Computing System
124
DCG Computing System
121
Curation Computing System
122
120
Datasources
140a-n
Third-Party Services
150
Enterprise User
110
Enterprise Endpoints
110a-n
Enterprise Knowledge Base
111

FIG. 1B

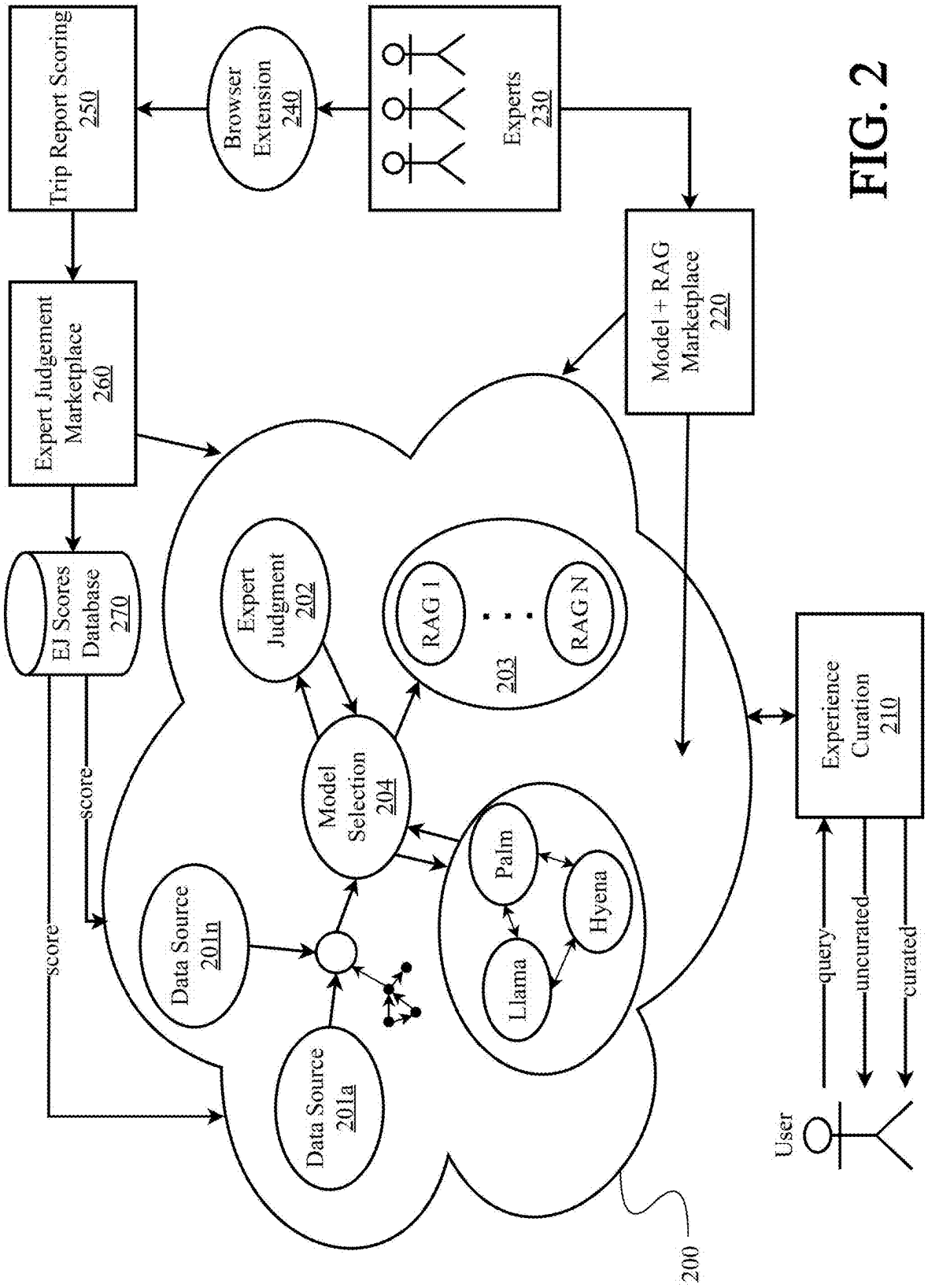

Trip Report Scoring 250
Browser Extension 240
Experts 230
Expert Judgement Marketplace 260
Model + RAG Marketplace 220
EJ Scores Database 270
score
score
Expert Judgment 202
RAG 1
RAG N
203
Model Selection 204
Data Source 201n
Data Source 201a
Palm
Llama
Hyena
Experience Curation 210
query
uncurated
curated
User
200

FIG. 2

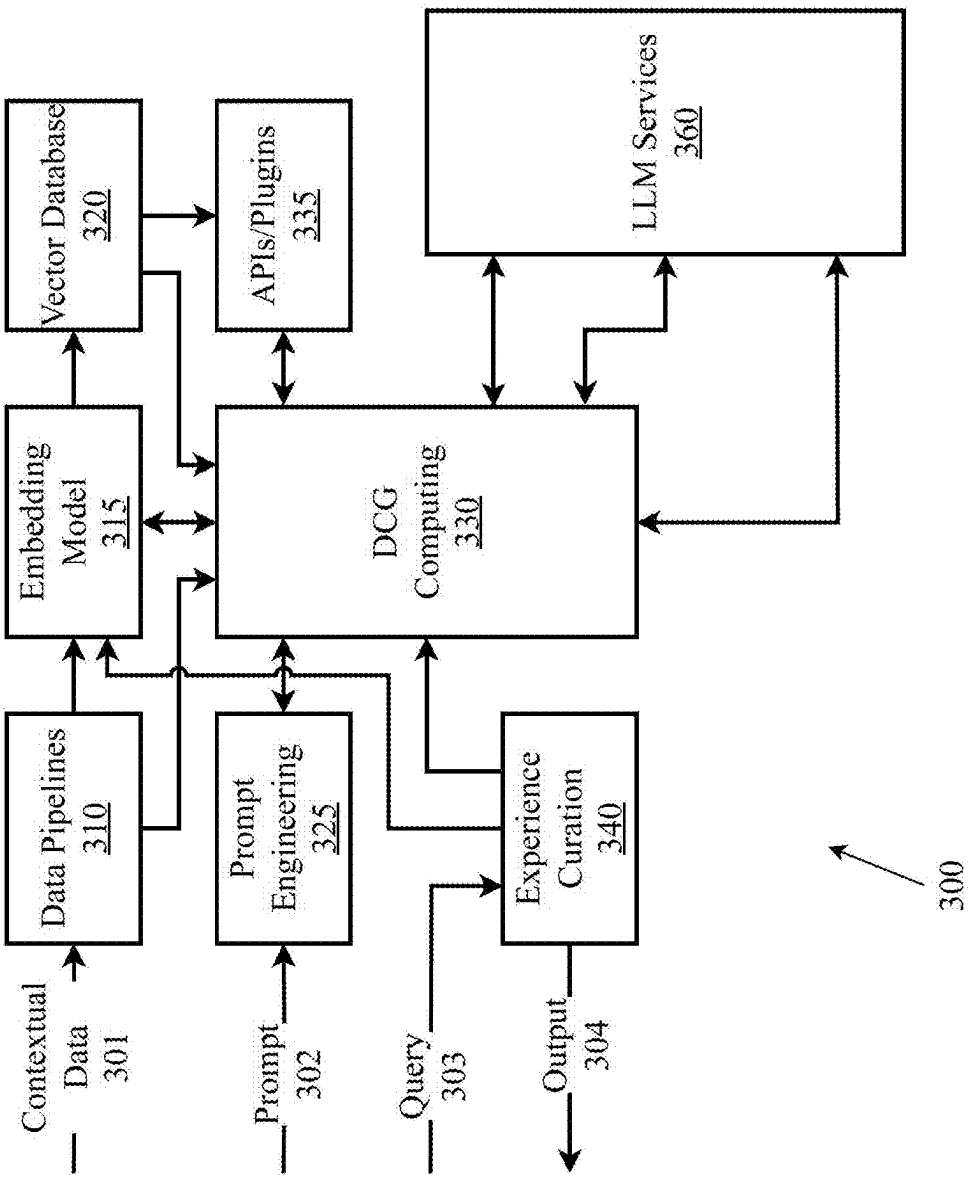

Contextual Data 301
Data Pipelines 310
Embedding Model 315
Vector Database 320
Prompt 302
Prompt Engineering 325
APIs/Plugins 335
DCG Computing 330
Query 303
Experience Curation 340
Output 304
LLM Services 360
300

FIG. 3

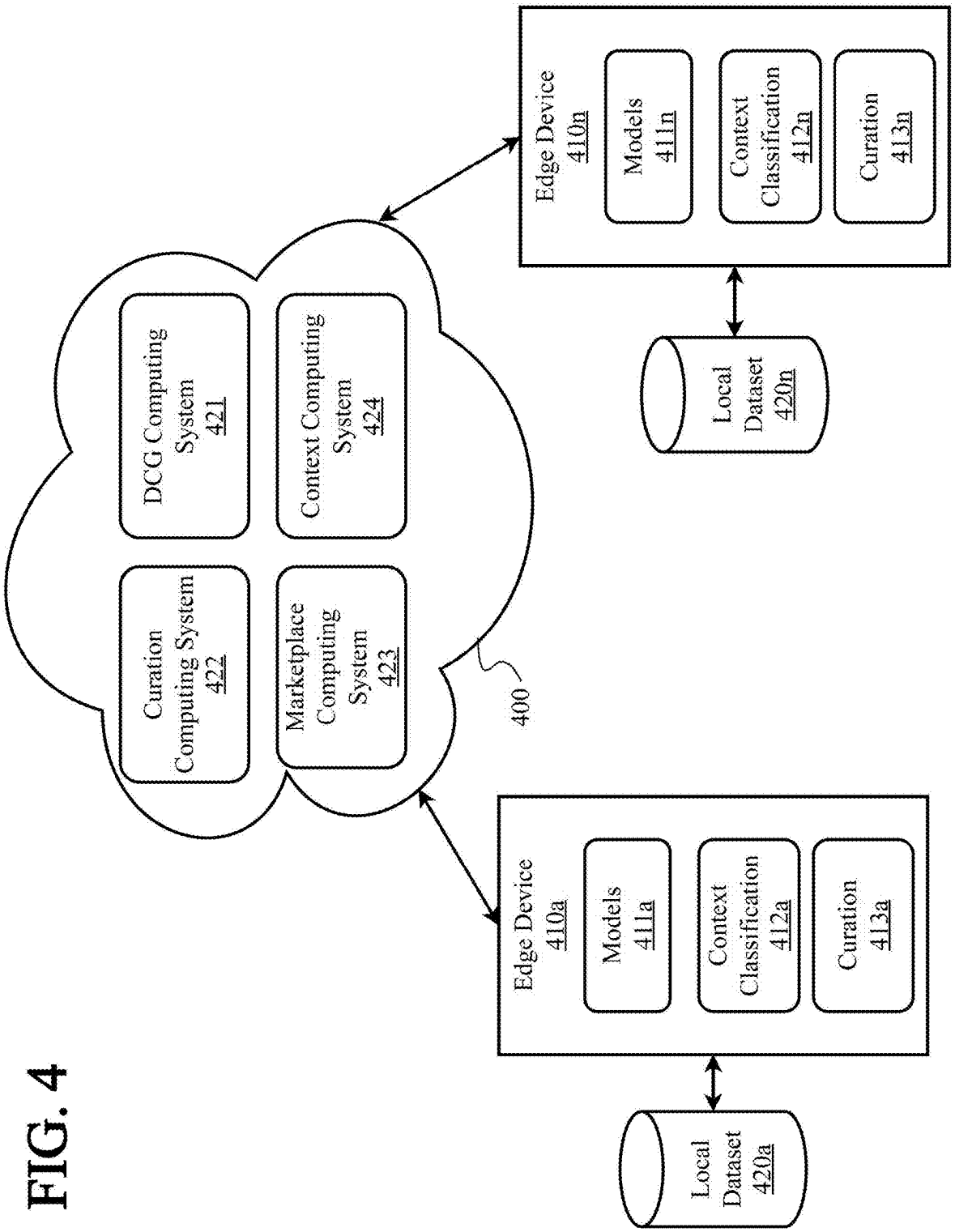
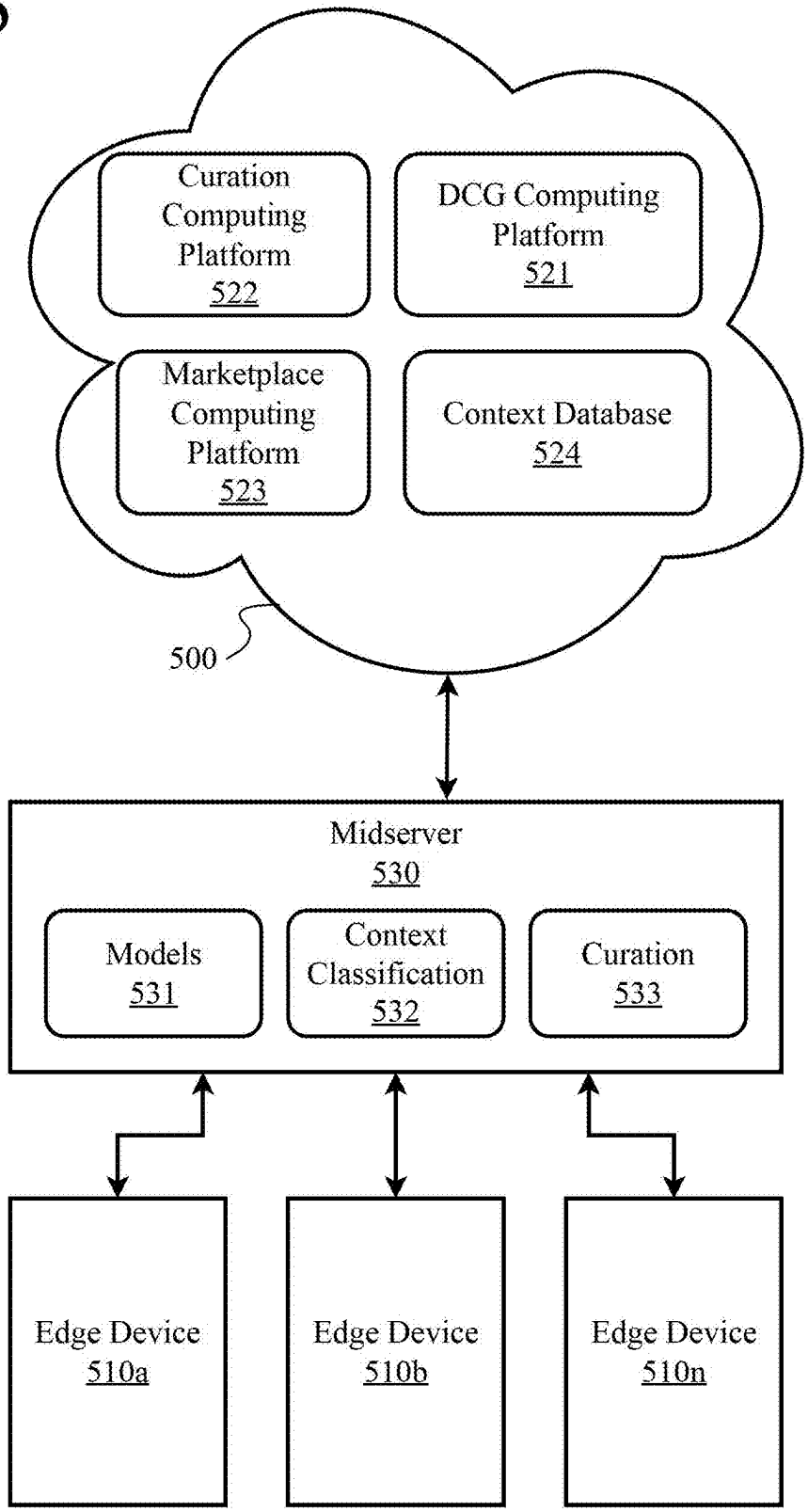

DCG Computing System 421
Context Computing System 424
Curation Computing System 422
Marketplace Computing System 423
400
Edge Device 410n
Models 411n
Context Classification 412n
Curation 413n
Local Dataset 420n
Edge Device 410a
Models 411a
Context Classification 412a
Curation 413a
Local Dataset 420a

FIG. 4

FIG. 5


Curation Computing Platform 522
DCG Computing Platform 521
Marketplace Computing Platform 523
Context Database 524
500
Midserver 530
Models 531
Context Classification 532
Curation 533
Edge Device 510a
Edge Device 510b
Edge Device 510n

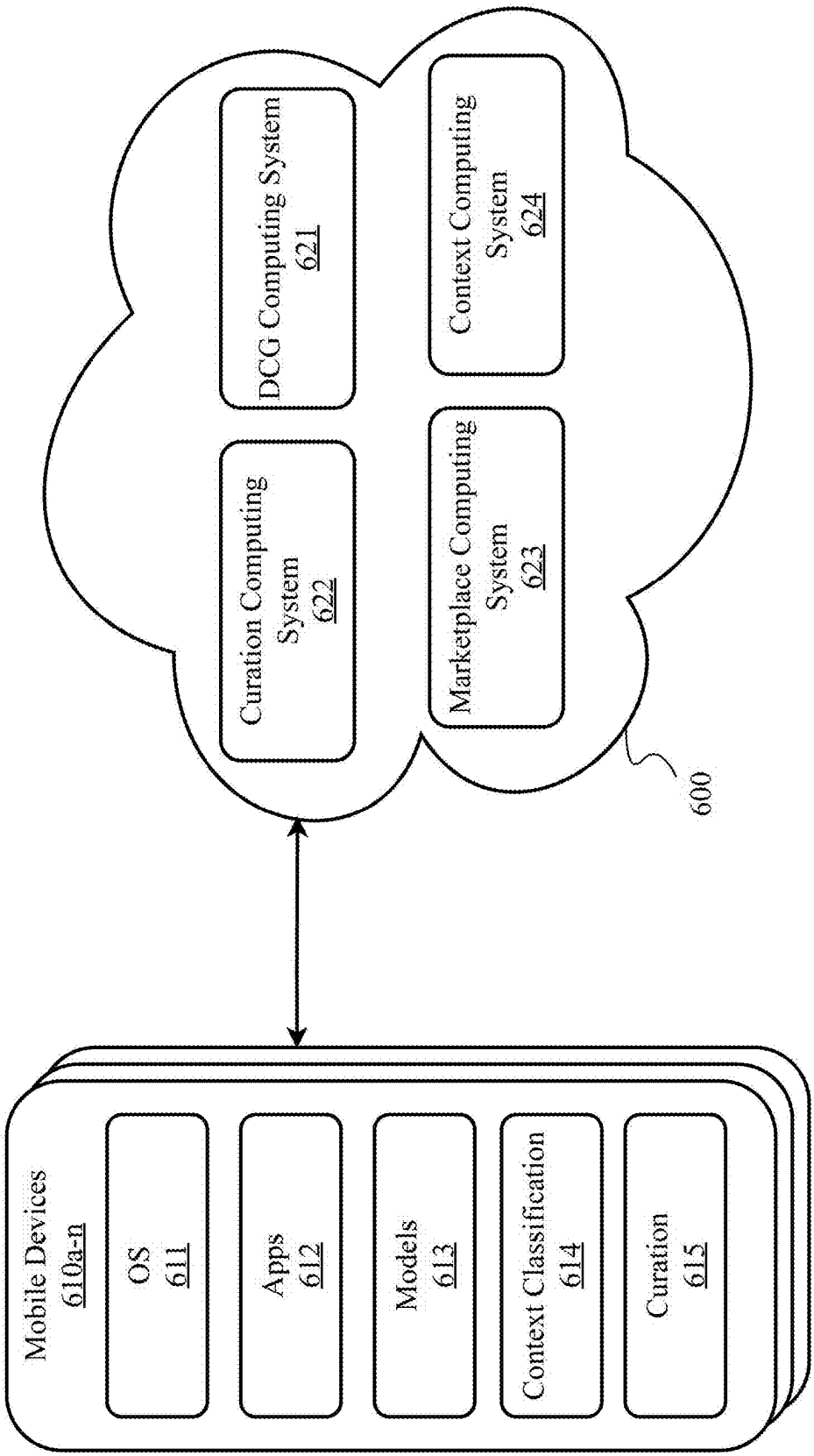

DCG Computing System
621
Context Computing System
624
Curation Computing System
622
Marketplace Computing System
623
600
Mobile Devices
610a-n
OS
611
Apps
612
Models
613
Context Classification
614
Curation
615

FIG. 6

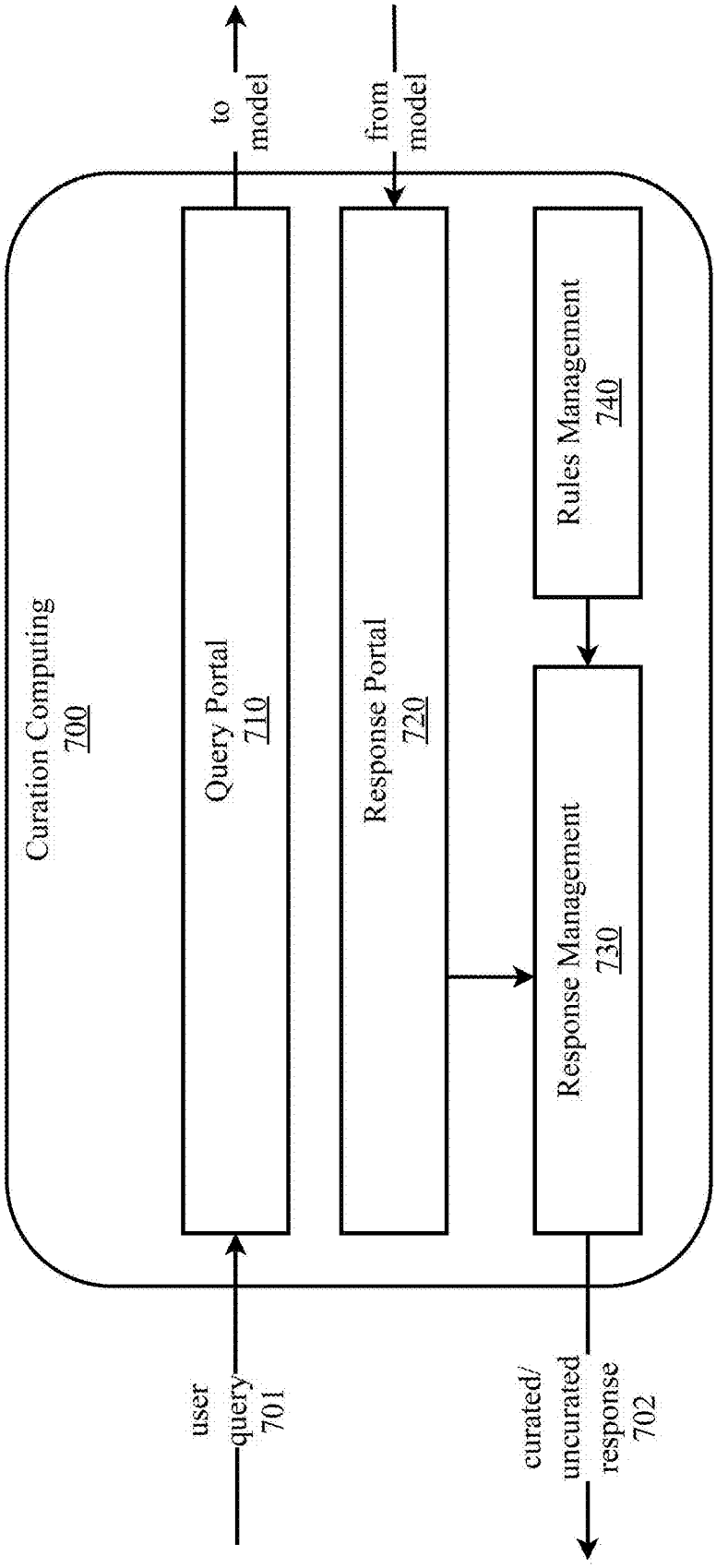

Curation Computing
700
Query Portal
710
Response Portal
720
Rules Management
740
Response Management
730
to
model
from
model
user
query
701
curated/
uncurated
response
702

FIG. 7

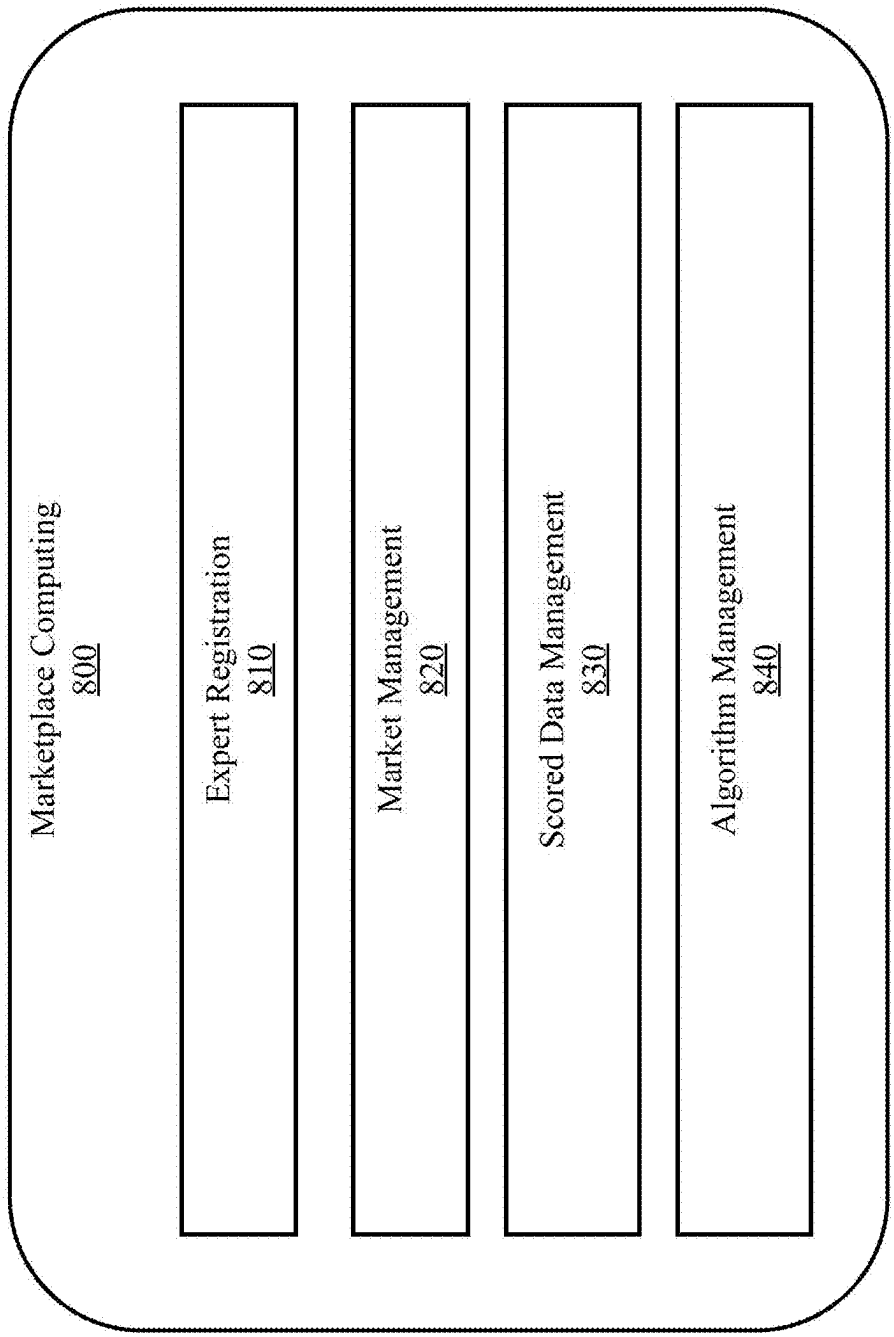

Marketplace Computing
800
Expert Registration
810
Market Management
820
Scored Data Management
830
Algorithm Management
840

FIG. 8

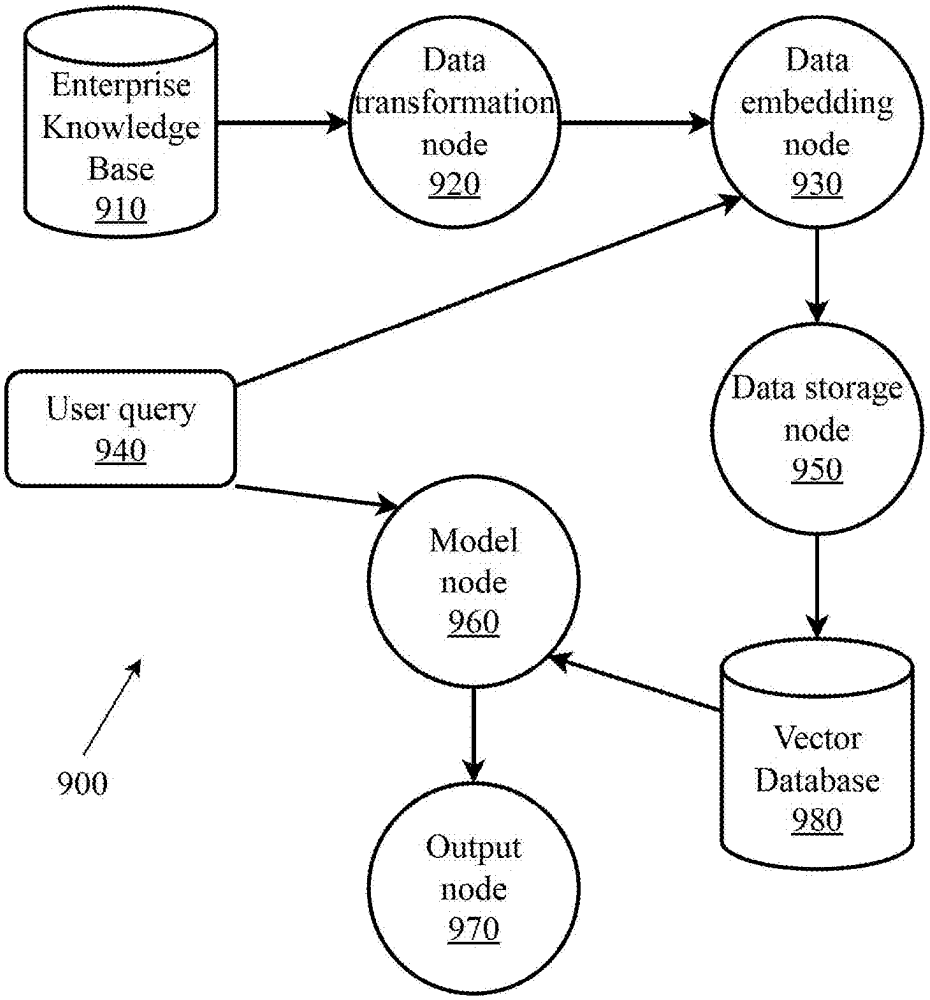
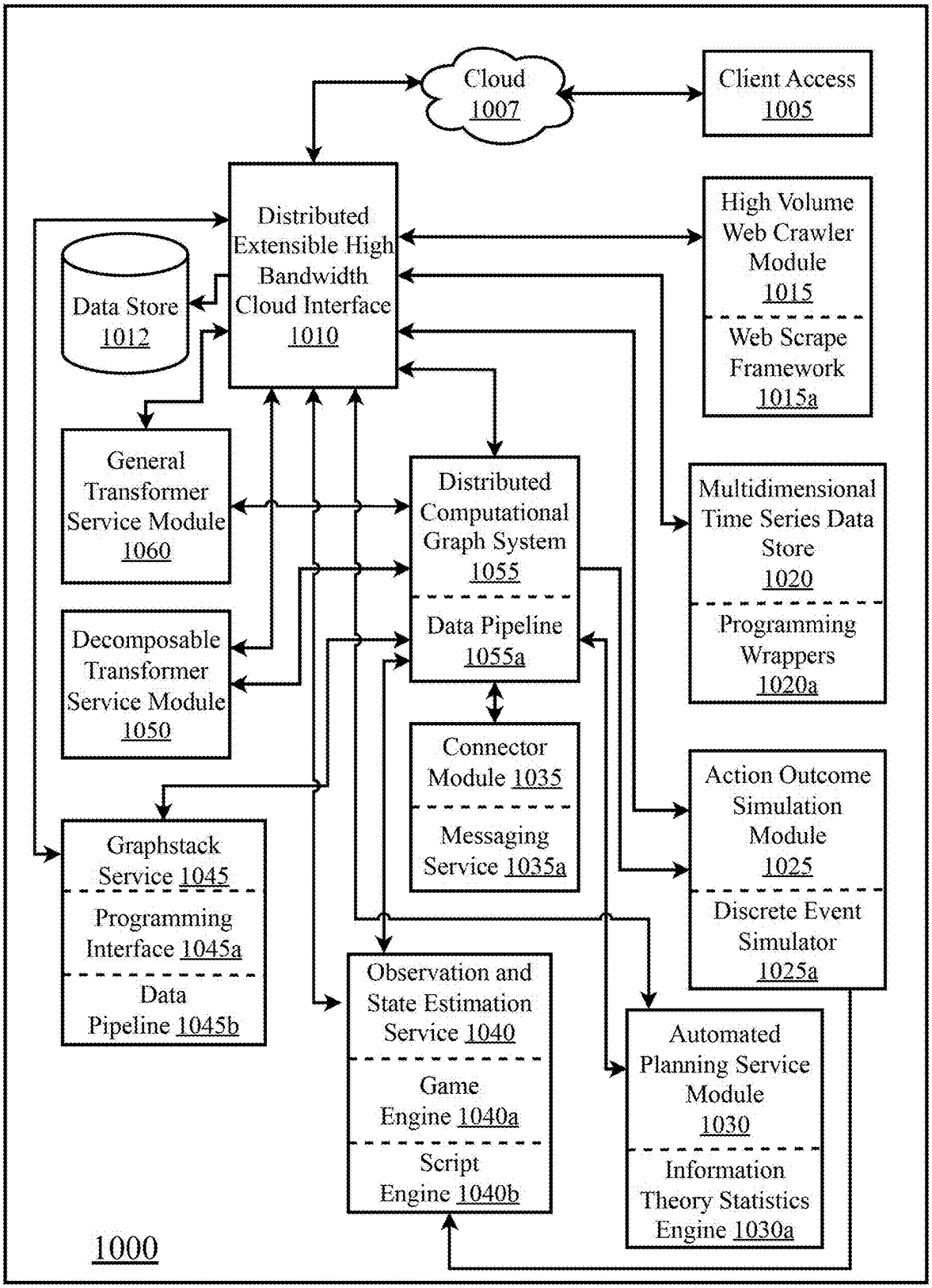

Enterprise Knowledge Base 910
Data transformation node 920
Data embedding node 930
User query 940
Data storage node 950
Model node 960
Vector Database 980
Output node 970
900

FIG. 9

FIG. 10


Cloud 1007
Client Access 1005
Distributed Extensible High Bandwidth Cloud Interface 1010
Data Store 1012
High Volume Web Crawler Module 1015
Web Scrape Framework 1015a
General Transformer Service Module 1060
Distributed Computational Graph System 1055
Data Pipeline 1055a
Multidimensional Time Series Data Store 1020
Programming Wrappers 1020a
Decomposable Transformer Service Module 1050
Connector Module 1035
Messaging Service 1035a
Action Outcome Simulation Module 1025
Discrete Event Simulator 1025a
Graphstack Service 1045
Programming Interface 1045a
Data Pipeline 1045b
Observation and State Estimation Service 1040
Game Engine 1040a
Script Engine 1040b
Automated Planning Service Module 1030
Information Theory Statistics Engine 1030a
1000

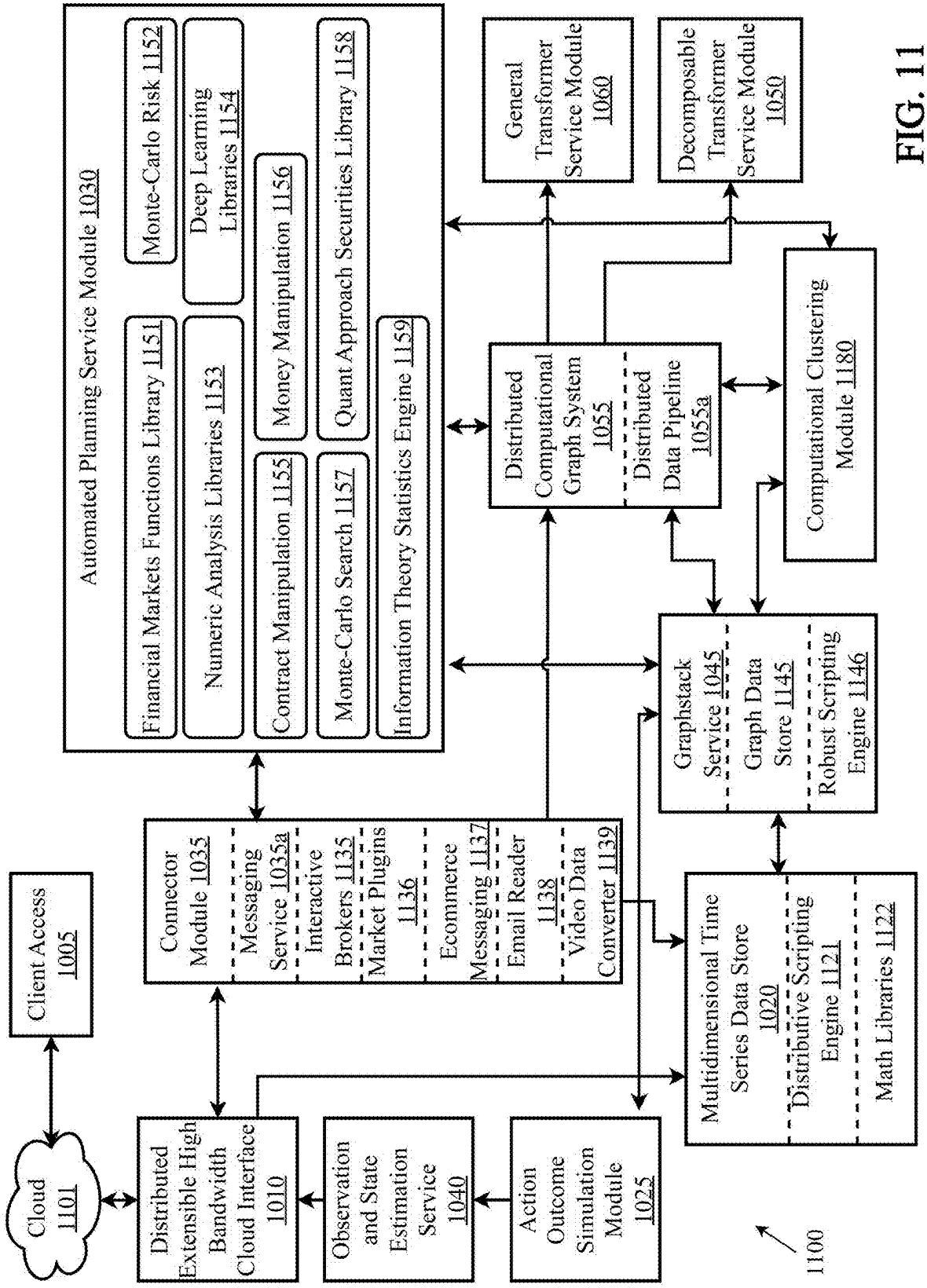

Automated Planning Service Module 1030
Financial Markets Functions Library 1151
Numeric Analysis Libraries 1153
Contract Manipulation 1155
Monte-Carlo Search 1157
Information Theory Statistics Engine 1159
Monte-Carlo Risk 1152
Deep Learning Libraries 1154
Money Manipulation 1156
Quant Approach Securities Library 1158
General Transformer Service Module 1060
Decomposable Transformer Service Module 1050
Distributed Computational Graph System 1055
Distributed Data Pipeline 1055a
Computational Clustering Module 1180
Graphstack Service 1045
Graph Data Store 1145
Robust Scripting Engine 1146
Client Access 1005
Connector Module 1035
Messaging Service 1035a
Interactive Brokers 1135
Market Plugins 1136
Ecommerce Messaging 1137
Email Reader 1138
Video Data Converter 1139
Multidimensional Time Series Data Store 1020
Distributive Scripting Engine 1121
Math Libraries 1122
Cloud 1101
Distributed Extensible High Bandwidth Cloud Interface 1010
Observation and State Estimation Service 1040
Action Outcome Simulation Module 1025
1100

FIG. 11

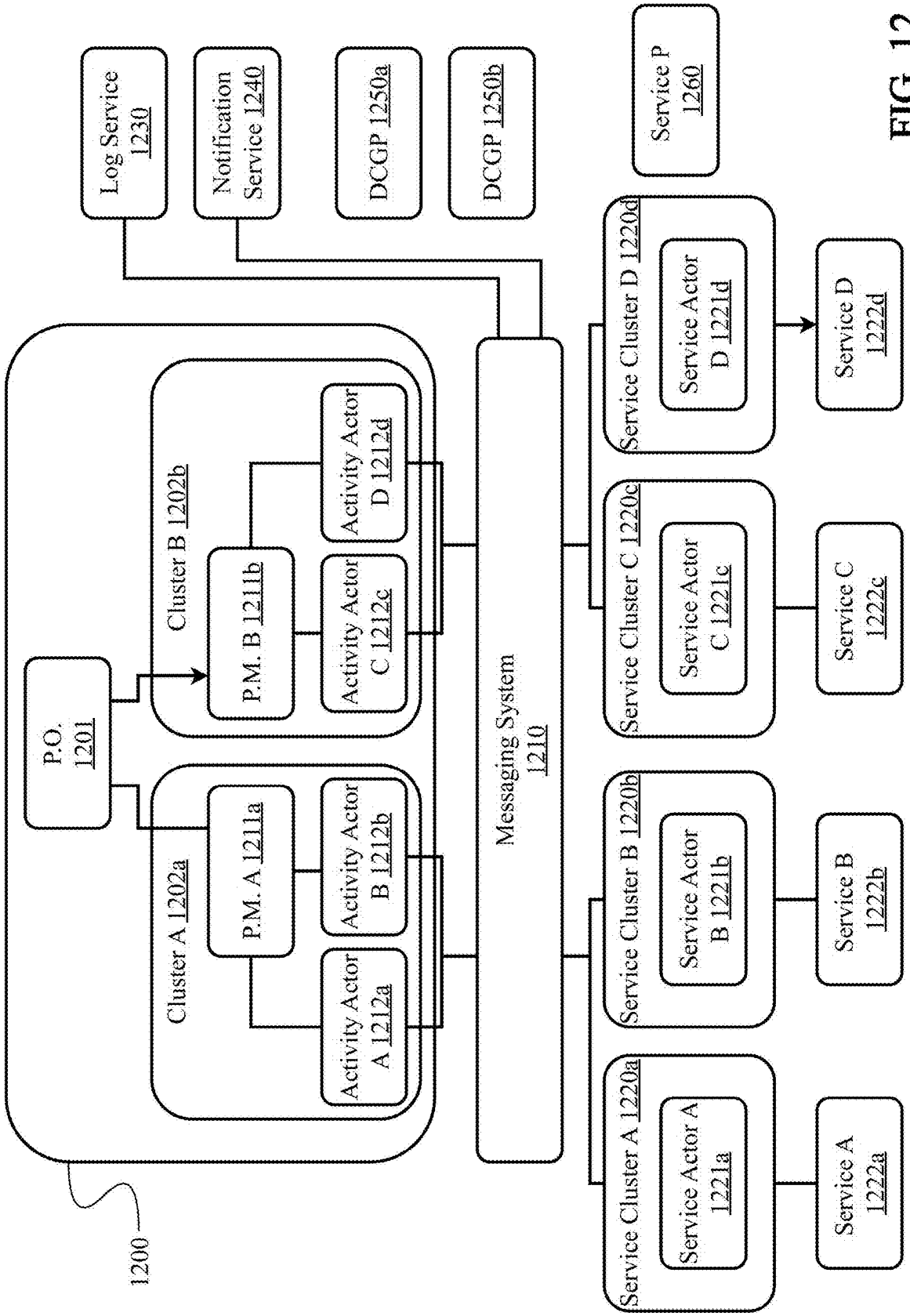

1200
P.O. 1201
Cluster A 1202a
P.M. A 1211a
Activity Actor A 1212a
Activity Actor B 1212b
Cluster B 1202b
P.M. B 1211b
Activity Actor C 1212c
Activity Actor D 1212d
Log Service 1230
Notification Service 1240
DCGP 1250a
DCGP 1250b
Messaging System 1210
Service Cluster A 1220a
Service Actor A 1221a
Service A 1222a
Service Cluster B 1220b
Service Actor B 1221b
Service B 1222b
Service Cluster C 1220c
Service Actor C 1221c
Service C 1222c
Service Cluster D 1220d
Service Actor D 1221d
Service D 1222d
Service P 1260

FIG. 12

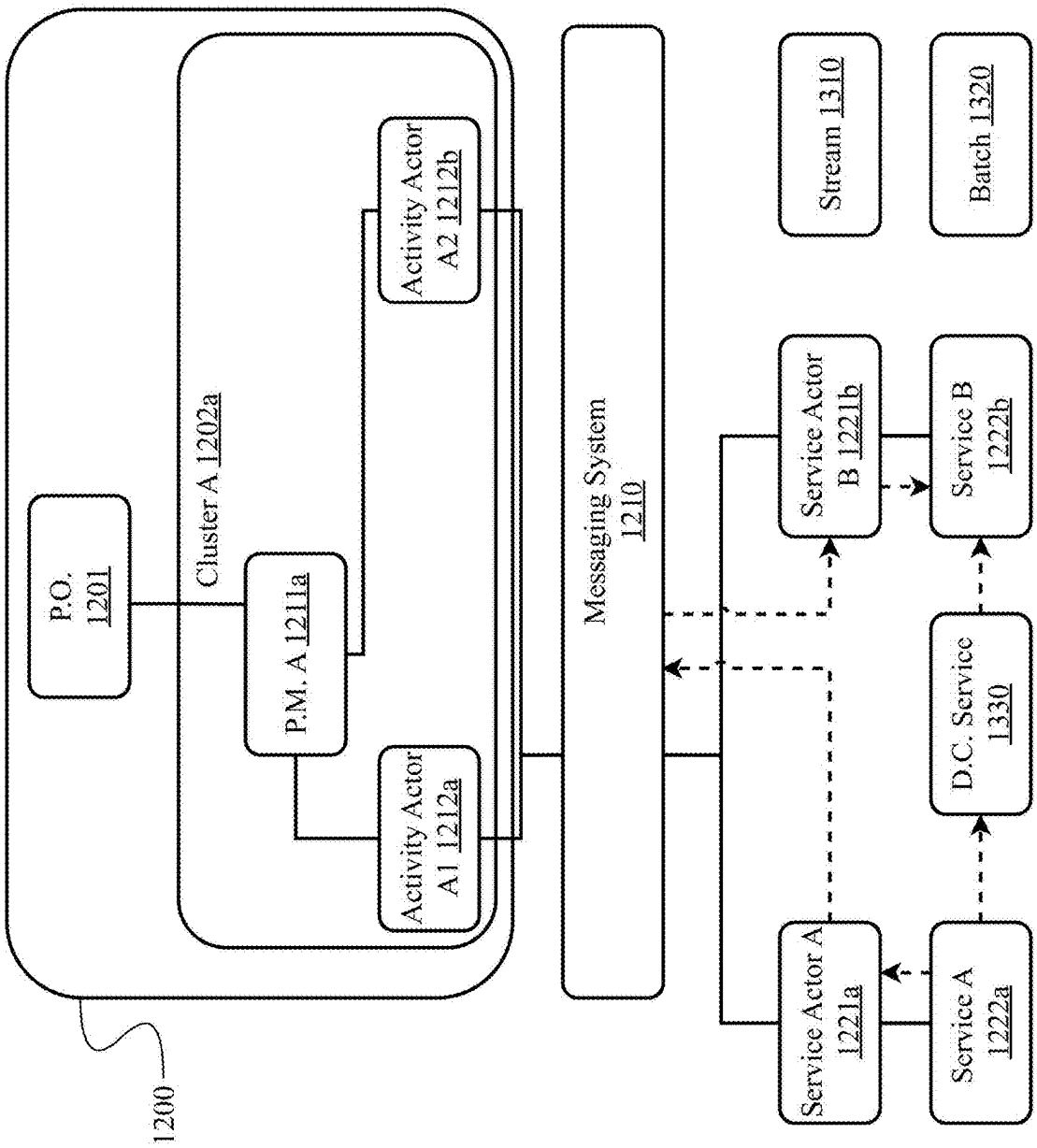

1200
P.O.
1201
Cluster A 1202a
P.M. A 1211a
Activity Actor
A1 1212a
Activity Actor
A2 1212b
Messaging System
1210
Service Actor A
1221a
Service Actor
B 1221b
Service A
1222a
D.C. Service
1330
Service B
1222b
Stream 1310
Batch 1320

FIG. 13

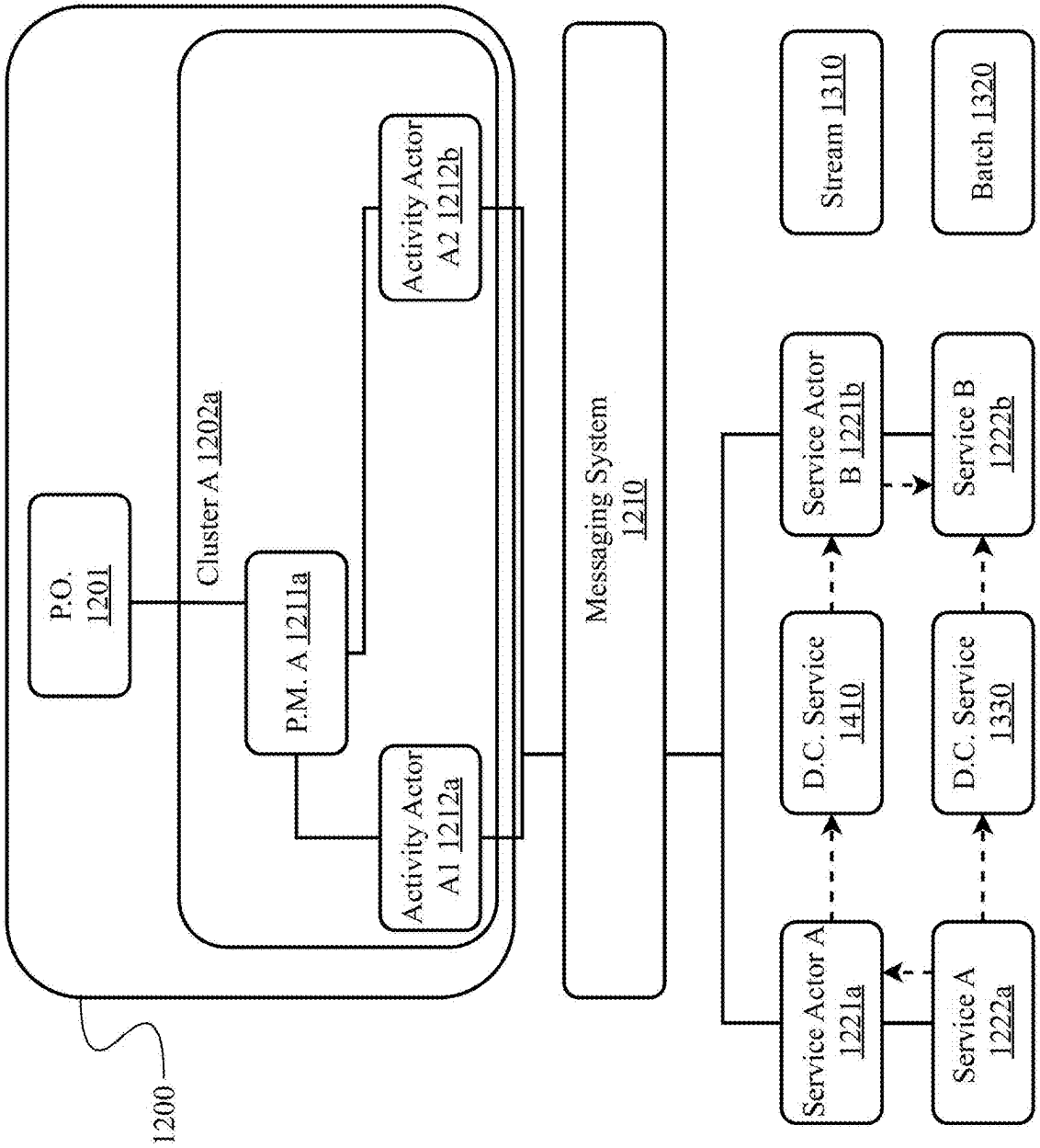

1200
P.O. 1201
Cluster A 1202a
P.M. A 1211a
Activity Actor A1 1212a
Activity Actor A2 1212b
Messaging System 1210
Service Actor A 1221a
D.C. Service 1410
Service Actor B 1221b
Service A 1222a
D.C. Service 1330
Service B 1222b
Stream 1310
Batch 1320

FIG. 14

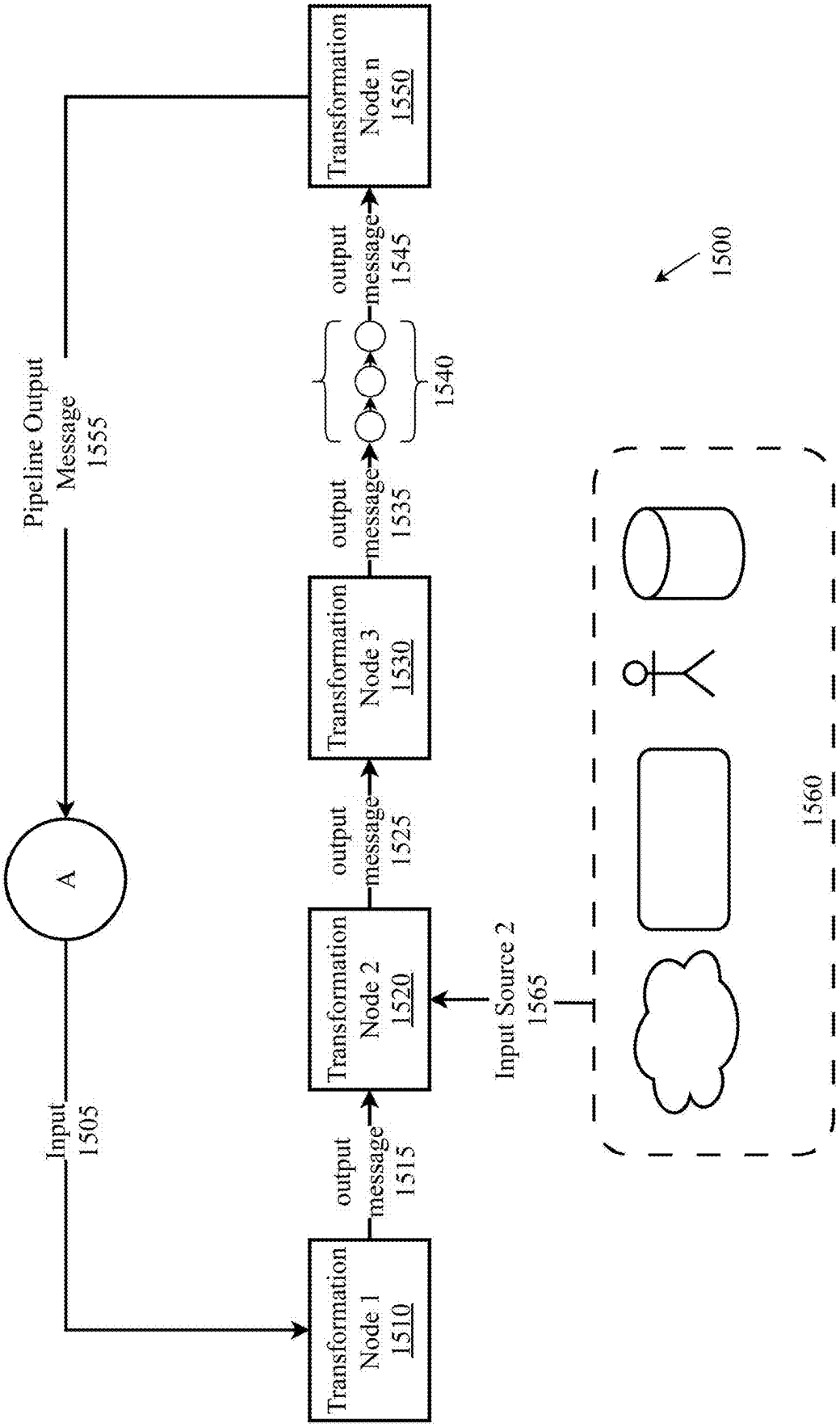

Transformation Node n 1550
output message 1545
1540
output message 1535
Transformation Node 3 1530
output message 1525
Transformation Node 2 1520
output message 1515
Transformation Node 1 1510
Pipeline Output Message 1555
A
Input 1505
Input Source 2 1565
1560
1500

FIG. 15

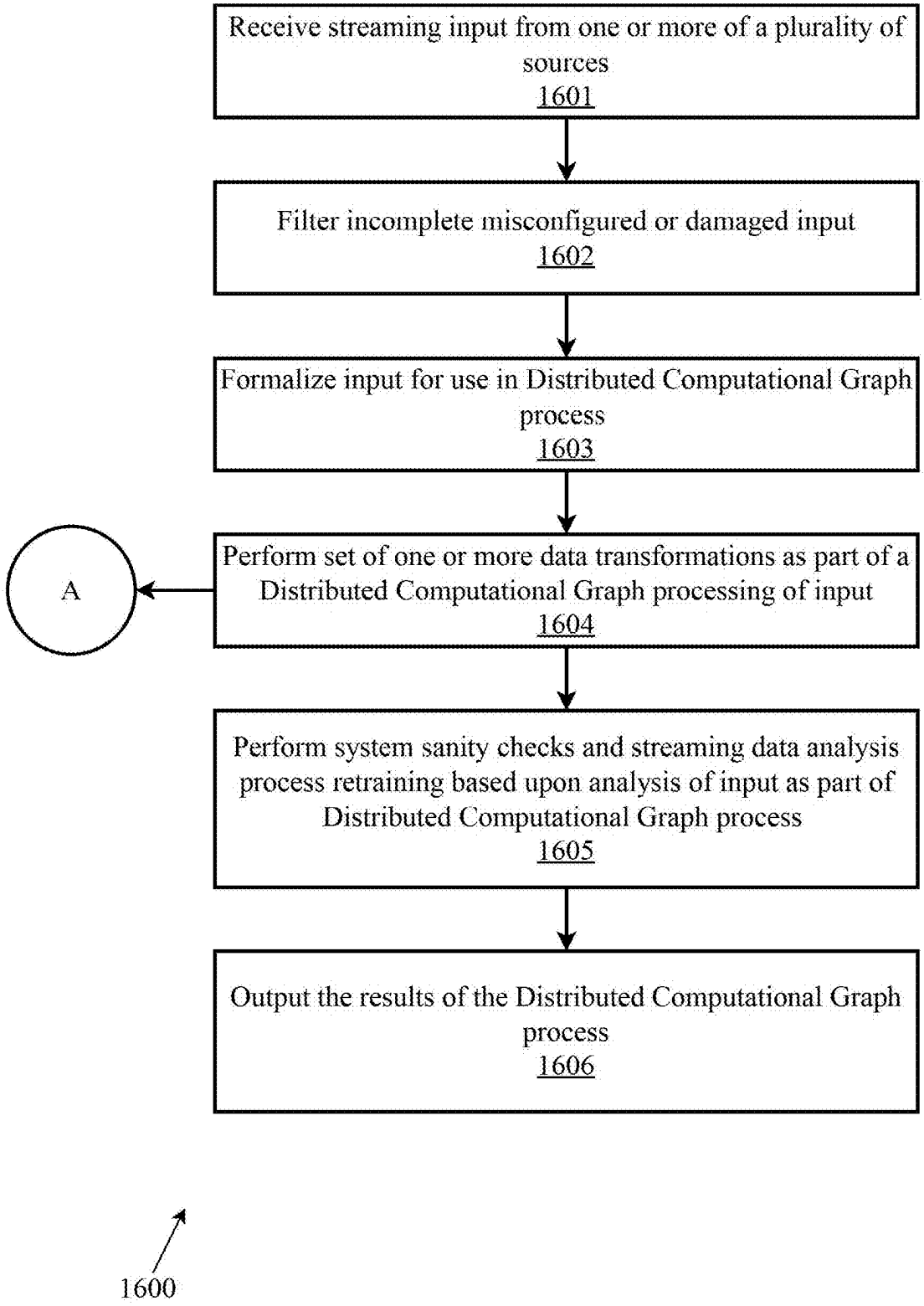

Receive streaming input from one or more of a plurality of sources
1601
Filter incomplete misconfigured or damaged input
1602
Formalize input for use in Distributed Computational Graph process
1603
Perform set of one or more data transformations as part of a Distributed Computational Graph processing of input
1604
A
Perform system sanity checks and streaming data analysis process retraining based upon analysis of input as part of Distributed Computational Graph process
1605
Output the results of the Distributed Computational Graph process
1606
1600

FIG. 16

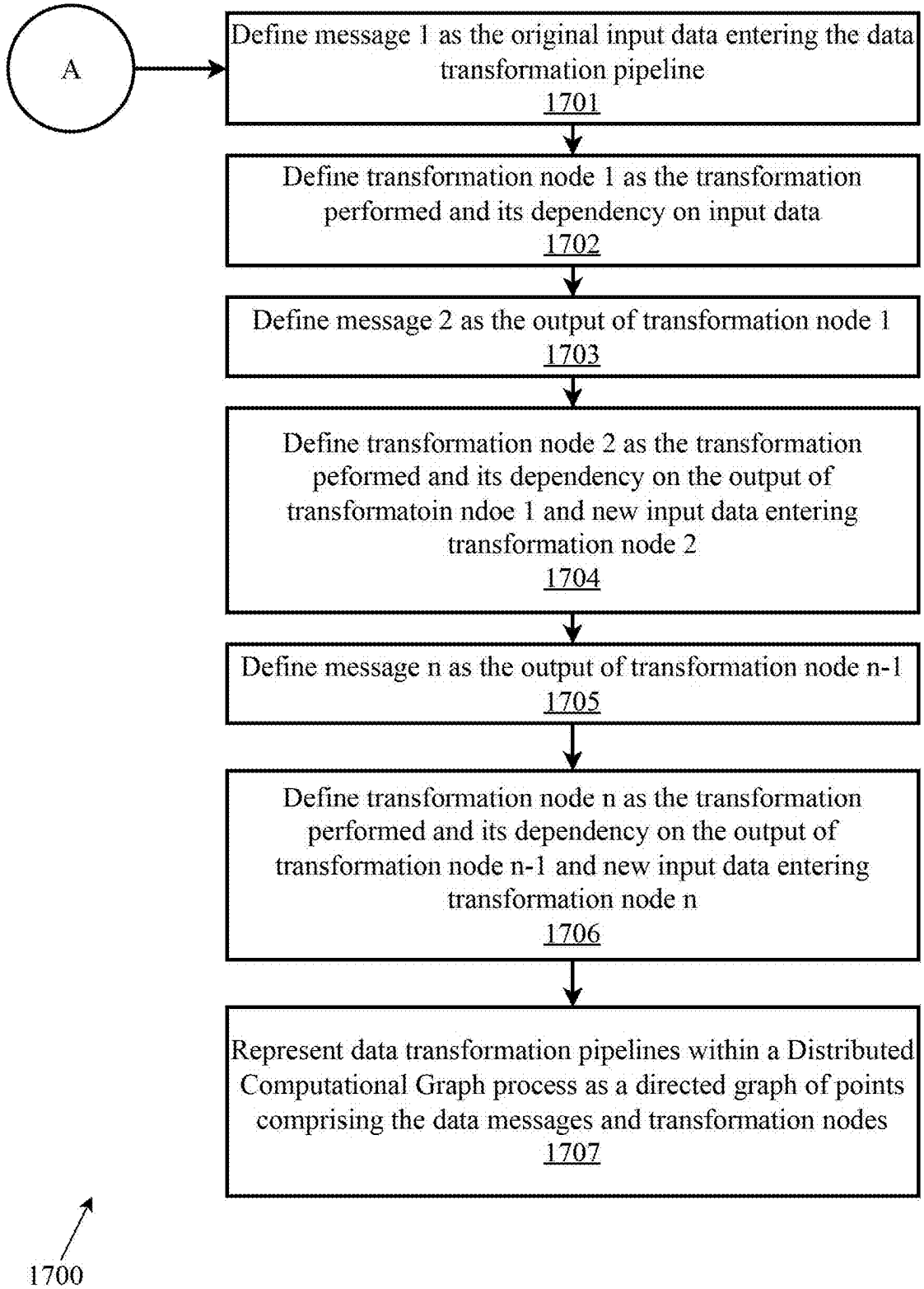

A
Define message 1 as the original input data entering the data transformation pipeline
1701
Define transformation node 1 as the transformation performed and its dependency on input data
1702
Define message 2 as the output of transformation node 1
1703
Define transformation node 2 as the transformation peformed and its dependency on the output of transformatoin ndoe 1 and new input data entering transformation node 2
1704
Define message n as the output of transformation node n-1
1705
Define transformation node n as the transformation performed and its dependency on the output of transformation node n-1 and new input data entering transformation node n
1706
Represent data transformation pipelines within a Distributed Computational Graph process as a directed graph of points comprising the data messages and transformation nodes
1707
1700

FIG. 17

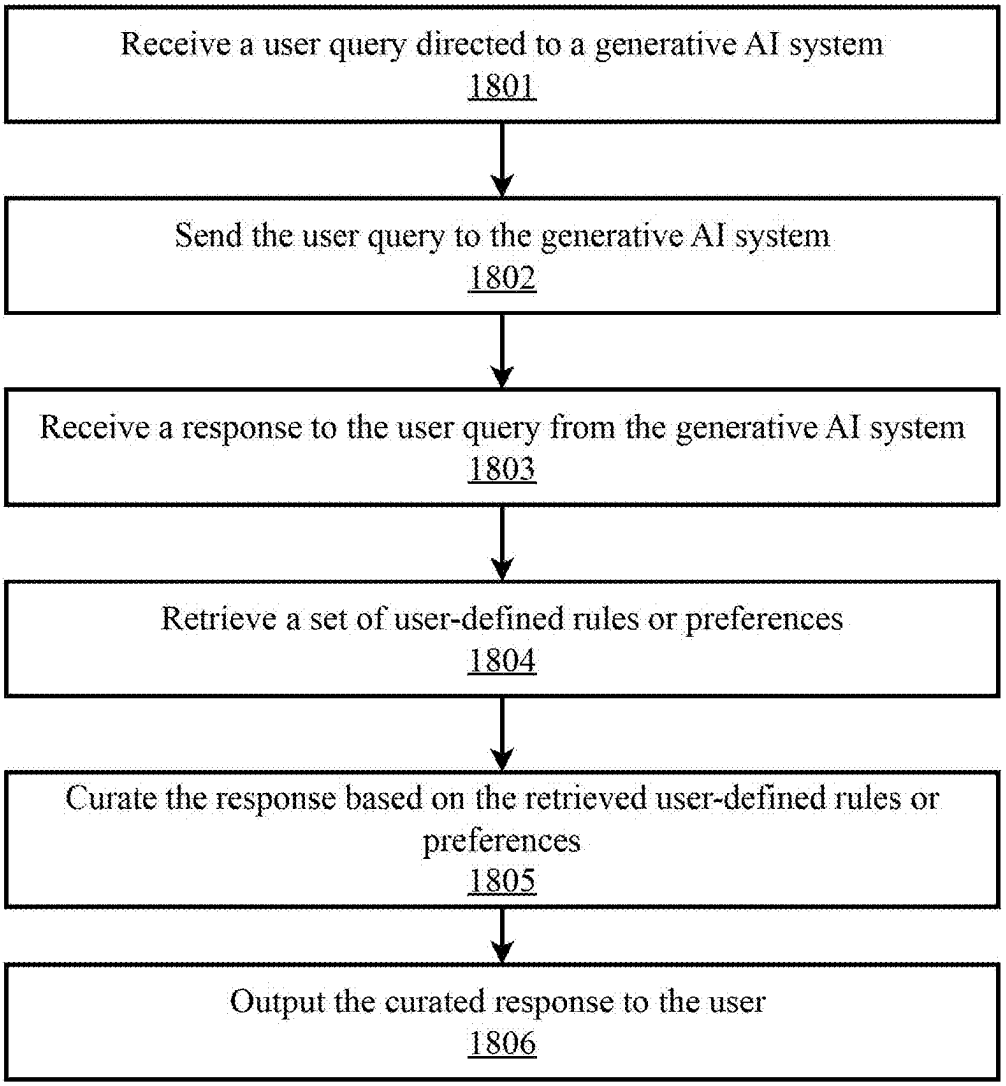

Receive a user query directed to a generative AI system
1801
Send the user query to the generative AI system
1802
Receive a response to the user query from the generative AI system
1803
Retrieve a set of user-defined rules or preferences
1804
Curate the response based on the retrieved user-defined rules or preferences
1805
Output the curated response to the user
1806

FIG. 18

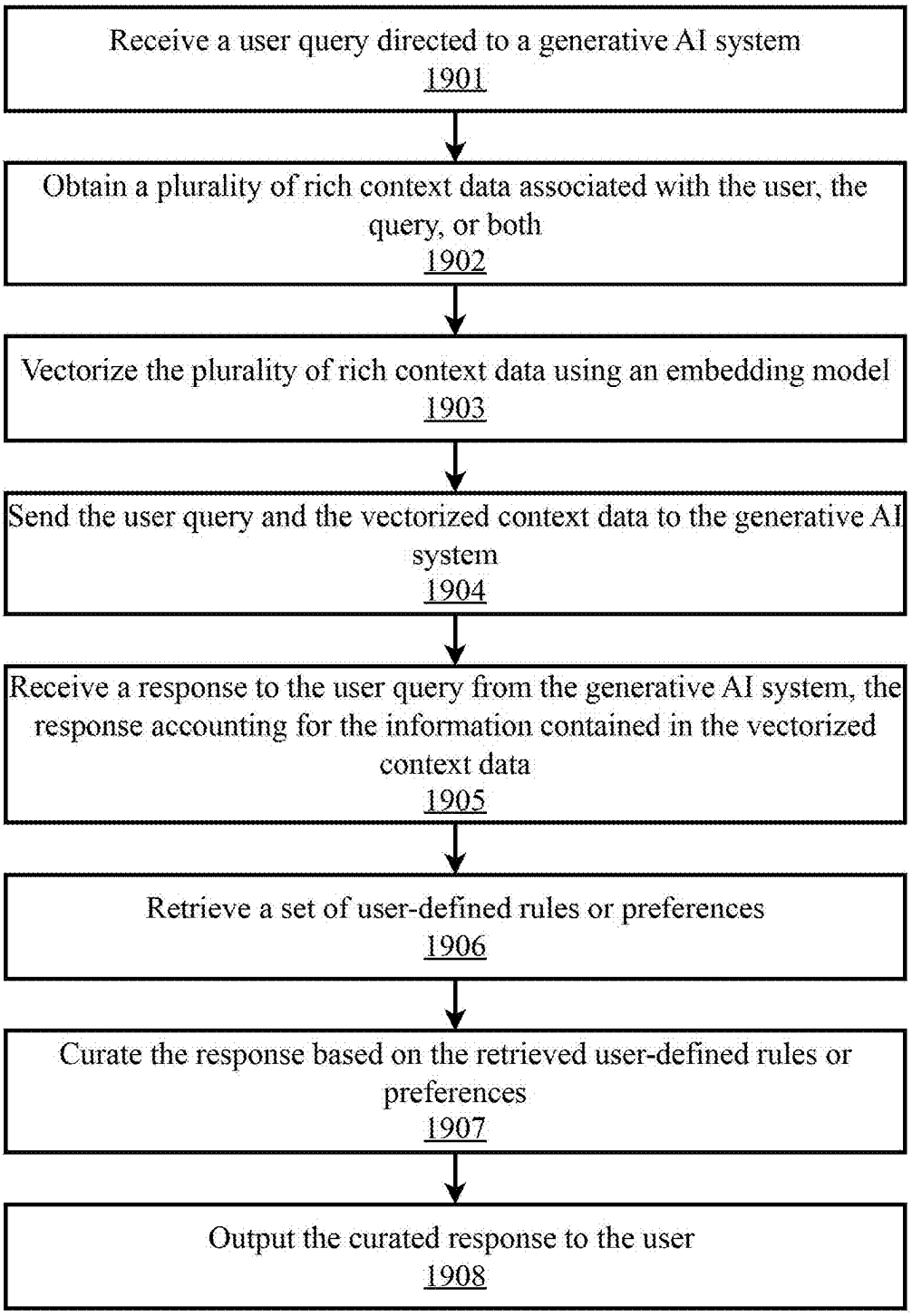

Receive a user query directed to a generative AI system
1901
Obtain a plurality of rich context data associated with the user, the query, or both
1902
Vectorize the plurality of rich context data using an embedding model
1903
Send the user query and the vectorized context data to the generative AI system
1904
Receive a response to the user query from the generative AI system, the response accounting for the information contained in the vectorized context data
1905
Retrieve a set of user-defined rules or preferences
1906
Curate the response based on the retrieved user-defined rules or preferences
1907
Output the curated response to the user
1908

FIG. 19

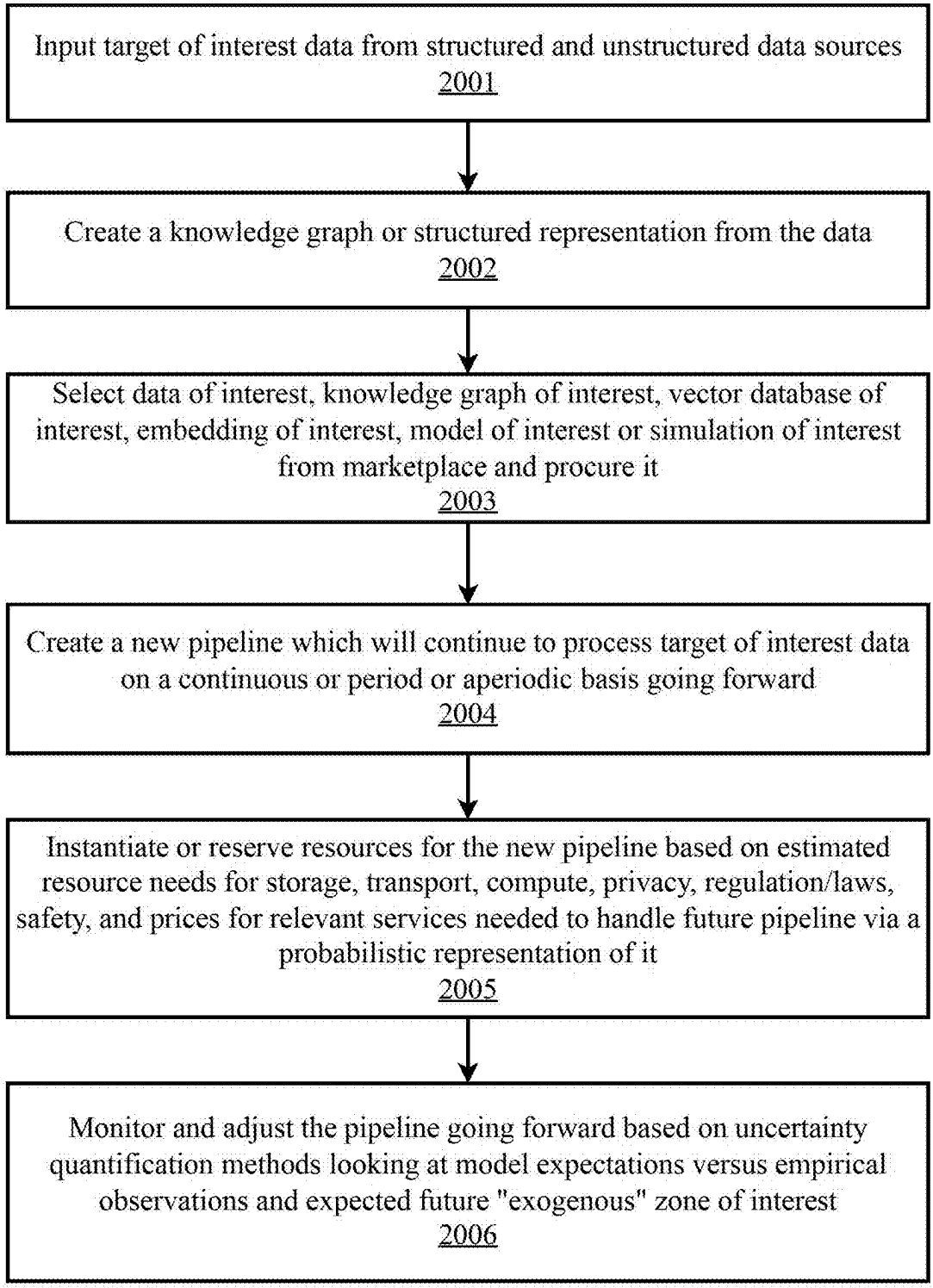

Input target of interest data from structured and unstructured data sources
2001
Create a knowledge graph or structured representation from the data
2002
Select data of interest, knowledge graph of interest, vector database of interest, embedding of interest, model of interest or simulation of interest from marketplace and procure it
2003
Create a new pipeline which will continue to process target of interest data on a continuous or period or aperiodic basis going forward
2004
Instantiate or reserve resources for the new pipeline based on estimated resource needs for storage, transport, compute, privacy, regulation/laws, safety, and prices for relevant services needed to handle future pipeline via a probabilistic representation of it
2005
Monitor and adjust the pipeline going forward based on uncertainty quantification methods looking at model expectations versus empirical observations and expected future "exogenous" zone of interest
2006

FIG. 20

FIG. 21

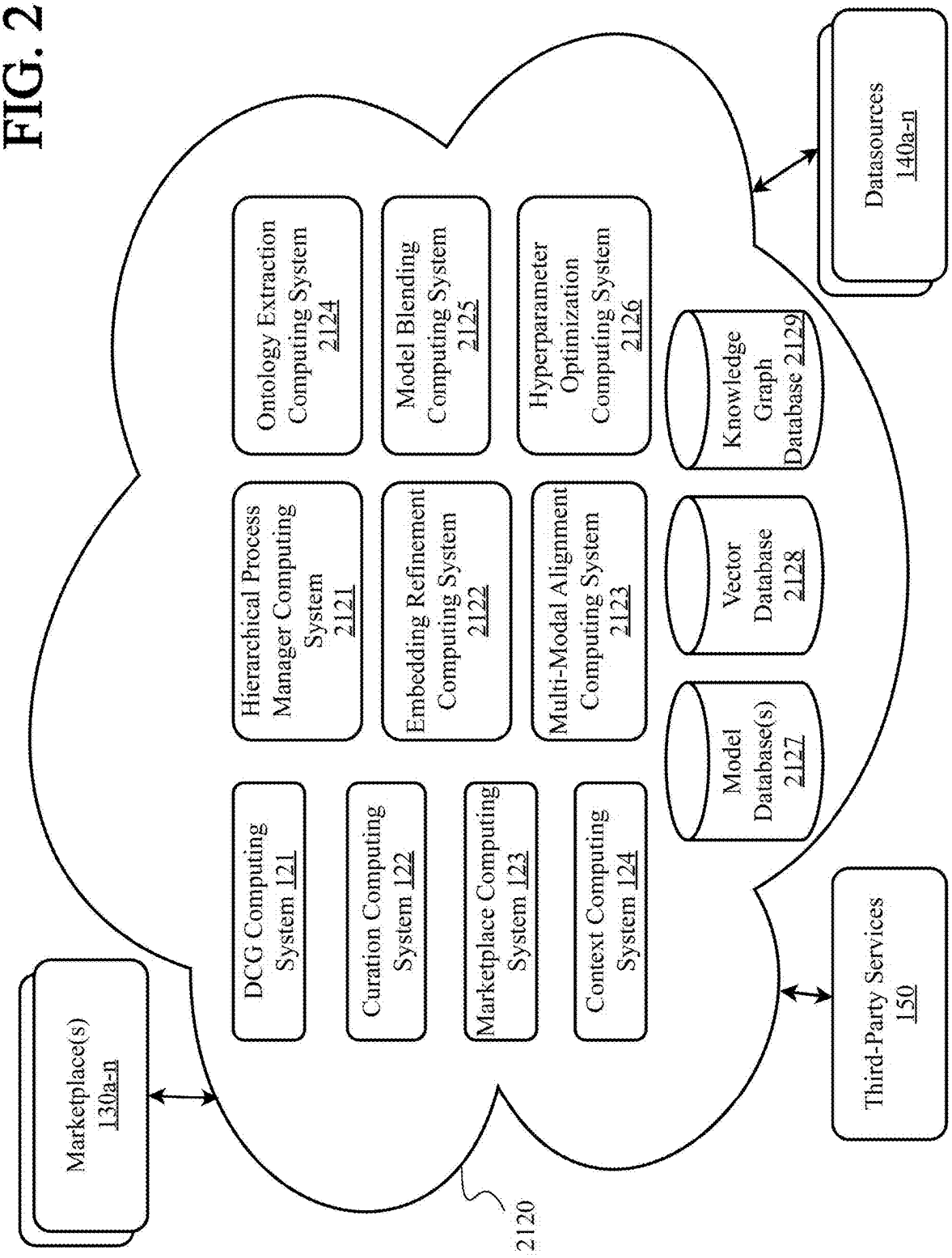
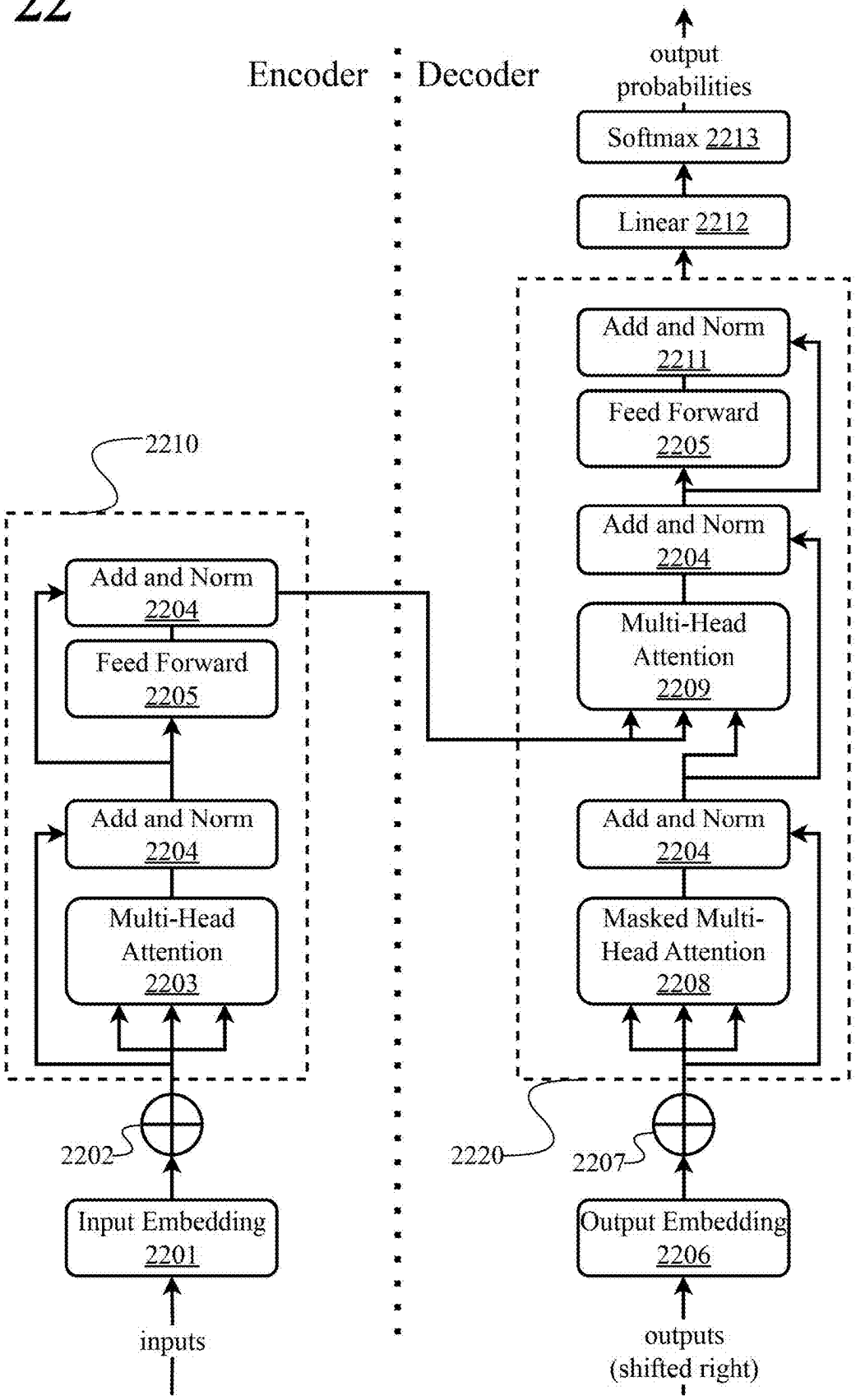

Marketplace(s) 130a-n
DCG Computing System 121
Curation Computing System 122
Marketplace Computing System 123
Context Computing System 124
Hierarchical Process Manager Computing System 2121
Embedding Refinement Computing System 2122
Multi-Modal Alignment Computing System 2123
Ontology Extraction Computing System 2124
Model Blending Computing System 2125
Hyperparameter Optimization Computing System 2126
Model Database(s) 2127
Vector Database 2128
Knowledge Graph Database 2129
Datasources 140a-n
Third-Party Services 150
2120

FIG. 22


Encoder
Decoder
output probabilities
Softmax 2213
Linear 2212
Add and Norm 2211
Feed Forward 2205
Add and Norm 2204
Multi-Head Attention 2209
Add and Norm 2204
Masked Multi-Head Attention 2208
2220
2207
Output Embedding 2206
outputs (shifted right)
2210
Add and Norm 2204
Feed Forward 2205
Add and Norm 2204
Multi-Head Attention 2203
2202
Input Embedding 2201
inputs

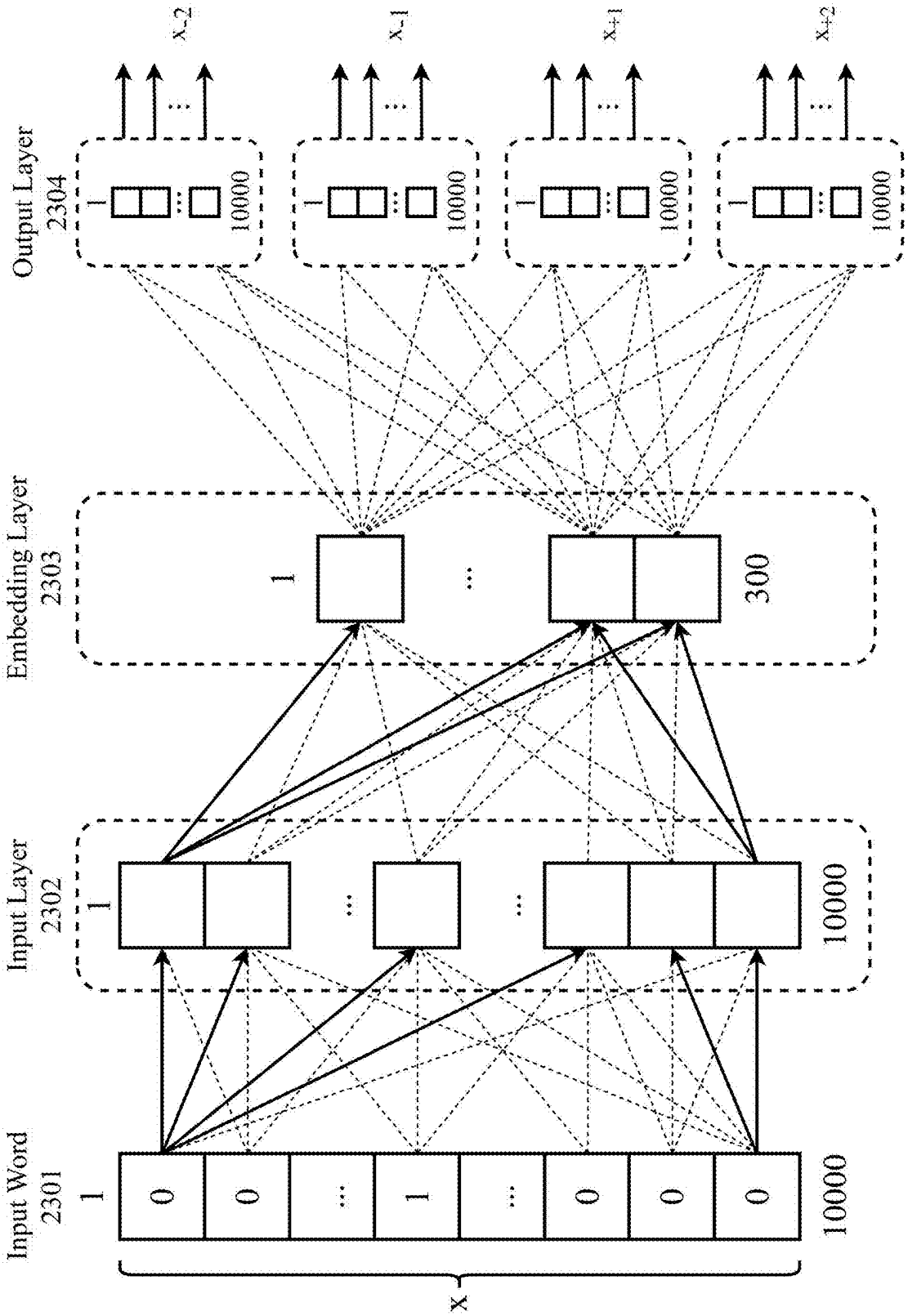

Input Word
2301
1
0
0
...
1
...
0
0
0
10000
x
Input Layer
2302
1
...
...
10000
Embedding Layer
2303
1
...
300
Output Layer
2304
1
...
10000
x-2
x-1
x+1
x+2

FIG. 23

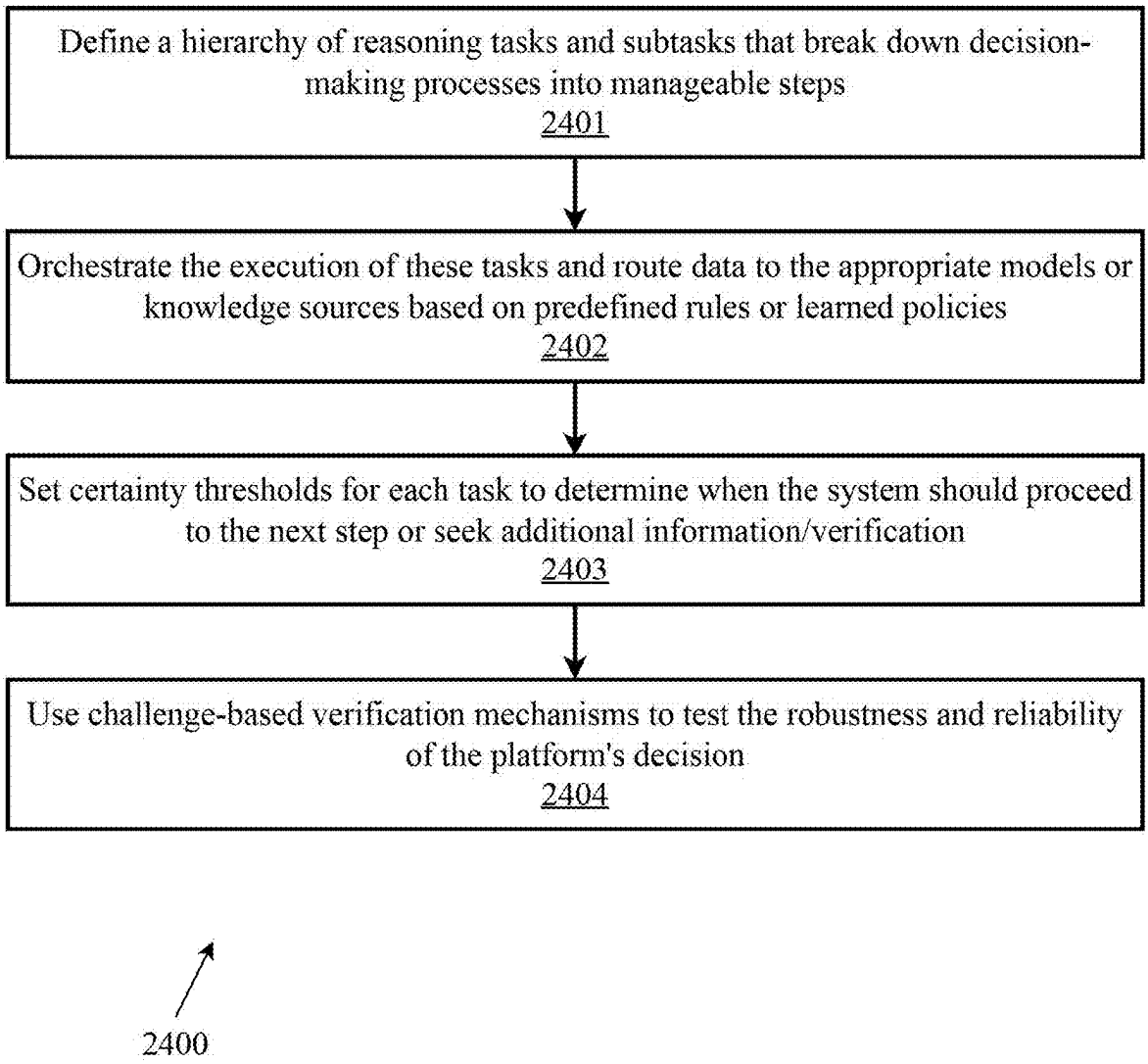

Define a hierarchy of reasoning tasks and subtasks that break down decision-making processes into manageable steps
2401
Orchestrate the execution of these tasks and route data to the appropriate models or knowledge sources based on predefined rules or learned policies
2402
Set certainty thresholds for each task to determine when the system should proceed to the next step or seek additional information/verification
2403
Use challenge-based verification mechanisms to test the robustness and reliability of the platform's decision
2404
2400

FIG. 24

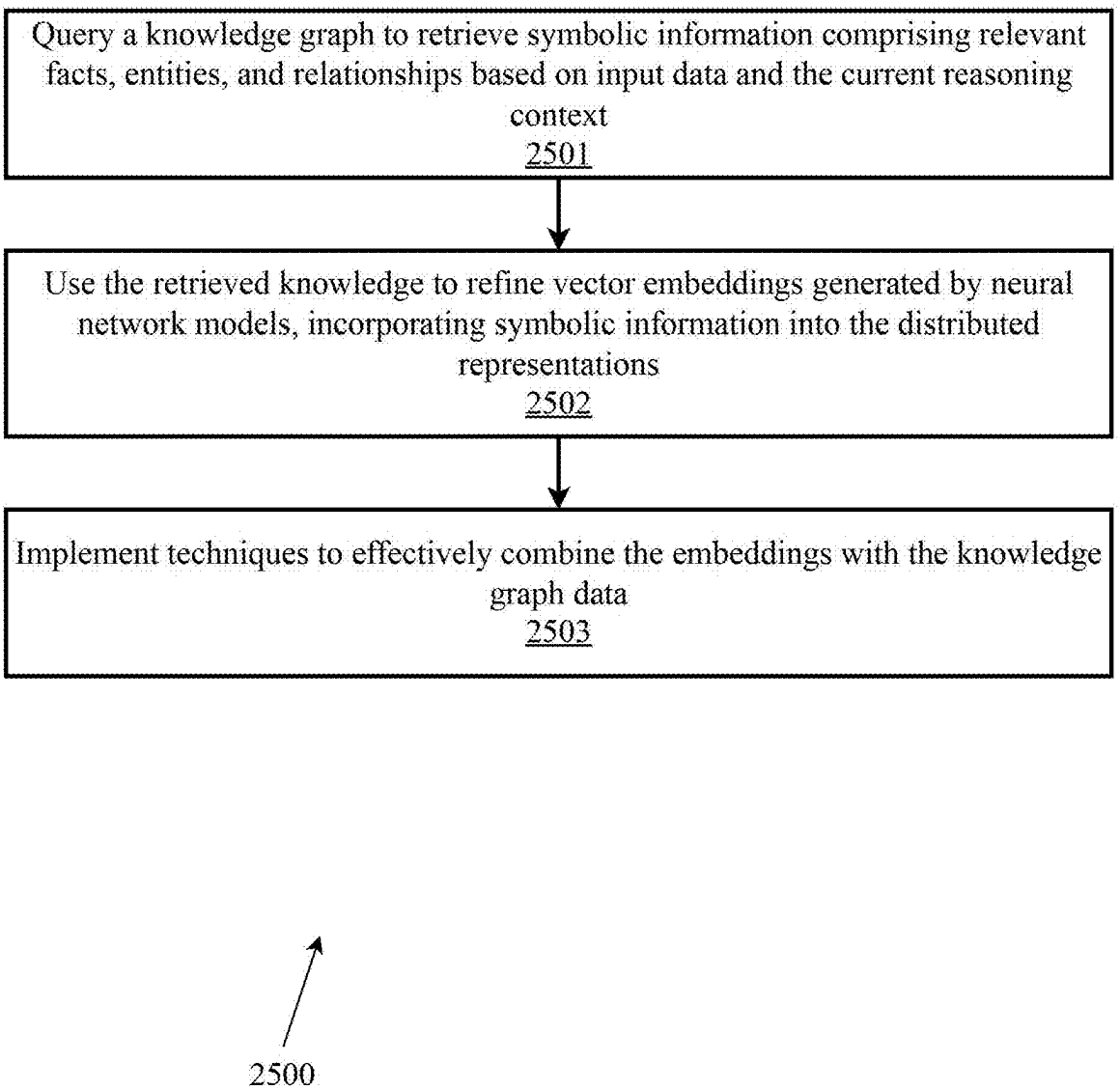

Query a knowledge graph to retrieve symbolic information comprising relevant facts, entities, and relationships based on input data and the current reasoning context
2501
Use the retrieved knowledge to refine vector embeddings generated by neural network models, incorporating symbolic information into the distributed representations
2502
Implement techniques to effectively combine the embeddings with the knowledge graph data
2503
2500

FIG. 25

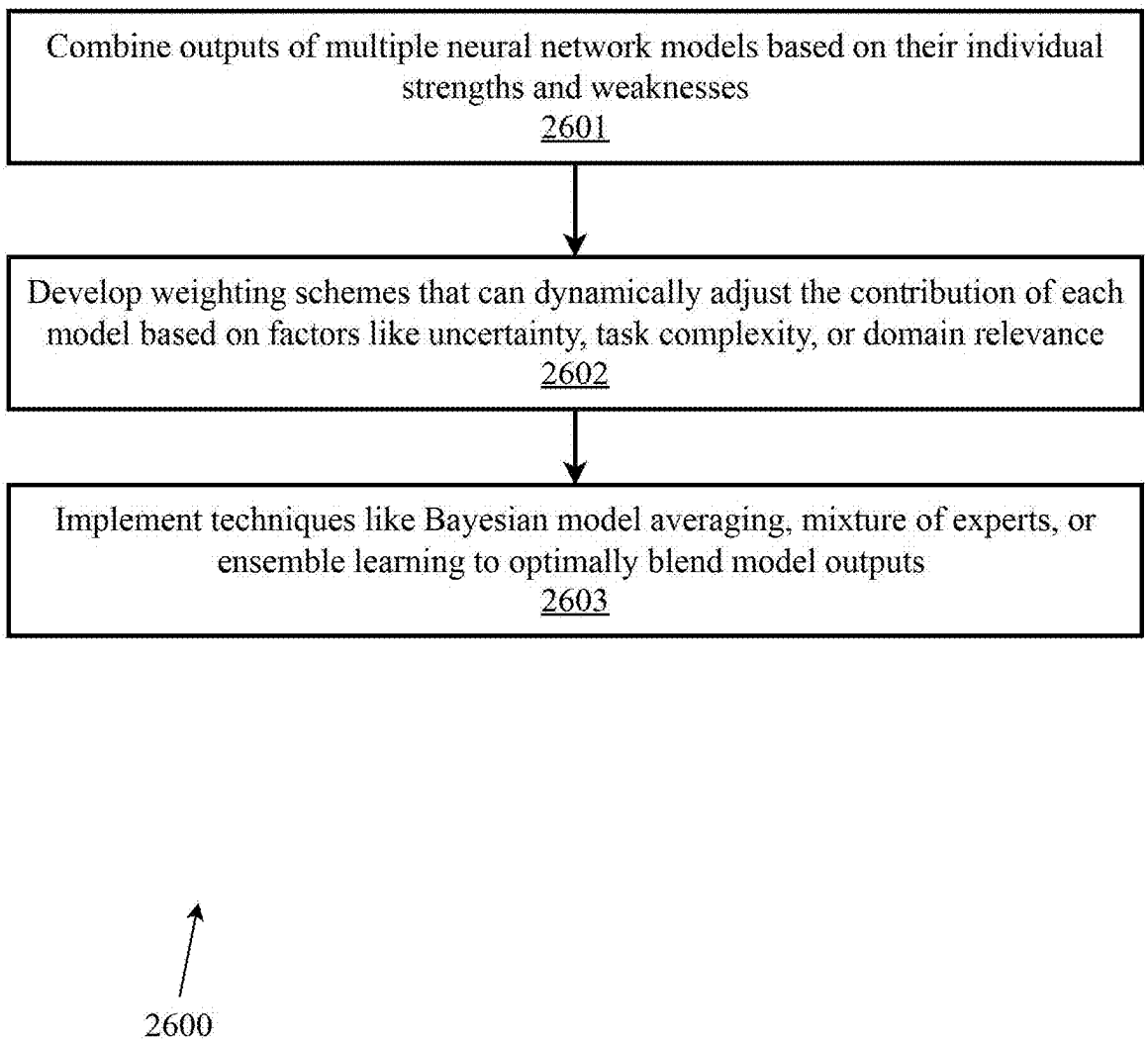

Combine outputs of multiple neural network models based on their individual strengths and weaknesses
2601
Develop weighting schemes that can dynamically adjust the contribution of each model based on factors like uncertainty, task complexity, or domain relevance
2602
Implement techniques like Bayesian model averaging, mixture of experts, or ensemble learning to optimally blend model outputs
2603
2600

FIG. 26

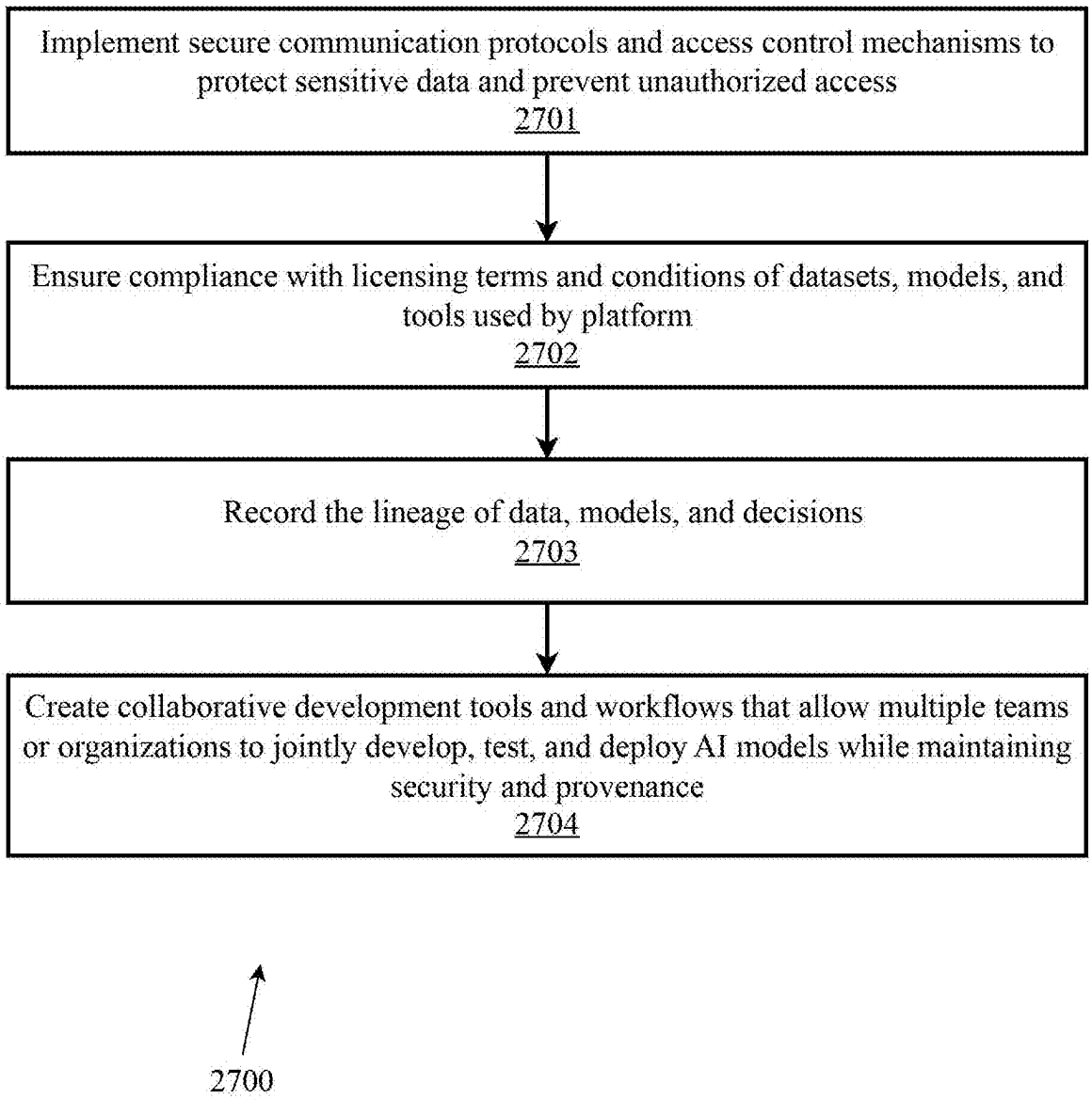

Implement secure communication protocols and access control mechanisms to protect sensitive data and prevent unauthorized access
2701
Ensure compliance with licensing terms and conditions of datasets, models, and tools used by platform
2702
Record the lineage of data, models, and decisions
2703
Create collaborative development tools and workflows that allow multiple teams or organizations to jointly develop, test, and deploy AI models while maintaining security and provenance
2704
2700

FIG. 27

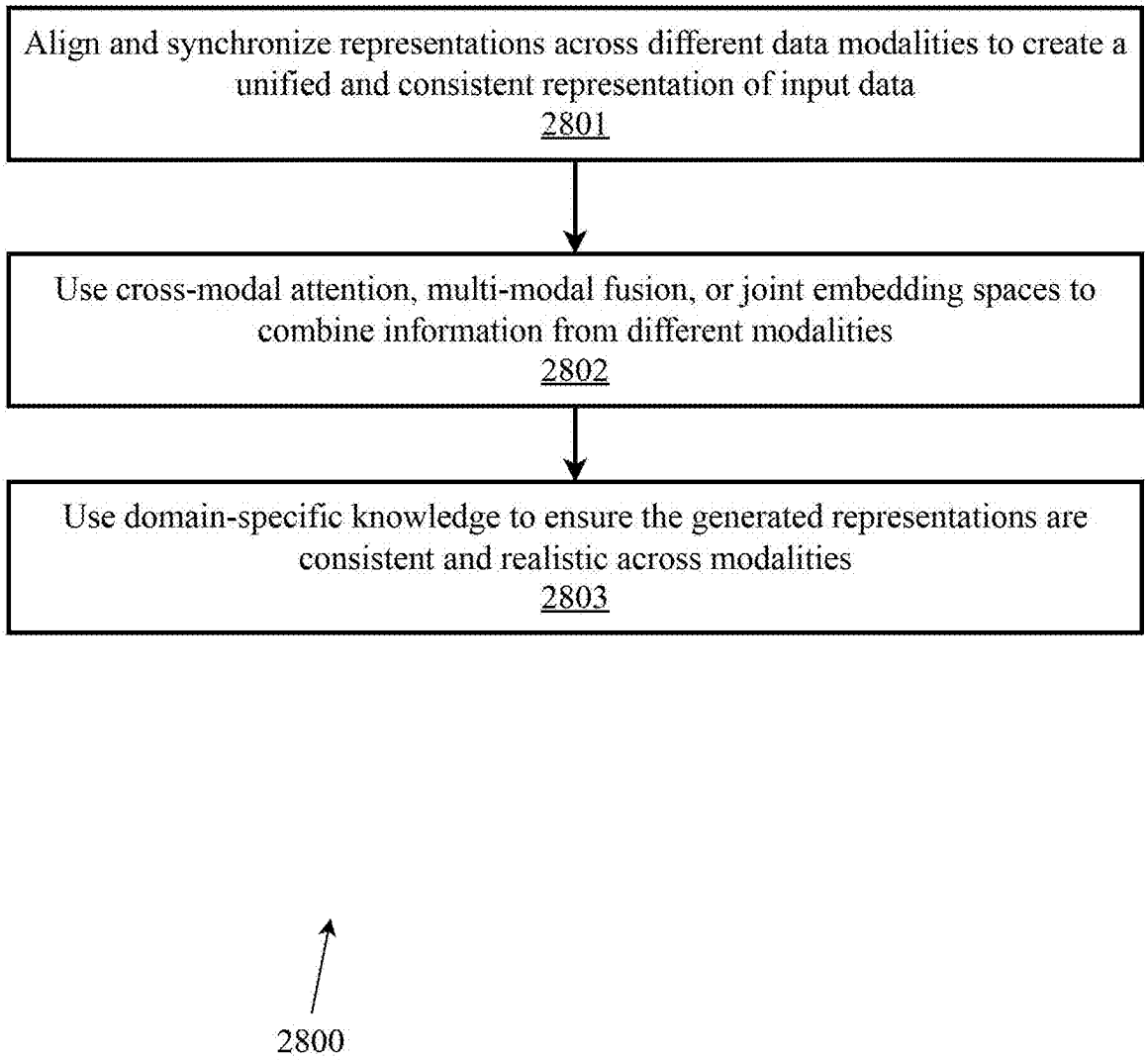

Align and synchronize representations across different data modalities to create a unified and consistent representation of input data
2801
Use cross-modal attention, multi-modal fusion, or joint embedding spaces to combine information from different modalities
2802
Use domain-specific knowledge to ensure the generated representations are consistent and realistic across modalities
2803
2800

FIG. 28

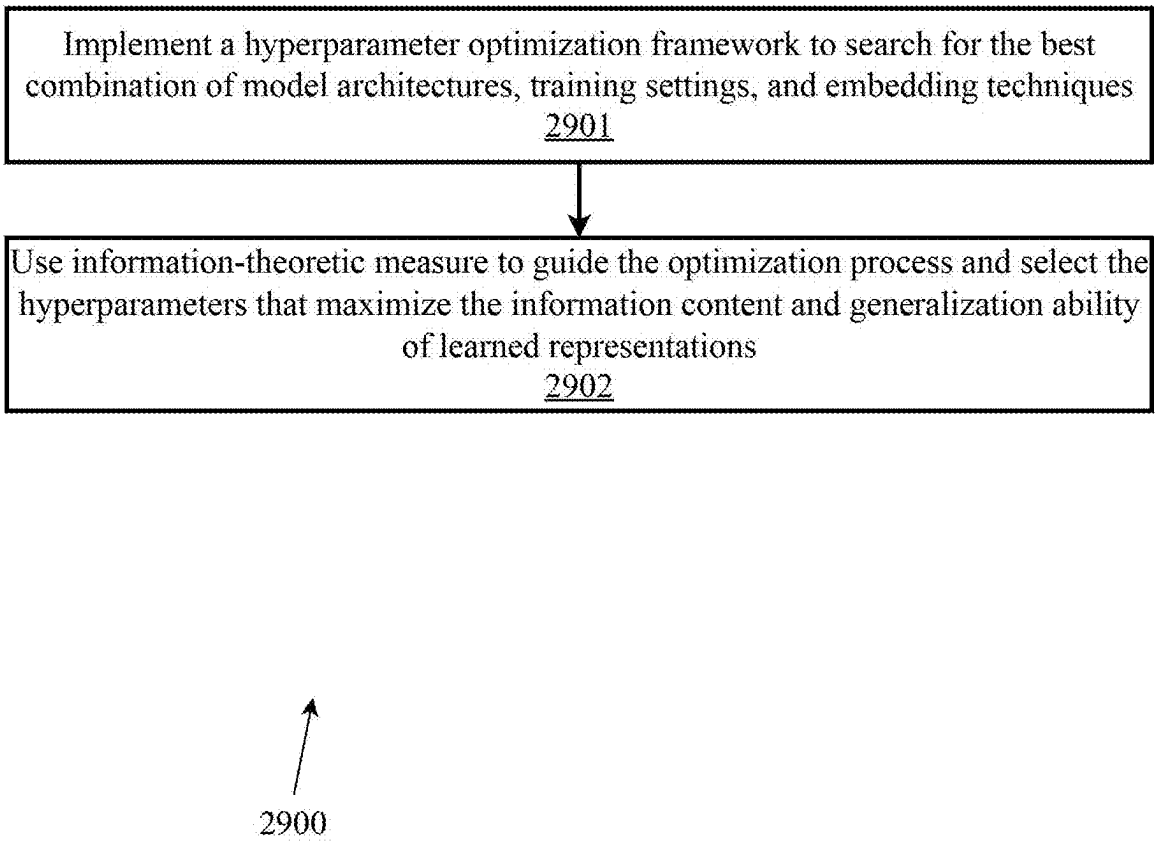

Implement a hyperparameter optimization framework to search for the best combination of model architectures, training settings, and embedding techniques
2901
Use information-theoretic measure to guide the optimization process and select the hyperparameters that maximize the information content and generalization ability of learned representations
2902
2900

FIG. 29

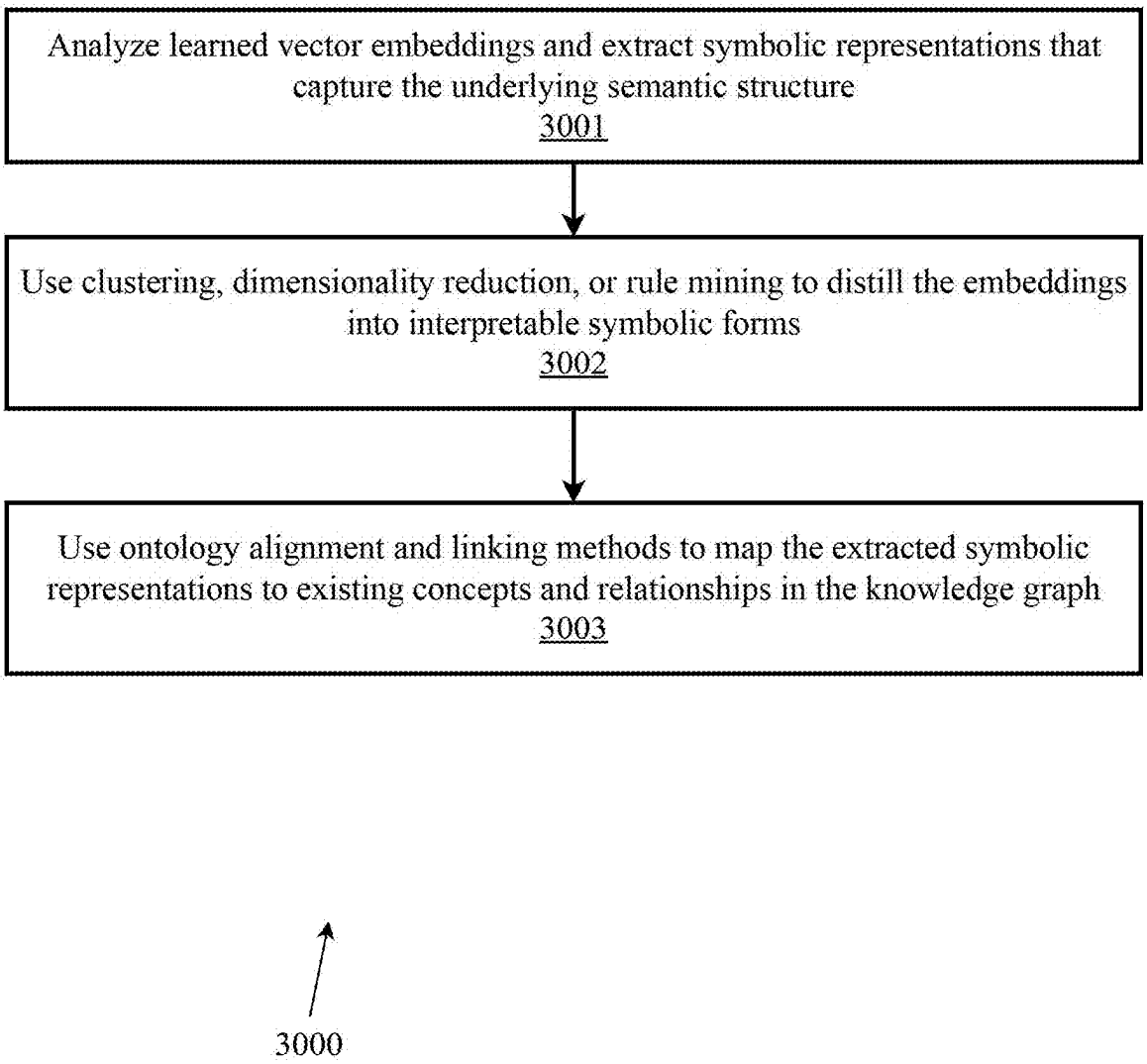

Analyze learned vector embeddings and extract symbolic representations that capture the underlying semantic structure
3001
Use clustering, dimensionality reduction, or rule mining to distill the embeddings into interpretable symbolic forms
3002
Use ontology alignment and linking methods to map the extracted symbolic representations to existing concepts and relationships in the knowledge graph
3003
3000

FIG. 30

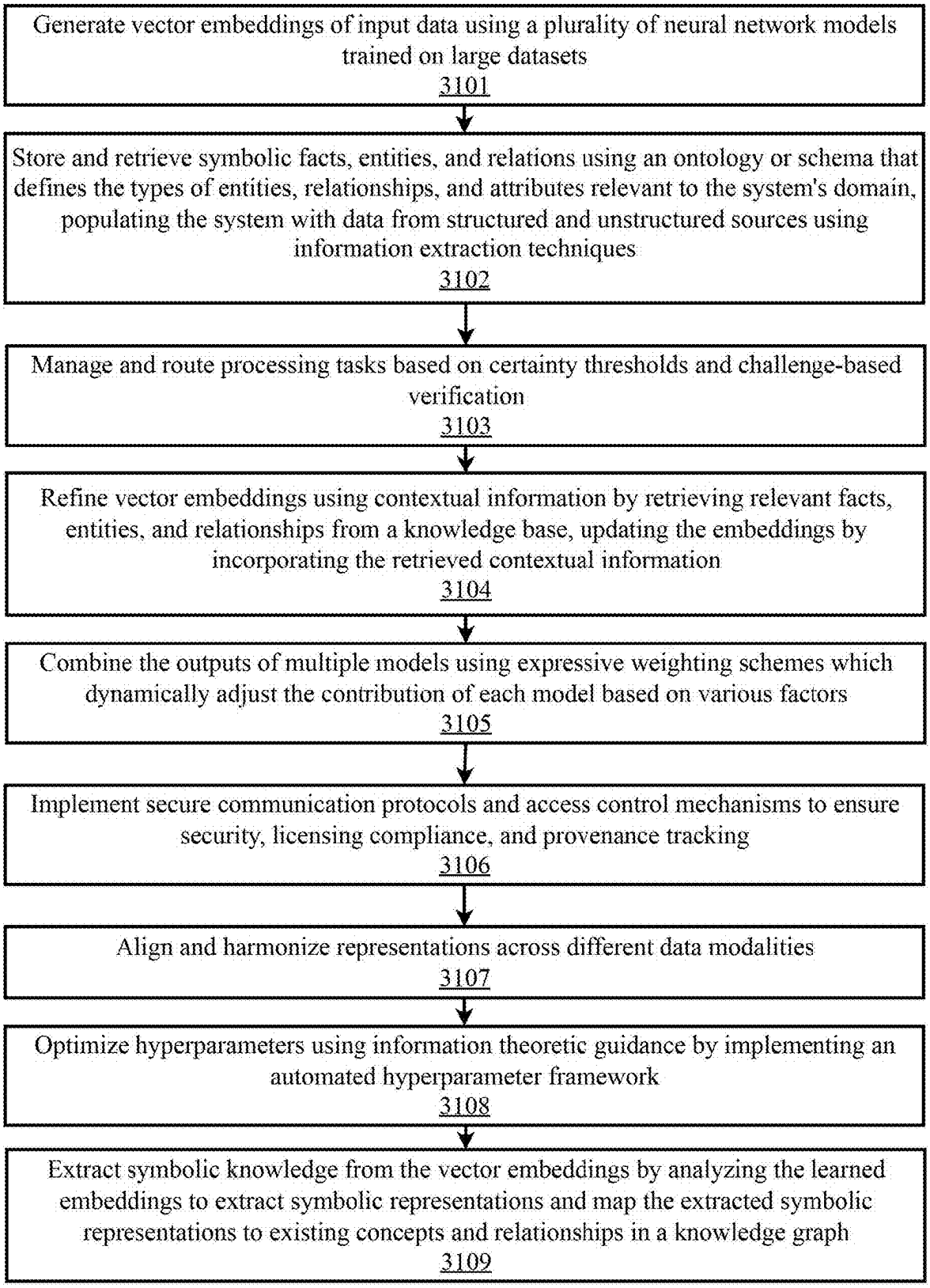

Generate vector embeddings of input data using a plurality of neural network models trained on large datasets
3101
Store and retrieve symbolic facts, entities, and relations using an ontology or schema that defines the types of entities, relationships, and attributes relevant to the system's domain, populating the system with data from structured and unstructured sources using information extraction techniques
3102
Manage and route processing tasks based on certainty thresholds and challenge-based verification
3103
Refine vector embeddings using contextual information by retrieving relevant facts, entities, and relationships from a knowledge base, updating the embeddings by incorporating the retrieved contextual information
3104
Combine the outputs of multiple models using expressive weighting schemes which dynamically adjust the contribution of each model based on various factors
3105
Implement secure communication protocols and access control mechanisms to ensure security, licensing compliance, and provenance tracking
3106
Align and harmonize representations across different data modalities
3107
Optimize hyperparameters using information theoretic guidance by implementing an automated hyperparameter framework
3108
Extract symbolic knowledge from the vector embeddings by analyzing the learned embeddings to extract symbolic representations and map the extracted symbolic representations to existing concepts and relationships in a knowledge graph
3109

FIG. 31

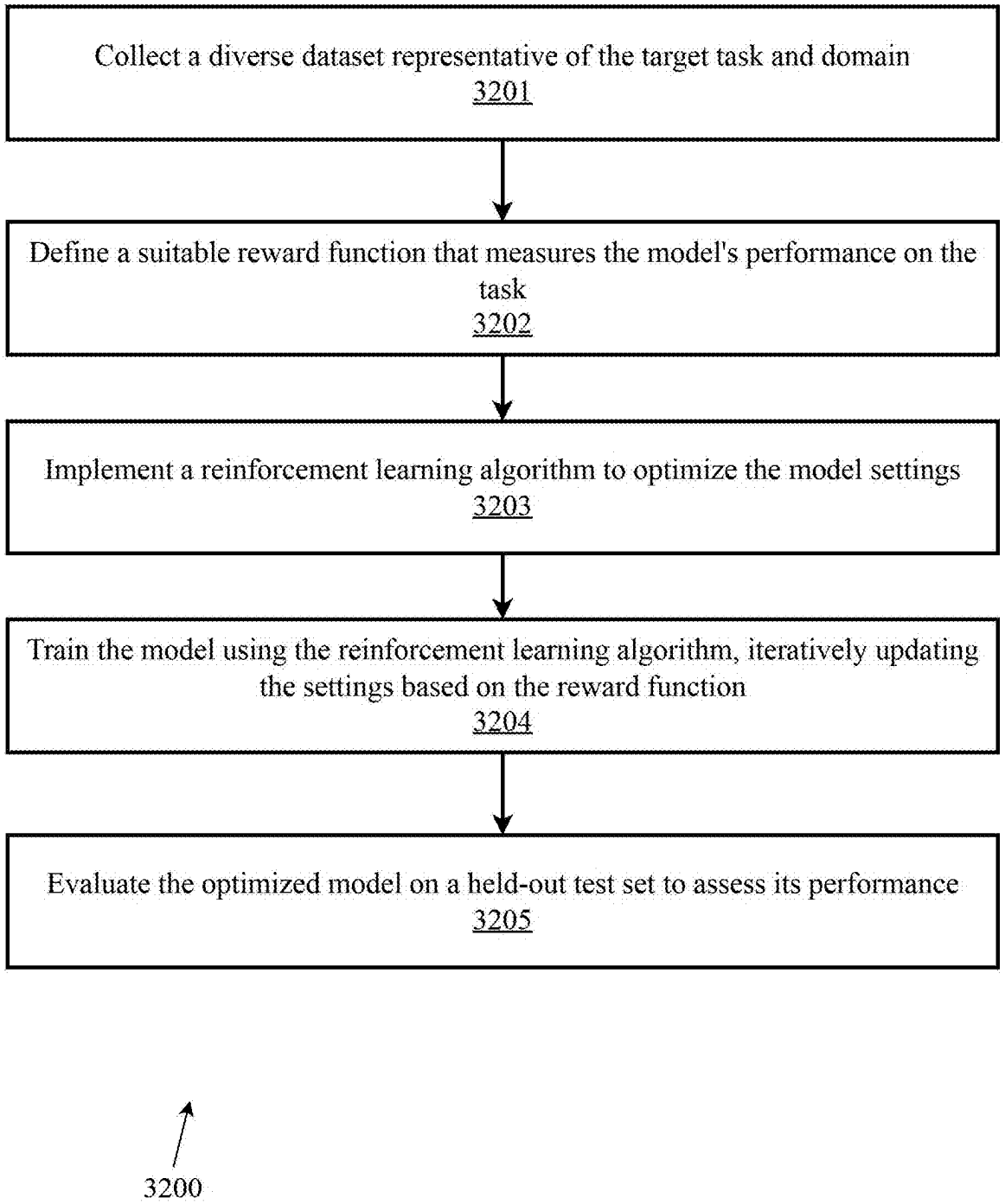

Collect a diverse dataset representative of the target task and domain
3201
Define a suitable reward function that measures the model's performance on the task
3202
Implement a reinforcement learning algorithm to optimize the model settings
3203
Train the model using the reinforcement learning algorithm, iteratively updating the settings based on the reward function
3204
Evaluate the optimized model on a held-out test set to assess its performance
3205
3200

FIG. 32

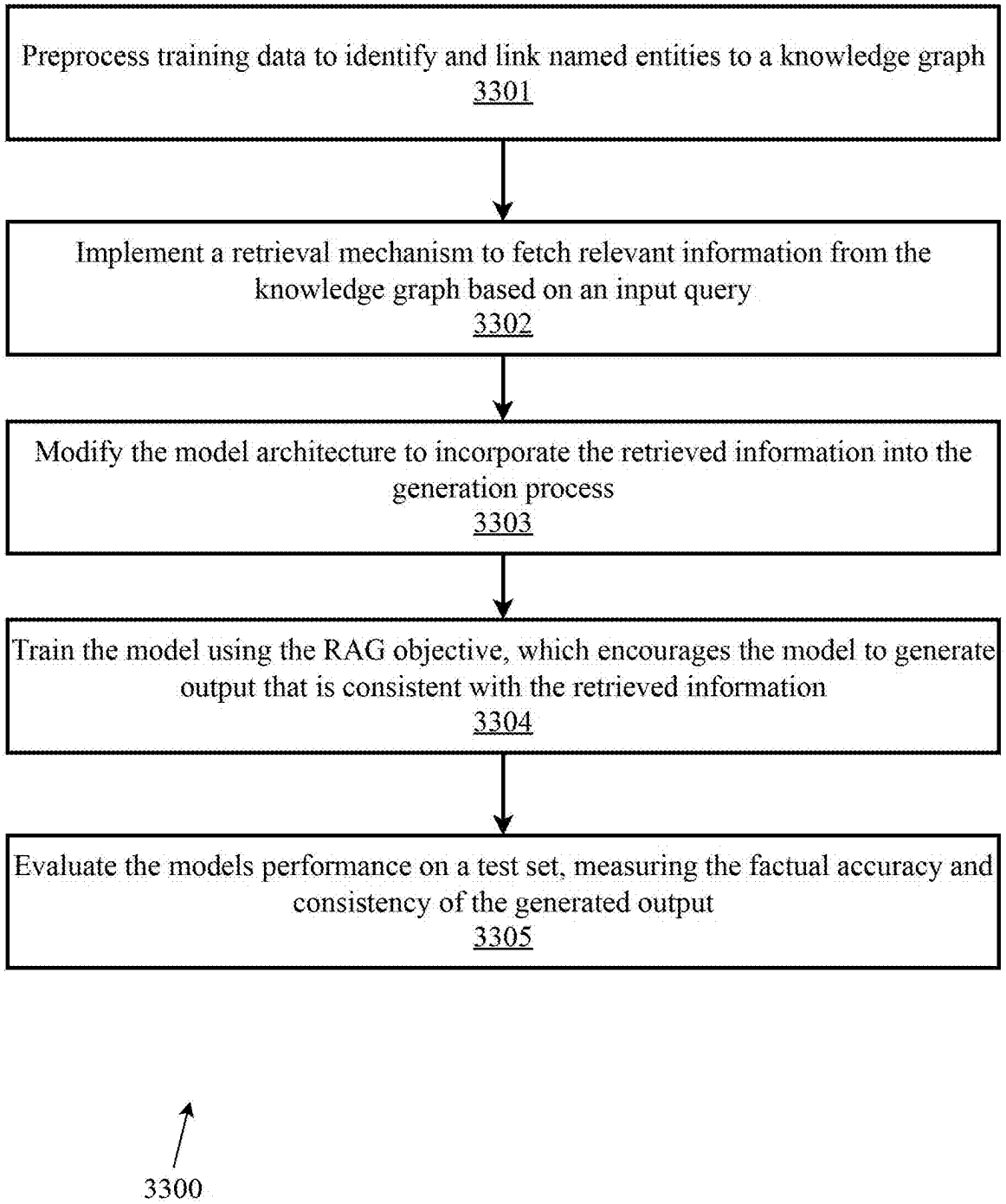

Preprocess training data to identify and link named entities to a knowledge graph
3301
Implement a retrieval mechanism to fetch relevant information from the knowledge graph based on an input query
3302
Modify the model architecture to incorporate the retrieved information into the generation process
3303
Train the model using the RAG objective, which encourages the model to generate output that is consistent with the retrieved information
3304
Evaluate the models performance on a test set, measuring the factual accuracy and consistency of the generated output
3305
3300

FIG. 33

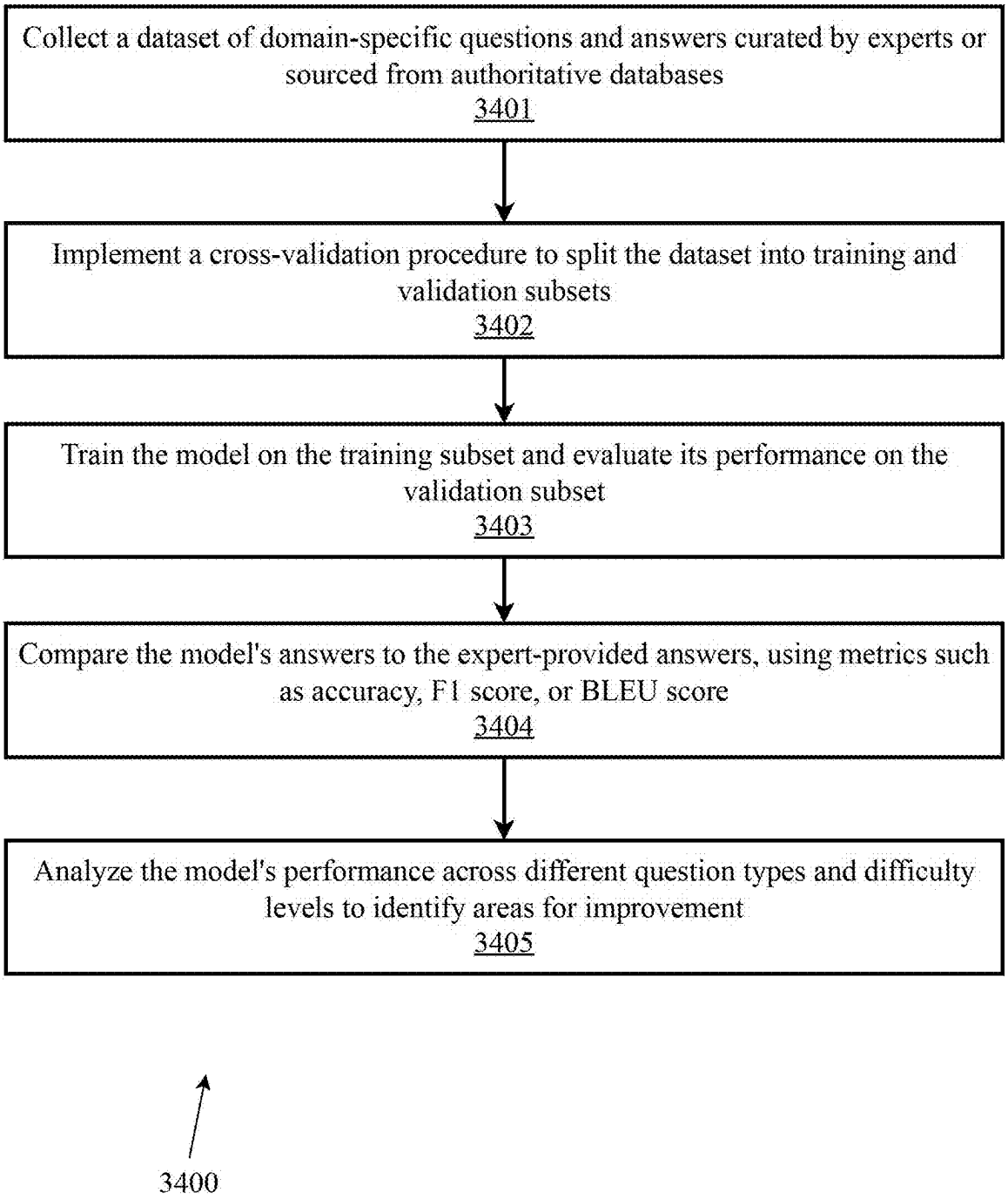

Collect a dataset of domain-specific questions and answers curated by experts or sourced from authoritative databases
3401
Implement a cross-validation procedure to split the dataset into training and validation subsets
3402
Train the model on the training subset and evaluate its performance on the validation subset
3403
Compare the model's answers to the expert-provided answers, using metrics such as accuracy, F1 score, or BLEU score
3404
Analyze the model's performance across different question types and difficulty levels to identify areas for improvement
3405
3400

FIG. 34

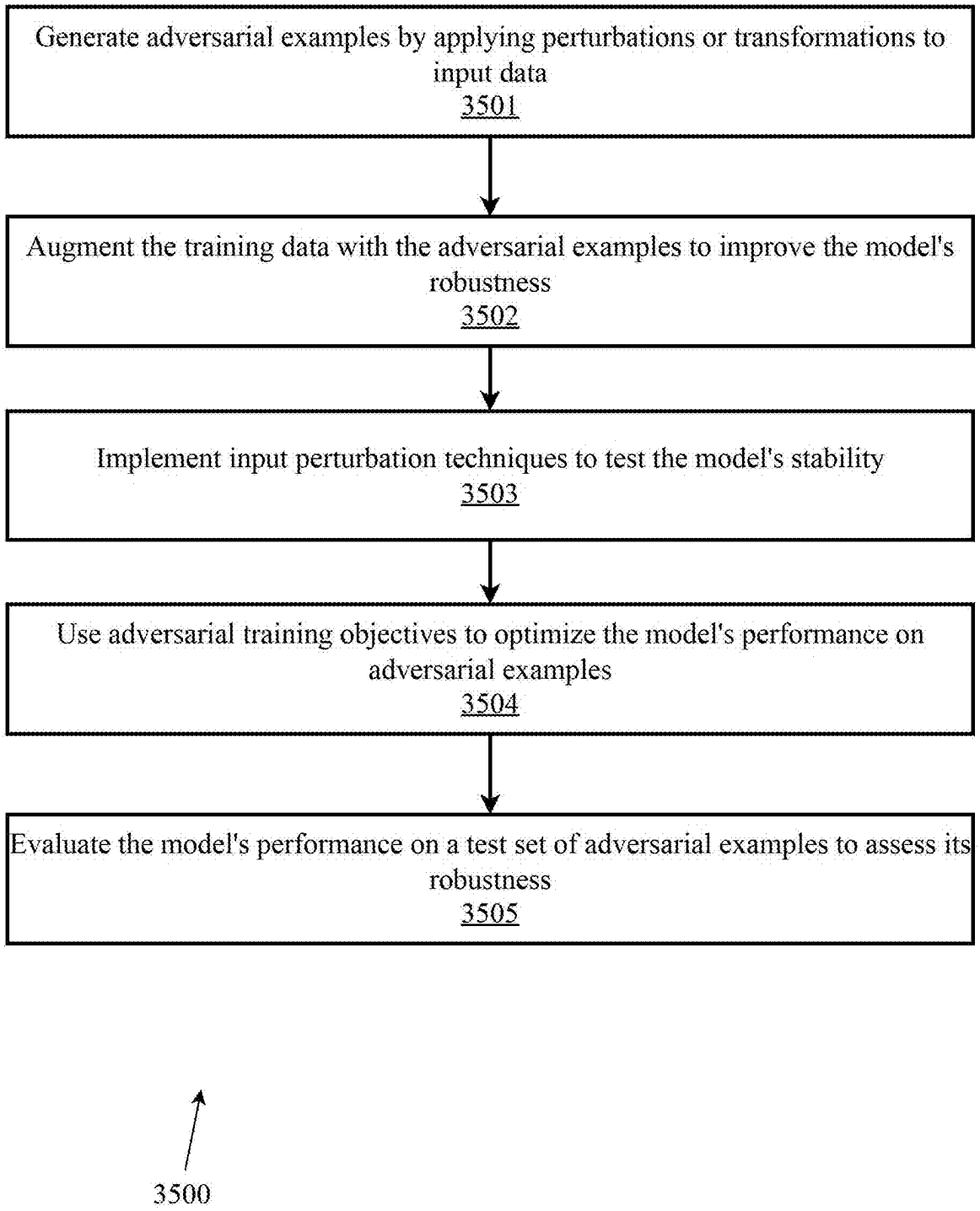

Generate adversarial examples by applying perturbations or transformations to input data
3501
Augment the training data with the adversarial examples to improve the model's robustness
3502
Implement input perturbation techniques to test the model's stability
3503
Use adversarial training objectives to optimize the model's performance on adversarial examples
3504
Evaluate the model's performance on a test set of adversarial examples to assess its robustness
3505
3500

FIG. 35

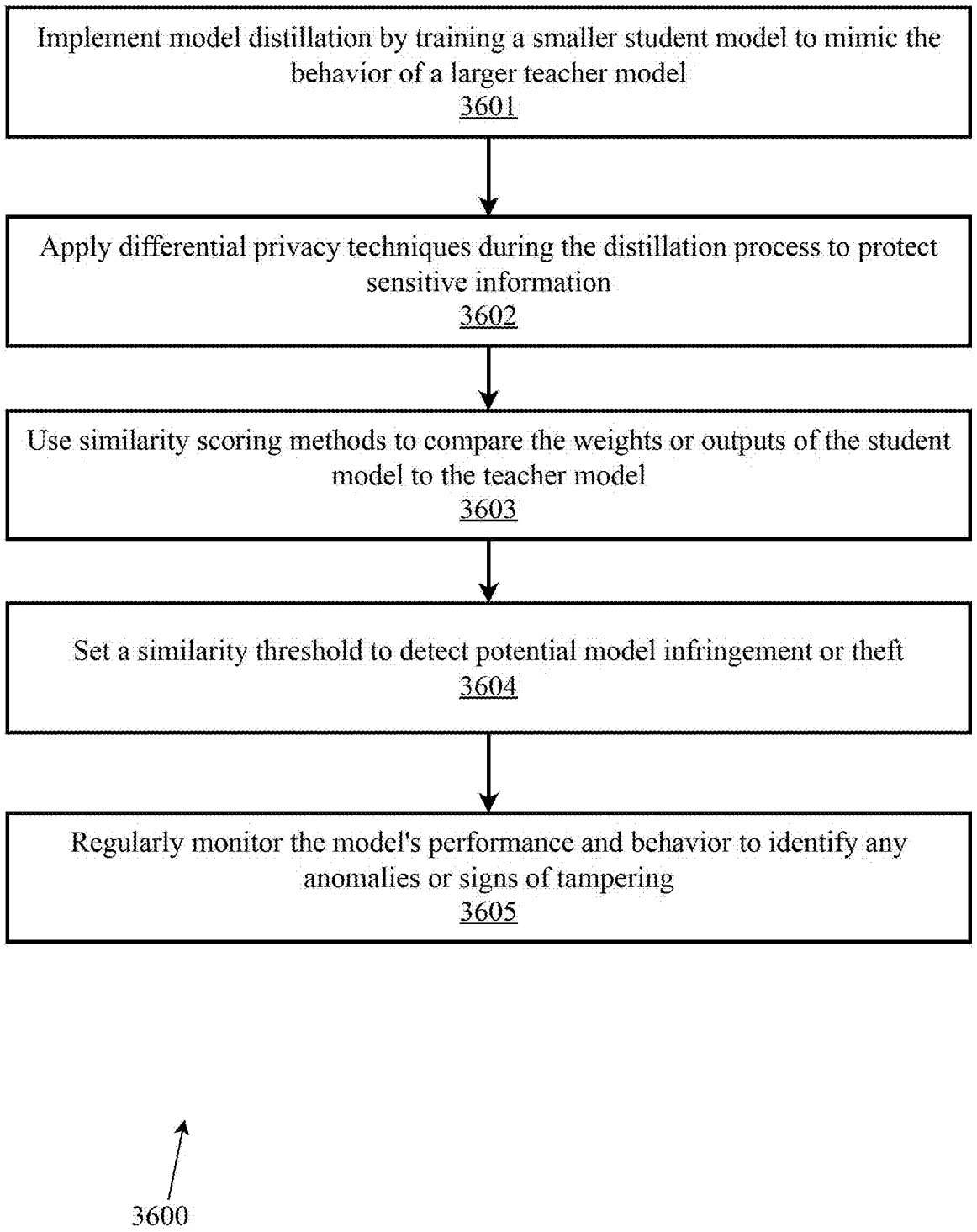

Implement model distillation by training a smaller student model to mimic the behavior of a larger teacher model
3601
Apply differential privacy techniques during the distillation process to protect sensitive information
3602
Use similarity scoring methods to compare the weights or outputs of the student model to the teacher model
3603
Set a similarity threshold to detect potential model infringement or theft
3604
Regularly monitor the model's performance and behavior to identify any anomalies or signs of tampering
3605
3600

FIG. 36

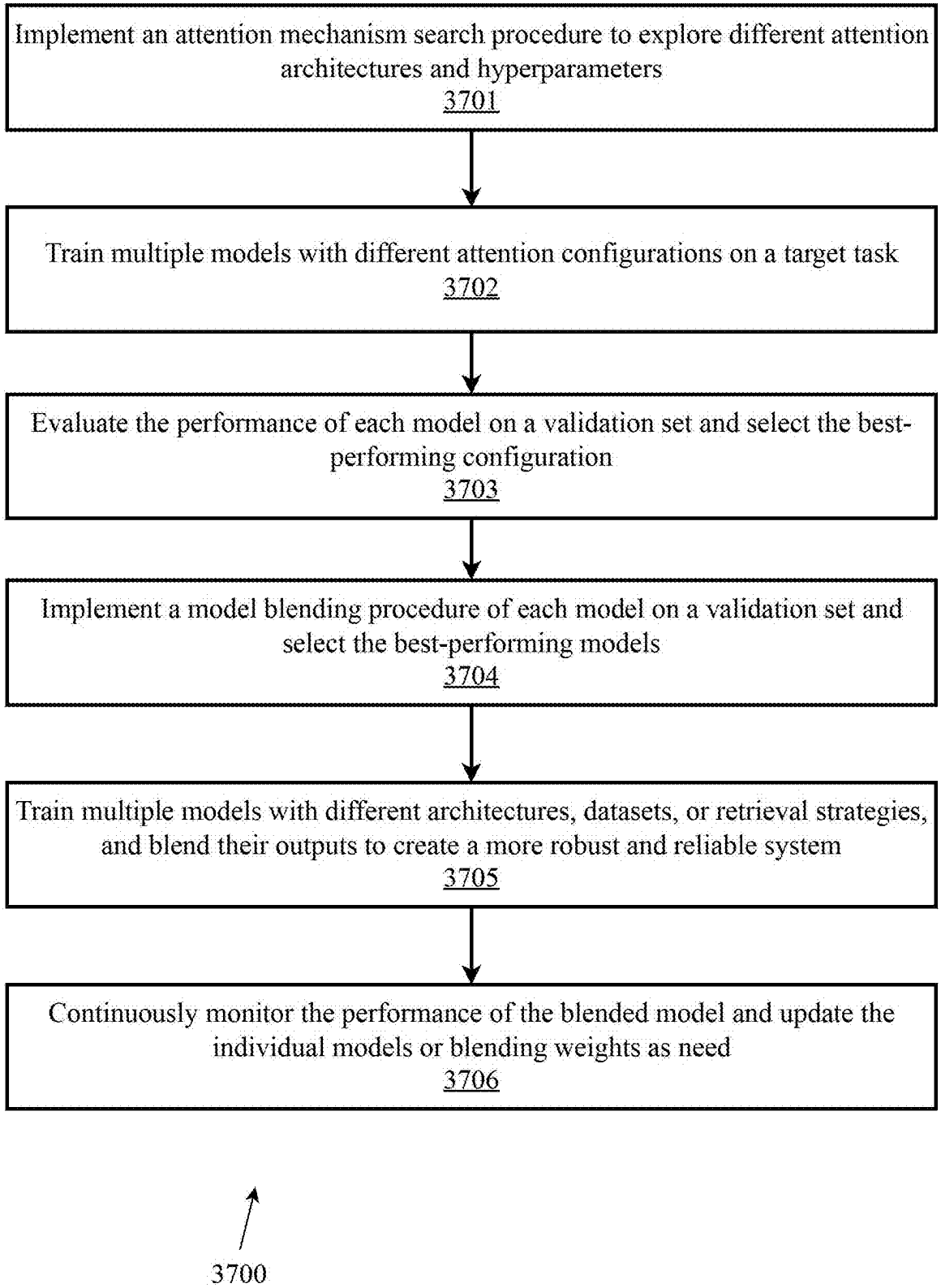

Implement an attention mechanism search procedure to explore different attention architectures and hyperparameters
3701
Train multiple models with different attention configurations on a target task
3702
Evaluate the performance of each model on a validation set and select the best-performing configuration
3703
Implement a model blending procedure of each model on a validation set and select the best-performing models
3704
Train multiple models with different architectures, datasets, or retrieval strategies, and blend their outputs to create a more robust and reliable system
3705
Continuously monitor the performance of the blended model and update the individual models or blending weights as need
3706
3700

FIG. 37

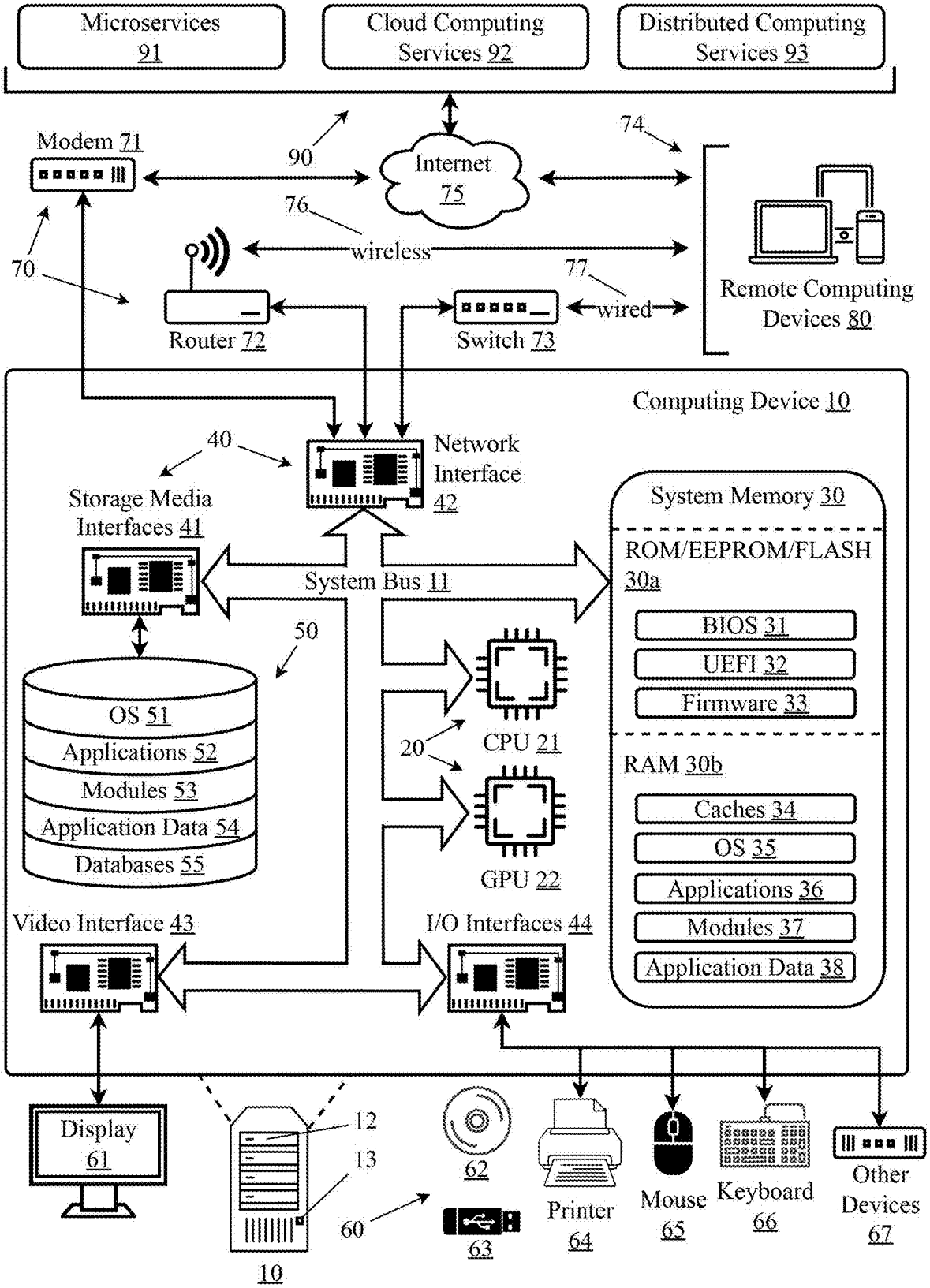

Microservices 91
Cloud Computing Services 92
Distributed Computing Services 93
Modem 71
90
Internet 75
74
76
wireless
70
77
wired
Router 72
Switch 73
Remote Computing Devices 80
Computing Device 10
40
Network Interface 42
Storage Media Interfaces 41
System Memory 30
ROM/EEPROM/FLASH 30a
BIOS 31
UEFI 32
Firmware 33
System Bus 11
50
OS 51
Applications 52
Modules 53
Application Data 54
Databases 55
20
CPU 21
GPU 22
RAM 30b
Caches 34
OS 35
Applications 36
Modules 37
Application Data 38
Video Interface 43
I/O Interfaces 44
Display 61
12
13
10
60
62
63
Printer 64
Mouse 65
Keyboard 66
Other Devices 67

FIG. 38

ADVANCED MODEL MANAGEMENT PLATFORM FOR OPTIMIZING AND SECURING AI SYSTEMS INCLUDING LARGE LANGUAGE MODELS

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] Priority is claimed in the application data sheet to the following patents or patent applications, each of which is expressly incorporated herein by reference in its entirety:

[0002] Ser. No. 18/668,137

[0003] Ser. No. 18/656,612

[0004] 63/551,328

BACKGROUND OF THE INVENTION

Field of the Art

[0005] The present invention is in the field of large-scale cloud computing, and more particularly to distributed computing platforms, leveraging graph-based specifications for data flows, transport and storage, and logic locality in data handling to enable artificial intelligence enhanced decision-making and automation and planning including those employing large language models, neuro-symbolic AI, and associated services across heterogeneous cloud, managed data center, edge, and wearable/mobile devices.

Discussion of the State of the Art

[0006] Current artificial intelligence (AI) systems, including large language models (LLMs) and generative AI (Gen AI), have limitations in their utility stemming from their lack of symbolic reasoning capabilities and integration of symbolic knowledge and limited capabilities for automated planning alongside the limited explainability of connectionist modeling approaches. There is a need for AI system architectures that can bridge symbolic and non-symbolic, i.e. connectionist, representations to enable more advanced, contextual reasoning while also considering critical factors like security, traceability, and collaborative model development and legal, privacy, and data owner restrictions around the locality of data across transport, storage and compute stages of data flow specified processes at both logical and physical levels.

[0007] Large language models and other connectionist AI techniques have demonstrated remarkable capabilities in various natural language processing, classification and inference tasks across text, sound, video, and even in chemical, molecule, mathematical and other specialized areas. However, they suffer from limitations such as hallucination, lack of validation, security vulnerabilities, and inadequate model management and suitability monitoring that negatively impact trust and applicability to mission critical utilization.

[0008] What is needed is an advanced model management platform for optimizing and securing large language models, neuro-symbolic AI systems, and aiding in efficient use of RAGs, transfer and federated learning, structured expert judgment, and fine-tuning capabilities in production environments.

SUMMARY OF THE INVENTION

[0009] Accordingly, the inventor has conceived and reduced to practice, an advanced model management platform for optimizing and securing artificial intelligence enhanced processes including those employing large language models and neuro symbolic models in real-world processes and production environments. The platform incorporates various techniques to address the limitations of current AI systems, including generative AI applications, such as hallucination, lack of validation, security vulnerabilities, and inadequate model management and fitness evaluation or challenges and explainability. The system employs combinations of random search, stochastic search and reinforcement learning algorithms, embedding and retrieval augmented generation (RAG) and knowledge graph enhancements for prompt or input improvements or prompt security/constraint satisfaction or output validation or use limitation, domain-specific knowledge corpus validation against expert or group of expert knowledge, transfer or federated learning enhancements or logic migration across mobile or edge or cloud resources, probabilistic consideration of distributed computing operational challenges, model distillation and output similarity scoring for security based on acceptable output checks and distance or consensus logic, adversarial training for robustness, and model type or attention mechanism search and model blending or consensus for advanced management or output weighting or downstream logic or planning inputs. By integrating these techniques, the platform significantly improves the performance, reliability, and security of generative AI systems across a wide range of reasoning tasks and domains. System may also take collections of specialized models, e.g. text, audio, image, physics, chemical, and combine such elements into spatial intelligence representations for scene or scenario-level planning of interest in many practical personal, business and robotics applications in domestic, commercial and industrial environments.

[0010] According to a preferred embodiment, a computing system for optimizing and securing generative AI models employing an advanced model management platform is disclosed, the computing system comprising: one or more hardware processors configured for: employing reinforcement learning algorithms to optimize a model's settings based on task-specific reward functions; using retrieval augmented generation (RAG) to retrieve relevant information from internal and external knowledge sources combined into a curated knowledge corpus and conditioning the model's output on retrieved facts or beliefs; validating model performance against human experts or crowds and authoritative databases or rule sets using cross-validation and domain-specific question-answering; employing model distillation, differential privacy, similarity scoring, and nearness models to create and secure the model and detect infringement; using adversarial training and input perturbation to test the robustness the model against poisoning attacks and adversarial examples; and incorporating attention mechanism search, model blending, and RAG to optimize the performance and reliability of the model for specific tasks.

[0011] According to another preferred embodiment, a computer-implemented method executed on an advanced model management platform for optimizing and securing generative AI models is disclosed, the computer-implemented method comprising: employing reinforcement learning algorithms to optimize a model's settings based on task-specific reward functions; using retrieval augmented generation (RAG) to retrieve relevant information from internal and external knowledge sources combined into a

curated knowledge corpus and conditioning the model's output on retrieved facts or beliefs; validating model performance against human experts or crowds and authoritative databases or rule sets using cross-validation and domain-specific question-answering; employing model distillation, differential privacy, similarity scoring, and nearness models to create and secure the model and detect infringement; using adversarial training and input perturbation to test the robustness the model against poisoning attacks and adversarial examples; and incorporating attention mechanism search, model blending, and RAG to optimize the performance and reliability of the model for specific tasks.

[0012] According to another preferred embodiment, a system for optimizing and securing generative AI models employing an advanced model management platform is disclosed, comprising one or more computers with executable instructions that, when executed, cause the system to: employ reinforcement learning algorithms to optimize a model's settings based on task-specific reward functions; use retrieval augmented generation (RAG) to retrieve relevant information from internal and external knowledge sources combined into a curated knowledge corpus and conditioning the model's output on retrieved facts or beliefs; validate model performance against human experts or crowds and authoritative databases or rule sets using cross-validation and domain-specific question-answering; employing model distillation, differential privacy, similarity scoring, and nearness models to create and secure the model and detect infringement; use adversarial training and input perturbation to test the robustness the model against poisoning attacks and adversarial examples; and incorporate attention mechanism search, model blending, and RAG to optimize the performance and reliability of the model for specific tasks.

[0013] According to another preferred embodiment, non-transitory, computer-readable storage media having computer-executable instructions embodied thereon that, when executed by one or more processors of a computing system employing an advanced model management platform for optimizing and securing generative AI models, cause the computing system to: employ reinforcement learning algorithms to optimize a model's settings based on task-specific reward functions; use retrieval augmented generation (RAG) to retrieve relevant information from internal and external knowledge sources combined into a curated knowledge corpus and conditioning the model's output on retrieved facts or beliefs; validate model performance against human experts or crowds and authoritative databases or rule sets using cross-validation and domain-specific question-answering; employing model distillation, differential privacy, similarity scoring, and nearness models to create and secure the model and detect infringement; use adversarial training and input perturbation to test the robustness the model against poisoning attacks and adversarial examples; and incorporate attention mechanism search, model blending, and RAG to optimize the performance and reliability of the model for specific tasks.

[0014] According to an aspect of an embodiment, the reinforcement learning algorithms comprise Proximal Policy Optimization or Asynchronous Advantage Actor-Critic algorithms.

[0015] According to an aspect of an embodiment, the model's output on retrieved facts further comprises entity linking and knowledge graph, vector database, or vectorized knowledge graph hybrid integration for enhancing model outputs or refining knowledge corpora.

[0016] According to an aspect of an embodiment, validating model performance further comprises comparing the model's responses to those provided by certified experts or reliable sources in specific domains.

[0017] According to an aspect of an embodiment, the platform uses cosine similarity or Euclidean distance in hyper dimensional vector space to detect model infringement, replication, influence, or theft.

[0018] According to an aspect of an embodiment, the adversarial training incorporates malicious examples into the training data to make the model more resilient against manipulated predictions.

[0019] According to an aspect of an embodiment, optimizing the performance and reliability of the model comprises searching through different model types, attention architectures and RAG configurations, model consensus or blending mechanisms to find the most effective setup for a given task and then to determine additional viable configurations to address operational resilience concerns for alternate, contingent or emergency data and logic configurations under ranges of operational scenarios and parameters, such as specific scenarios of interest declared by users, or scenarios of interest identified by the system.

[0020] According to an aspect of an embodiment, model blending comprises selecting from or blending outputs from multiple models or authoritative knowledge bases, each trained on, or obtained from, defined resource collections or with different retrieval strategies or hyperparameters.

BRIEF DESCRIPTION OF THE DRAWING FIGURES

[0021] FIG. **1**A is a block diagram illustrating an exemplary system architecture for a distributed, advanced model management platform for optimizing and securing AI models, according to an embodiment.

[0022] FIG. **1**B is a block diagram illustrating an exemplary system architecture for a distributed generative artificial intelligence reasoning and action platform, according to an embodiment.

[0023] FIG. **2** is a block diagram illustrating an exemplary aspect of a distributed generative AI reasoning and action platform incorporating various additional contextual data.

[0024] FIG. **3** is a diagram illustrating incorporating symbolic reasoning in support of LLM-based generative AI, according to an aspect of a neuro-symbolic generative AI reasoning and action platform.

[0025] FIG. **4** is a block diagram illustrating an exemplary architecture for a neuro-symbolic generative AI reasoning and action platform configured for federated learning at a plurality of edge devices, according to an embodiment.

[0026] FIG. **5** is a block diagram illustrating an exemplary architecture for a neuro-symbolic generative AI reasoning and action platform configured to utilize a midserver to act as a computing intermediary between a plurality of edge devices and the platform.

[0027] FIG. **6** is a block diagram illustrating an exemplary mobile device configured for experience curation using embedded capabilities and functionality provided by a neuro-symbolic generative AI reasoning and action platform, according to an embodiment.

[0028] FIG. **7** is a block diagram illustrating an exemplary aspect of a distributed generative artificial intelligence reasoning and action platform, a curation computing system.

[0029] FIG. **8** is a block diagram illustrating an exemplary aspect of a distributed generative artificial intelligence reasoning and action platform, a marketplace computing system.

[0030] FIG. **9** is a block diagram illustrating a simple example of a distributed computational graph representation for providing neuro-symbolic artificial intelligence capabilities, including generative AI, according to an aspect.

[0031] FIG. **10** is a block diagram illustrating an exemplary aspect of an embodiment of a distributed computational graph computing system utilizing an advanced cyber decision platform (ACDP) for external network reconnaissance and contextual data collection.

[0032] FIG. **11** is a block diagram illustrating another exemplary aspect of an embodiment of a distributed computational graph computing systems utilizing an advanced cyber decision platform.

[0033] FIG. **12** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph, according to one aspect.

[0034] FIG. **13** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph, according to one aspect.

[0035] FIG. **14** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph, according to one aspect.

[0036] FIG. **15** is a block diagram of an architecture for a transformation pipeline within a system for predictive analysis of very large data sets using a distributed computational graph computing system which can coordinate primary, alternate, contingent and emergency configurations (i.e., resilient logic and data persistent specifications relying on different cyber physical graph states or dependencies).

[0037] FIG. **16** is a process flow diagram of a method for predictive analysis of very large data sets using the distributed computational graph

[0038] FIG. **17** is a process flow diagram of a method for an aspect of modeling the transformation pipeline module as a directed graph using graph theory.

[0039] FIG. **18** is a flow diagram illustrating an exemplary method for providing experience curation, according to an aspect of an embodiment.

[0040] FIG. **19** is a flow diagram illustrating an exemplary method for providing experience curation with using rich contextual data, according to an aspect of an embodiment.

[0041] FIG. **20** is a flow diagram illustrating an exemplary method for using a distributed computation graph system for creating structured representations or knowledge graphs from various data sources, and setting up a pipeline for continuous processing and monitoring of that data, according to an embodiment.

[0042] FIG. **21** is a block diagram illustrating an exemplary system architecture for a distributed, composite symbolic and non-symbolic AI platform for advanced reasoning, according to an embodiment.

[0043] FIG. **22** is a block diagram illustrating an exemplary model architecture of the Transformer, consisting of an Encoder and a Decoder.

[0044] FIG. **23** is a block diagram illustrating an exemplary basic embedding layer generation process, according to an embodiment.

[0045] FIG. **24** is a flow diagram illustrating an exemplary method for routing processing based on certainty threshold and/or challenge-based verification, according to an embodiment.

[0046] FIG. **25** is a flow diagram illustrating an exemplary method for retrieving relevant contextual data from a knowledge graph database and enriching vector embeddings with the contextual data, according to an embodiment.

[0047] FIG. **26** is a flow diagram illustrating an exemplary method for applying expressive weighting schemes to model combinations, according to an embodiment.

[0048] FIG. **27** is a flow diagram illustrating an exemplary method for using feedback loops considering security, licensing, provenance, and collaborative development, according to an embodiment.

[0049] FIG. **28** is a flow diagram illustrating an exemplary method for multi-modal alignment for consistent representations across data types, according to an embodiment.

[0050] FIG. **29** is a flow diagram illustrating an exemplary method for hyperparameter optimization using information-theoretic guidance, according to an embodiment.

[0051] FIG. **30** is a flow diagram illustrating an exemplary method for linking embeddings to knowledge graphs, according to an embodiment.

[0052] FIG. **31** is a flow diagram illustrating an exemplary method for advanced reasoning using a composite artificial intelligence platform, according to an embodiment.

[0053] FIG. **32** is a flow diagram illustrating an exemplary method for fitness for purpose optimization of a generative AI model, according to an embodiment.

[0054] FIG. **33** is a flow diagram illustrating an exemplary method for hallucination mitigation of a generative AI model, according to an embodiment.

[0055] FIG. **34** is a flow diagram illustrating an exemplary method for model validation of a generative AI model, according to an embodiment.

[0056] FIG. **35** is a flow diagram illustrating an exemplary method for model training and sandboxing of a generative AI model, according to an embodiment.

[0057] FIG. **36** is a flow diagram illustrating an exemplary method for providing security and defense of a generative AI model, according to an embodiment.

[0058] FIG. **37** is a flow diagram illustrating an exemplary method for model management of a generative AI model, according to an embodiment.

[0059] FIG. **38** illustrates an exemplary computing environment on which an embodiment described herein may be implemented.

DETAILED DESCRIPTION OF THE INVENTION

[0060] The inventor has conceived, and reduced to practice, an advanced model management platform for optimizing and securing artificial intelligence enhanced processes including those employing large language models and neuro symbolic models. The platform incorporates various techniques to address the limitations of current AI systems, including generative AI applications, such as hallucination, lack of validation, security vulnerabilities, and inadequate model management and fitness evaluation or challenges. The system employs semantic meaning, stochastic search,

reinforcement learning algorithms, retrieval augmented generation (RAG) or knowledge graph enhancement for prompt or input improvements or prompt security/constraint satisfaction or output validation or use limitation, domain-specific knowledge corpus validation against expert or group of expert knowledge, transfer or federated learning enhancements or logic migration across mobile or edge or cloud resources, probabilistic consideration of distributed computing operational challenges, model distillation and output similarity scoring for security based on acceptable output checks and distance or consensus logic, adversarial training for robustness, and model type or attention mechanism search and model blending or consensus for advanced management or output weighting or downstream logic or planning inputs or modeling simulation systems. By integrating these techniques, the platform significantly improves the performance, reliability, and security of artificial intelligence enhanced reasoning and generative AI systems across a wide range of tasks and domains.

[0061] The platform emphasizes the importance of considering various types of semantics, including, but not limited to, symbolic, distributional, compositional distributional, and information-theoretic compositional distributional semantics. This consideration allows the platform to capture and represent meaning at different levels of abstraction and compositionality, enabling more comprehensive and nuanced understanding of the input data. By explicitly addressing these different types of semantics, the platform can leverage the strengths of each approach and combine them in a unified framework.

[0062] Symbolic semantics relies on explicit, structured representations of meaning using symbols and logical expressions. In this approach, the meaning of a concept is defined by its relationships to other concepts in a symbolic knowledge base, often represented using ontologies or logic-based formalisms. Symbolic semantics enables precise and interpretable reasoning, as the meaning is explicitly encoded in the symbols and their relationships. However, symbolic semantics can be brittle and struggle with handling ambiguity, context-dependence, and the open-ended nature of language and historical reliance on expert codified data corpora.

[0063] Distributional semantics is based on the idea that the meaning of a word or concept can be inferred from its distribution across a large corpus of text data. This approach represents words as dense vectors (embeddings) in a high-dimensional space, where the proximity between vectors reflects their semantic similarity. Distributional semantics is driven by the statistical co-occurrence patterns of words in the data, capturing the idea that words with similar meanings tend to appear in similar contexts. While distributional semantics can capture rich semantic relationships and handle ambiguity, it lacks the explicit structure and interpretability of symbolic semantics.

[0064] Compositional distributional semantics aims to combine the strengths of distributional semantics with the compositionality of language, allowing for the construction of meaning from smaller units. In this approach, the meaning of a phrase or sentence is computed by composing the distributional representations (embeddings) of its constituent words or subphrases. Compositional distributional semantics enables the generation of embeddings for novel or unseen phrases, based on the compositionality principle that the meaning of a complex expression is determined by the meanings of its parts and their mode of combination. Various compositional models have been proposed, such as additive models, multiplicative models, and neural network-based models (e.g., recursive neural networks, transformers).

[0065] Information-theoretic compositional distributional semantics incorporates principles from information theory to quantify and optimize the information content and transmission in compositional distributional models. This approach aims to capture the mutual information between the components of a compositional representation, ensuring that the composed meaning preserves the relevant information from the individual constituents. Information-theoretic measures, such as entropy, mutual information, and cross-entropy, are used to guide the learning and composition process, promoting representations that are informative, compact, and generalizable. By grounding compositional distributional semantics in information theory, this approach seeks to improve the interpretability, robustness, and efficiency of the resulting semantic representations.

[0066] The distinction and integration of these different types of semantics are important for the platform's goal of achieving advanced reasoning and understanding in AI systems. By considering symbolic semantics, the invention can leverage the structured and interpretable aspects of meaning representation. Distributional semantics allows for capturing the statistical patterns and relationships in large-scale text data. Compositional distributional semantics enables the construction of meaning from smaller units, while information-theoretic principles guide the optimization of the compositional process.

[0067] By combining these different semantic approaches, the platform aims to create a more comprehensive and expressive semantic representation that can handle the complexities of language and reasoning. The integration of symbolic and distributional semantics, along with compositional and information-theoretic principles, allows for a richer and more robust understanding of the input data, leading to improved performance in various AI tasks such as natural language understanding, knowledge representation, and inference.

[0068] The platform can employ reinforcement learning algorithms, such as Proximal Policy Optimization (PPO), Asynchronous Advantage Actor-Critic (A3C), or Soft Action-Critic (SAC) to optimize model settings like temperature and token length based on task-specific reward functions.

[0069] Soft Actor-Critic is an off-policy reinforcement learning algorithm that combines the benefits of both policy-based and value-based methods. It is designed to maximize both the expected reward and the entropy of the policy, which encourages exploration and helps prevent the agent from getting stuck in suboptimal solutions. SAC aims to maximize the entropy of the policy alongside the expected return. By adding an entropy term to the objective function, the agent is encouraged to explore more diverse actions, leading to better exploration and improved sample efficiency. SAC is an off-policy algorithm, meaning it can learn from data collected by any policy, not just the current policy being optimized. This allows for more efficient use of collected experience and enables the use of replay buffers to store and reuse past experiences. SAC employs an actor-critic architecture, where the actor (policy) is responsible for selecting actions, and the critic (value function) estimates the expected return for state-action pairs. The critic guides

the actor towards better actions by providing a learned value estimate. SAC learns a stochastic policy, which means the agent outputs a probability distribution over actions rather than a deterministic action. This allows for better exploration and can handle continuous action spaces effectively. SAC introduces a temperature parameter that balances the trade-off between exploration and exploitation. The algorithm automatically adjusts the temperature during training to maintain a desired level of entropy, eliminating the need for manual tuning.

[0070] The platform may use retrieval augmented generation (RAG) to retrieve relevant information from external knowledge sources and condition the model's prompts and/or output on retrieved data and/or facts. This ensures that the generated text is more grounded in reality and less likely to contain hallucinated information.

[0071] The platform can validate model performance against human experts (or in some cases expert models) and authoritative databases (e.g., relational, NoSQL, graph, knowledge graph, vector, document, hybrid vectorized knowledge graph) using techniques like cross-validation and domain-specific question-answering. This helps assess the model's reliability and performance in specific domains.

[0072] The platform may employ model distillation and differential privacy to create smaller, more secure models that retain the performance of larger models. Similarity scoring and nearness models are used to detect model infringement and theft.

[0073] The platform can use adversarial training and input perturbation to test the robustness of models against poisoning attacks and other adversarial examples. This helps improve the model's resilience and stability.

[0074] The platform may incorporate attention mechanism/model type search and model blending and/or consensus to optimize the performance and reliability of models for specific tasks. RAGs, knowledge graph verification, and/or composite/authoritative vectorized knowledge graphs may be integrated into the model architecture to retrieve and incorporate relevant information from external knowledge sources. Such a process may also be used in single stages of evaluation such as a safety or security measure on model inputs or on RAG or input augmentation or refinement, and again on model output comparison, blending, model-based, or rule-based or simulation-based checks.

[0075] Hyperparameter optimization explores ideal embedding generation techniques, training datasets, model architectures and other factors, guided by information theoretic metrics.

[0076] Symbolic knowledge extraction from embeddings enables linkage of the learned representations to structured ontologies, allowing neural and symbolic knowledge to be bridged for reasoning.

[0077] According to an embodiment, the disclosed invention is capable of probabilistic modeling of compute, transport, and storage asset availability, performance, reliability and security to address practical operational challenges which may cause objective function maximization routines to encourage system to have some level of data or logic duplication in support of system resilience. This stems from practical challenges in distributed computing made famous in the fallacies of distributed computing originally published at Sun Microsystems: The network is reliable; Latency is zero Bandwidth is infinite; The network is secure; Topology doesn't change; There is one administrator; Transport cost is zero; The network is homogeneous. Acknowledging such limitations in probabilistic modeling of distributed computing, especially in AI enhanced processes with logic and data federation across wearable, mobile, edge, and cloud resource pools and the potential for inter-device gossip (e.g. phone to watch) for data and compute tasks necessitates consideration of viable data flow/logic processes in a distributed computational graph specified process across primary, alternate, contingent, and emergency configurations depending on enabling technology asset availability and performance.

[0078] One or more different aspects may be described in the present application. Further, for one or more of the aspects described herein, numerous alternative arrangements may be described; it should be appreciated that these are presented for illustrative purposes only and are not limiting of the aspects contained herein or the claims presented herein in any way. One or more of the arrangements may be widely applicable to numerous aspects, as may be readily apparent from the disclosure. In general, arrangements are described in sufficient detail to enable those skilled in the art to practice one or more of the aspects, and it should be appreciated that other arrangements may be utilized and that structural, logical, software, electrical and other changes may be made without departing from the scope of the particular aspects. Particular features of one or more of the aspects described herein may be described with reference to one or more particular aspects or figures that form a part of the present disclosure, and in which are shown, by way of illustration, specific arrangements of one or more of the aspects. It should be appreciated, however, that such features are not limited to usage in the one or more particular aspects or figures with reference to which they are described. The present disclosure is neither a literal description of all arrangements of one or more of the aspects nor a listing of features of one or more of the aspects that must be present in all arrangements.

[0079] Headings of sections provided in this patent application and the title of this patent application are for convenience only, and are not to be taken as limiting the disclosure in any way.

[0080] Devices that are in communication with each other need not be in continuous communication with each other, unless expressly specified otherwise. In addition, devices that are in communication with each other may communicate directly or indirectly through one or more communication means or intermediaries, logical or physical.

[0081] A description of an aspect with several components in communication with each other does not imply that all such components are required. To the contrary, a variety of optional components may be described to illustrate a wide variety of possible aspects and in order to more fully illustrate one or more aspects. Similarly, although process steps, method steps, algorithms or the like may be described in a sequential order, such processes, methods and algorithms may generally be configured to work in alternate orders, unless specifically stated to the contrary. In other words, any sequence or order of steps that may be described in this patent application does not, in and of itself, indicate a requirement that the steps be performed in that order. The steps of described processes may be performed in any order practical. Further, some steps may be performed simultaneously despite being described or implied as occurring non-simultaneously (e.g., because one step is described after the

other step). Moreover, the illustration of a process by its depiction in a drawing does not imply that the illustrated process is exclusive of other variations and modifications thereto, does not imply that the illustrated process or any of its steps are necessary to one or more of the aspects, and does not imply that the illustrated process is preferred. Also, steps are generally described once per aspect, but this does not mean they must occur once, or that they may only occur once each time a process, method, or algorithm is carried out or executed. Some steps may be omitted in some aspects or some occurrences, or some steps may be executed more than once in a given aspect or occurrence.

[0082] When a single device or article is described herein, it will be readily apparent that more than one device or article may be used in place of a single device or article. Similarly, where more than one device or article is described herein, it will be readily apparent that a single device or article may be used in place of the more than one device or article.

[0083] The functionality or the features of a device may be alternatively embodied by one or more other devices that are not explicitly described as having such functionality or features. Thus, other aspects need not include the device itself.

[0084] Techniques and mechanisms described or referenced herein will sometimes be described in singular form for clarity. However, it should be appreciated that particular aspects may include multiple iterations of a technique or multiple instantiations of a mechanism unless noted otherwise. Process descriptions or blocks in figures should be understood as representing modules, segments, or portions of code which include one or more executable instructions for implementing specific logical functions or steps in the process. Alternate implementations are included within the scope of various aspects in which, for example, functions may be executed out of order from that shown or discussed, including substantially concurrently or in reverse order, depending on the functionality involved, as would be understood by those having ordinary skill in the art.

Definitions

[0085] As used herein, "explainability" (also referred to as "interpretability") is the concept that a machine learning model and its output can be explained in a way that "makes sense" to a human being at an acceptable level.

[0086] As used herein, "graph" is a representation of information and relationships, where each primary unit of information makes up a "node" or "vertex" of the graph and the relationship between two nodes makes up an edge of the graph. Nodes can be further qualified by the connection of one or more descriptors or "properties" to that node. For example, given the node "James R," name information for a person, qualifying properties might be "183 cm tall," "DOB 08/13/1965" and "speaks English". Similar to the use of properties to further describe the information in a node, a relationship between two nodes that forms an edge can be qualified using a "label". Thus, given a second node "Thomas G," an edge between "James R" and "Thomas G" that indicates that the two people know each other might be labeled "knows." When graph theory notation (Graph=(Vertices, Edges)) is applied this situation, the set of nodes are used as one parameter of the ordered pair, V and the set of 2 element edge endpoints are used as the second parameter of the ordered pair, E. When the order of the edge endpoints within the pairs of E is not significant, for example, the edge James R, Thomas G is equivalent to Thomas G, James R, the graph is designated as "undirected." Under circumstances when a relationship flows from one node to another in one direction, for example James R is "taller" than Thomas G, the order of the endpoints is significant. Graphs with such edges are designated as "directed." In the distributed computational graph system, transformations within transformation pipeline are represented as directed graph with each transformation comprising a node and the output messages between transformations comprising edges. Distributed computational graph stipulates the potential use of non-linear transformation pipelines which are programmatically linearized. Such linearization can result in exponential or impractical growth of resource consumption. The most sensible approach to overcome this possibility is to introduce new transformation pipelines or elements of pipelines just as they are needed, creating only those that are ready to compute. Such method results in transformation graphs which are highly variable in size and node, edge composition as the system processes data streams and persists elements of the process or of the involved data at various timescales and localities. Those familiar with the art will realize that transformation graph may assume many shapes and sizes with a vast topology of edge relationships and node types. It is also important to note that the resource topologies available at a given execution time for a given pipeline may be highly dynamic due to changes in available node or edge types or topologies (e.g. different servers, data centers, devices, network links, etc.) being available, and this is even more so when legal, regulatory, privacy and security considerations are included in a DCG pipeline specification or recipe in the DSL. Since the system can have a range of parameters (e.g. authorized to do transformation x at compute locations of a, b, or c) the JIT, JIC, JIP elements can leverage system state information (about both the processing system and the observed system of interest) and planning or modeling modules to compute at least one parameter set (e.g. execution of pipeline may say based on current conditions use compute location b) at execution time. This may also be done at the highest level or delegated to lower level resources when considering the spectrum from centralized cloud clusters (i.e. higher) to extreme edge (e.g. a wearable, or phone or laptop). The examples given were chosen for illustrative purposes only and represent a small number of the simplest of possibilities. These examples should not be taken to define the possible graphs expected as part of operation of the invention and may include additional kinds of optimizations or resilience considerations (e.g. in cislunar systems) where uncertainty or variance in assets or viable topologies is particularly problematic compared to earthbound assets.

[0087] As used herein, "transformation" is a function performed on zero or more streams of input data which results in a single stream of output which may or may not then be used as input for another transformation. Transformations may comprise any combination of machine, human or machine-human interactions Transformations need not change data that enters them, one example of this type of transformation would be a storage transformation which would receive input and then act as a queue for that data for subsequent transformations. As implied above, a specific transformation may generate output data in the absence of input data. A time stamp serves as an example. In the

invention, transformations are placed into pipelines such that the output of one transformation may serve as an input for another. These pipelines can consist of two or more transformations with the number of transformations limited only by the resources of the system. Historically, transformation pipelines have been linear with each transformation in the pipeline receiving input from one antecedent and providing output to one subsequent with no branching or iteration. Other pipeline configurations are possible. The invention is designed to permit several of these configurations including, but not limited to: linear, afferent branch, efferent branch and cyclical.

[0088] A "pipeline," as used herein and interchangeably referred to as a "data pipeline" or a "processing pipeline," refers to a set of data streaming activities and batch activities. Streaming and batch activities can be connected indiscriminately within a pipeline and compute, transport or storage (including temporary in-memory persistence such as Kafka topics) may be optionally inferred/suggested by the system or may be expressly defined in the pipeline domain specific language.

[0089] The system may leverage a Distributed Computational Graph (DCG) framework to instantiate pipelines in a cyber-physical graph specific manner. Given a set of available or expected technology and communication assets, the system determines the applicable DCG topology that is contextualized and optimized for the resource pool and tasks at hand over finite time horizons. This allows the DCG to efficiently map and distribute the pipeline activities across heterogeneous compute resources that may span mobile, edge, cloud, and other environments in historical, current, and probabilistic future states to include resources such as but not limited to physical networking, logical networking, hypervisor, physical host, virtualized host or container, application, session, or trace when considering log data, error and administrative data, performance monitoring data, and other forms of observability and security information made known to the system.

[0090] The DCG maintains an adaptive resource allocation strategy, dynamically activating and deactivating subgraphs of the pipeline based on factors such as system objectives, resource availability, performance requirements, and cost constraints leveraging historical and current estimated system states and data as well as various forward estimates, models, simulations or projections, be they obtained through simulation modeling, machine learning, statistical approaches, or artificial intelligence techniques, generative or otherwise. At any point in time, only a limited number of DCG subgraphs may be active, with the inactive portions persisted for later use from in-memory, disk, database, or archival storage with various times and costs associated with such placement for rehydration as needed. DCGs also need not be executed solely within a given resource pool as the DLS supports evaluation and exchange with DCG execution processes at cloud, edge, content delivery network (CDN), host, mobile, wearable and other resource types. The system may also leverage emerging network protocols such as Disruption Tolerant Networking (DTN) for space and cislunar communications where more extensive intermediate data persistence and transmission nodes and capabilities may be needed for interplanetary Internet services.

[0091] Events flow through the streaming activity actors in the active DCG subgraphs in a reactive way. At the junction of a streaming activity to batch activity, there exists a StreamBatchProtocol data object. This object is responsible for determining when and if the batch process is run, based on one or more of three possibilities: regular timing interval, every N events, a certain data size or chunk, or optionally an internal (e.g. APM or trace or resource based trigger) or external trigger (e.g. from another user, pipeline, or exogenous service). The events or data about the events are held in a queue (e.g. Kafka or Redis) or similar until processing. In cases where event types are extensive and similar it is possible to engage in further compression of data for transmission and analysis processes with techniques such as vectorization with an associated legend—such as in a case where 100 static event types with many words might be reduced to 100 integers—one corresponding to each unique event and a one-time ledger transmission. System may engage in exchange of such ledgers or vector equivalents of them between system components to further increase performance across composite objective function evaluation of cumulative network compute, storage and transport costs across finite time horizons.

[0092] Each batch activity may contain a "source" data context (this may be a streaming context if the upstream activities are streaming), and a "destination" data context (which is passed to the next activity). Streaming activities may sometimes have an optional "destination" streaming data context (optional meaning: caching/persistence of events vs. ephemeral).

[0093] The system may also comprise a database containing all data pipelines as templates, recipes, or as run at execution time to enable post-hoc reconstruction or re-evaluation with a modified topology of the resources (e.g., compute, transport or storage), transformations, or data involved. This allows the DCG to dynamically re-plan and optimize the pipeline deployment based on changes in the underlying cyber-physical resource graph and its historical, current, or future state estimates.

Conceptual Architecture

[0094] FIG. **1**A is a block diagram illustrating an exemplary system architecture for a distributed, advanced model management platform for optimizing and securing AI models **170**, according to an embodiment. According to the embodiment, the platform **170** aims to enable vast automation of modeling/analysis workflows by exploring large potential parameter combinations, model optimization, and underlying resource uses/configurations to support. Platform **170** can be configured for extracting and curating knowledge into structured ontologies to complement neuro-symbolic AI capabilities.

[0095] Furthermore, platform **170** may incorporate a hierarchical architecture that enables the migration and replication of logic and data across different layers, such as peer-to-peer communication between distributed nodes or upward propagation to cloud-based services. This functionality allows for efficient dissemination and synchronization of model updates, knowledge bases, and operational data throughout the system. In some implementations, the platform can employ gossip protocols to facilitate peer-to-peer communication, enabling decentralized sharing of information and updates among distributed nodes. This approach ensures robust and scalable propagation of data and logic across the network, even in the presence of intermittent connectivity or node failures. In addition, the platform may

support upward migration of data and logic to cloud-based services, allowing for centralized aggregation, analysis, and global optimization of AI models. This centralized control plane can perform higher-level tasks such as model ensemble generation, meta-learning, and federated learning, leveraging the collective knowledge and resources of the distributed nodes. The combination of peer-to-peer gossip and upward migration to the cloud enables platform **170** to maintain a balance between local autonomy and global coordination, adapting to the specific requirements and constraints of different deployment scenarios. This hierarchical architecture enhances the platform's ability to optimize and secure generative AI models across diverse computing environments, from edge devices to cloud-based services.

[0096] According to the embodiment, platform **170** is configured as a cloud-based computing platform comprising various system or sub-system components configured to provide functionality directed to the execution of optimizing and securing generative AI models such as, for example LLMs and diffusion models. Exemplary platform systems can include a model optimization computing system **171**, a hallucination mitigation computing system **172**, a model validation computing system **173**, a model training sandboxing computing system **174**, a security and defense computing system **175**, and a model management computing system **176**. Platform **170** may further comprise various databases for storing a plurality of models **2127**, vectors/embeddings **2128** or RAGs, and knowledge graphs **2129**. In some embodiments, systems **171-176**, **121-124**, and **2121-2126** may each be implemented as standalone software applications or as a services/microservices architecture which can be deployed (via platform **170**, **2120**, or **120**) to perform a specific task or functionality. In such an arrangement, services can communicate with each other over an appropriate network using lightweight protocols such as HTTP, gRPC, Kafka, protobuffs, or other message queues. This allows for asynchronous and decoupled communication between services. Services may be scaled independently based on demand, which allows for better resource utilization and improved performance. Improved modularity and encapsulation can also enable easier movement of logic routines from different devices or virtualized resources across a geographically distributed and heterogeneous device operated system. Services may be deployed using containerization technologies such as Docker or containerd and orchestrated using container orchestration platforms like Kubernetes. This allows for easier deployment and management of services.

[0097] It should be appreciated that some embodiments of platform **170** may comprise more or less components than what is illustrated in FIG. **1**A. For example, one or more computing system components as described with respect to FIG. **1**B and FIG. **21** may be implemented in some aspects of platform **170**, dependent upon the embodiment. In some embodiments, platform **170** may further comprise one or more of systems **121-124** and **2121-2126**.

[0098] According to the embodiment, model optimization computing system **171** is present and configured to utilize one or more optimization routines to identify the most suitable model settings (e.g., temperature, token length) for a given task. This approach can help balance which small (e.g., student) models are created, saved, and utilized, thereby improving efficiency, effectiveness, and fitness for purpose. Model optimization system **171** may use reinforcement learning algorithms, such as Proximal Policy Optimization (PPO), Asynchronous Advantage Actor-Critic (A3C), and/or SAC to optimize model settings like temperature and token length. These algorithms learn to select the best settings based on a reward function that measures the model's performance on a specific task. For example, consider a text summarization task wherein platform **170** may optimize the temperature and token length to generate concise and accurate summaries. The reward function could compare the generated summaries against human-written summaries using metrics like Recall-Oriented Understudy for Gisting Evaluation (ROUGE) or Bilingual Evaluation Understudy (BLEU) scores. As another example, consider a dialogue generation task wherein platform **170** could optimize the settings to generate engaging and coherent responses. The reward function could incorporate user feedback, such as engagement metrics and sentiment analysis, to guide the optimization process. Reward maximization of a function should be considered but the system may also be capable of considering finite operating parameter ranges and/or time horizons for looking at the congruence of policy/plan and theoretical limits vs modeled limits vs observed limits.

[0099] ROUGE is a set of metrics used to evaluate the quality of a summary or a machine-generated text by comparing it to one or more reference texts. It measures the overlap between the generated text and the reference texts in terms of n-grams (unigrams, bigrams, etc.). ROUGE-N calculates the recall, which is the ratio of the number of matching n-grams between the generated text and the reference texts to the total number of n-grams in the reference texts. ROUGE-L measures the longest common subsequence (LCS) between the generated text and the reference texts, considering sentence-level structure.

[0100] BLEU is an algorithm for evaluating the quality of machine-translated text by comparing it to one or more reference translations. It calculates the precision of n-grams (usually up to 4-grams) in the machine-translated text compared to the reference translations. BLEU computes the geometric mean of the modified n-gram precisions and applies a brevity penalty to penalize short translations. The BLEU score ranges from 0 to 1, with higher scores indicating better translation quality.

[0101] Both ROUGE and BLEU provide automated methods to evaluate the quality of generated text by comparing it to human-created reference texts. They have been extensively used in research and development to assess the performance of various NLP models and techniques. However, it's important to note that these metrics have their limitations. They focus on lexical overlap and may not fully capture the semantic meaning, coherence, or fluency of the generated text. Therefore, it's recommended to use these metrics in combination with human evaluation and other qualitative assessment methods to get a comprehensive understanding of the model's performance.

[0102] When it comes to fitness for purpose optimization, there are several model settings that can be optimized for both LLMs and diffusion models. For LLMs, model settings such as learning rate, batch size, attention head count, embedding size, dropout rate, and activation function may be optimized to improve model performance and security. The learning rate determines the step size at which the model's weights are updated during training. Optimizing the

learning rate or locality or federation or transfer learning incorporation can help the ultimate model converge faster and achieve better performance. The batch size is the number of training examples used in each iteration of the training process. Optimizing the batch size can help balance computational efficiency and model convergence. The number of attention heads in a transformer-based LLM can impact the model's ability to capture different aspects of the input. Optimizing the attention head count can help improve the model's performance on specific tasks. The embedding size is the dimensionality of the word embeddings used to represent input tokens. Optimizing the embedding size can help balance model complexity and representational capacity. Dropout is a regularization technique that randomly drops out neurons during training to prevent overfitting. Optimizing the dropout rate can help improve the model's generalization ability. The choice of activation function (e.g., Sigmoid, ReLU, GELU, Swish, etc.) can impact the model's ability to learn complex patterns. Optimizing the activation function can help improve the model's performance on specific tasks.

[0103] For diffusion models, model settings can include, but are not limited to, a number of diffusion steps, noise schedule, learning rate, batch size, model architecture, and loss function. The number of diffusion steps determines the granularity of the diffusion process. Optimizing the number of steps can help balance image quality and computational efficiency. The noise schedule determines the amount of noise added to the input image at each diffusion step. Optimizing the noise schedule can help improve the quality and diversity of the generated images. Similar to LLMs, optimizing the learning rate can help the diffusion model converge faster and achieve better performance. Optimizing the batch size can help balance computational efficiency and model convergence in diffusion models. The choice of model architecture (e.g., U-Net, ResNet, Transformer, etc.) can impact the diffusion model's ability to generate high-quality images. Optimizing the model architecture can help improve the model's performance on specific image generation tasks. The choice of loss function (e.g., mean squared error, perceptual loss, adversarial loss, etc.) can impact the quality and realism of the generated images. Optimizing the loss function can help improve the model's ability to generate images that are perceptually similar to real images.

[0104] These are just a few examples of the model settings that can be optimized for fitness for purpose in LLMs and diffusion models. The specific settings and their optimal values may vary depending on the task, dataset, and computational resources available. The advanced model management platform **170** can use techniques like reinforcement learning, Bayesian optimization, or grid search to automatically discover the best settings for a given task and model architecture.

[0105] In an embodiment, Liquid Neural Nets (LNNs) may be used by the system and incorporate Liquid Time Constants to aid in ongoing model evolution and adaptation following the initial training routine while in a deployed configuration. Unlike normal neural nets, LNNs model system dynamics using first order differential equations instead of activation functions specified as implicit nonlinearities. In yet another embodiment, a Tau Neural Network may be used by the system. Tau represents a learnable time constant that controls the rate of change in the hidden state of a continuous-depth model and may be added to a model(s) to improve the model's performance or behavior. LNN training is typically achieved via Backpropagation Through Time (BPTT) solving which can unroll the network into a long feedforward network and capture the feedforward results including hidden ordinary differential equations (ODE) states and using the aggregate results and errors to update weights at each time step. Since LNNs are helpfully bounded and immune to gradient explosion, they are attractive and may be efficient, expressive, and transparent for a number of applications even if at the cost of some complexity to design and solve and susceptibility to gradient vanishing.

[0106] According to the embodiment, hallucination mitigation computing system **172** is present and configured to connect the output from a given prompt (directed to a generative AI model) to a knowledge base with actual semantic meaning to address the issue of model hallucinations (i.e., generation of false information). Techniques like consensus evaluation across multiple models and dynamic retraining with economic and regulatory awareness may further mitigate hallucinations. Hallucination mitigation system **172** may additionally, or alternatively, use techniques like entity linking and knowledge graph, vector database, and/or vectorized knowledge graph hybrid integration to connect the generated content to a structured knowledge base. This would involve using named entity recognition to identify entities in the output and linking them to corresponding nodes in the knowledge graph. Platform **170** could employ consensus evaluation by comparing outputs of multiple models and selecting the most consistent and reliable information. For example, when generating a news article, platform **170** could link the mentioned entities (e.g., people, organizations, locations, etc.) to a knowledge base such as, for example, Wikidata or Wikipedia. This would help ensure that the generated information is grounded in real-world facts and relationships. In an exemplary question-answering task, platform **170** could compare the outputs of multiple models and select the answer that appears most frequently or has the highest confidence score. This consensus evaluation could help filter out hallucinated or inconsistent answers.

[0107] In addition to entity linking and knowledge graph integration, platform **170** can use Retrieval Augmented Generation (RAG) to mitigate hallucinations. RAG involves retrieving relevant information from an external knowledge source (e.g., documents, databases, RAG marketplaces **130***a-n*) based on the input query and using that information to guide the generation process. By conditioning the model's output on retrieved facts, RAG can help ensure that the generated text is more grounded in reality and less likely to contain hallucinated information. For example, consider a question-answering task, wherein platform **170** could use RAG to retrieve relevant passages from a large document collection based on the input question. The model would then generate an answer based on the retrieved passages, reducing the risk of hallucinating information not present in the knowledge source. If a generated response was factually correct except for one portion, the platform can extract the factually incorrect portion and resubmit to obtain correct information. As another example, a dialogue generation task, RAG could be used to retrieve relevant background information about the conversation topic from a curated database. The model would then incorporate this informa-

tion into its responses, making the conversation more informative and less likely to contain false or inconsistent statements.

[0108] According to the embodiment, model validation computing system **173** is present and configured to apply certification, challenge-based, and/or model blend concepts to validate model outputs. These can include expert human (e.g., expert judgment/scores marketplace) or knowledge base overlays, symbolic knowledge integration, more expressive RAGs/weightings, and hierarchical process definitions for specialized routing. Validating models against domain experts (e.g., human or, in some cases, models) and authoritative databases could help assess their performance and reliability. Platform **170** could use techniques like cross-validation and domain-specific question-answering to validate the performance of models against human experts and authoritative databases. This would involve creating a dataset of questions and answers specific to a domain (e.g., medicine, law) and comparing the model's responses to those provided by certified experts or reliable sources. As an example, consider a medical diagnosis task, platform **170** could validate a model's performance by comparing its diagnoses to those provided by certified medical professionals. The validation dataset could include a range of medical cases with varying complexity and rareness. In a legal advice task for example, platform **170** could validate a model's responses against a database of legal precedents and expert opinions. The validation process could involve asking the model to provide legal advice on specific scenarios and comparing its responses to those found in the authoritative database.

[0109] According to some implementations, platform **170** can use RAG in combination with other techniques like attention mechanism/model type search and model consensus and/or blending or output selection to optimize the performance and reliability of models for specific tasks. RAG can be incorporated into the model architecture as an additional component that interacts with the attention mechanism and influences the generation process. The platform could search through different RAG configurations (both input and output), such as varying the retrieval mechanism (e.g., dense vs. sparse retrieval) or the way retrieved information is integrated into the model (e.g., concatenation, cross-attention), to find the most effective setup for a given task and then to determine additional viable configurations to address operational resilience concerns for alternate, contingent or emergency data and logic configurations. For example, consider a fact-checking task wherein the platform can use RAG to retrieve relevant evidence from a large corpus of news articles and fact-checking websites. The model would then use this evidence to assess the veracity of a given claim, with the attention mechanism focusing on the most informative parts of the retrieved evidence. The platform could search through different RAG configurations to find the one that achieves the best balance between retrieval quality and generation accuracy. Another example involving a summarization task, RAG could be used to retrieve relevant background information and supporting details from a large document collection. The model would then use this retrieved information to generate a more comprehensive and accurate summary, with the attention mechanism helping to select the most salient points. The platform could blend multiple RAG-based models, each trained on different document collections or with different retrieval strategies, to create a more robust and reliable summarization system. In an embodiment, optimizing the performance and reliability of a model comprises searching through different model types, attention architectures and RAG configurations, model consensus or blending mechanisms to find the most effective setup for a given task and then to determine additional viable configurations to address operational resilience concerns for alternate, contingent or emergency data and logic configurations under ranges of operational scenarios and parameters, such as specific scenarios (or states or state transitions) of interest declared by users, or scenarios of interest identified by the system.

[0110] By incorporating Retrieval Augmented Generation into advanced model management platform **170**, the system can more effectively mitigate hallucinations and improve the factual accuracy of generated text. RAG complements other techniques like entity linking and knowledge graph integration by providing a flexible and task-specific way to retrieve and incorporate relevant information from external knowledge sources. The platform's ability to search through different RAG configurations and blend multiple RAG-based models further enhances its potential to optimize performance and reliability for a wide range of applications.

[0111] According to the embodiment, model training sandboxing computing system **174** is present and configured to implement techniques like poison testing, certified narrow models, and parametric studies to perturb the model for certifications. Furthermore, the platform can generate random prompts to identify problematic outputs and maintain session state for users or groups to develop a "user/group RAG." Model training sandbox system **174** may use techniques like adversarial training and input perturbation to test the robustness of models against poisoning attacks and other adversarial examples. Adversarial training involves incorporating malicious examples into the training data to make the model more resilient, while input perturbation adds random noise or transformations to the input data to test the model's stability. For example, consider a sentiment analysis task, the platform could use adversarial training to incorporate examples of text with intentionally misleading or ambiguous sentiment. This would help the model become more robust against attempts to manipulate its predictions. As another example comprising an image classification task, the platform could use input perturbation to add random rotations, translations, or noise to the input images. This would help assess the model's ability to correctly classify images under various distortions and transformations.

[0112] In some implementations, model training sandbox system **174** may employ "red vs. green" techniques for optimizing and validating models using different datasets of scenarios. The "red" dataset or scenario represents challenging, adversarial, or out-of-distribution examples that are used to test the model's robustness and ability to handle edge cases. These examples may be artificially generated or collected from real-world situations where the model is likely to face difficulties. The "green" dataset or scenario represents typical, in-distribution examples that are used to assess the model's performance under normal conditions. These examples are usually similar to the data used during training and are expected to be handled well by the model. The "red vs green" approach involves training and evaluating models on both "red" and "green" datasets or scenarios to ensure that they can perform well under various condi-

tions. This approach helps identify and address potential weaknesses or blind spots in the model's performance.

[0113] As an example, in a sentiment analysis task, the "green" dataset may contain standard product reviews with clear positive or negative sentiment. The "red" dataset may include sarcastic, ambiguous, or emotionally neutral reviews that are harder for the model to classify accurately. As another example, for an object detection model in an autonomous vehicle, the "green" scenario may involve clear, daytime images of roads with well-defined lane markings and traffic signs. The "red" scenario may include nighttime images, poor weather conditions, or complex urban environments with many obstacles and pedestrians. By evaluating the model's performance on both "red" and "green" examples, advanced model management platform **170** can identify areas for improvement and optimize the model to handle a wider range of situations. This approach contributes to the overall goal of creating more robust, reliable, and adaptable models that can perform well under various conditions

[0114] According to the embodiment, security and defense computing system **175** is present and configured to use small (or hybrid), sufficiently trained models to achieve suitable performance with superior operating dynamics and less sensitive information leakage. Additionally, security and defense system **175** may implement similarity scoring and nearness models to detect model infringement and theft. The system **175** can utilize cosine similarity or Euclidean distance in a hyper dimensional vector space to detect model infringement, replication, influence, and/or theft, according to an embodiment. Security and defense system **175** may further implement techniques like model distillation and differential privacy to create smaller, more secure models that retain the performance of larger models. Model distillation involves training a smaller model to mimic the behavior of a larger model, while differential privacy adds noise to the training data to prevent the model from memorizing sensitive information. As an example, consider a sensitive task like processing financial data, platform **170** could use model distillation to create a smaller model that retains the performance of a larger model trained on the full dataset. This smaller model could be deployed in a more secure environment with limited access. Platform **170** could also use similarity scoring and nearness models, such as cosine similarity or Euclidean distance, to detect model infringement and theft. To detect model theft, the platform may compare the weights or outputs of a suspected stolen model to those of the original model using similarity scoring. If the similarity exceeds a certain threshold, it could indicate that the model has been copied or infringed upon.

[0115] In some implementations, security and defense system **175** may integrate with an exchange system configured to register and store generative AI models, outputs, datasets, and model parameters/hyperparameters. For example, neural network weights may be assigned hashes to identify and associate the weights with a particular neural network model (e.g., LLM, diffusion model, etc.). The hashed weights may be stored in the integrated exchange system and used to monitor for model infringement evidence from users, regulators, etc. to retain some of the copyright and IP right concerns.

[0116] According to the embodiment, model management computing system **176** is present and configured to search through attention mechanisms with or without RAGs using test batteries of input prompts. This can involve using model blends/batteries, wherein multiple models need to agree on critical decisions, and incorporating human validation when necessary. Techniques like attention mechanism search and model blending may be used to optimize the performance and reliability of models for specific tasks. Attention mechanism search involves exploring different attention architectures, such as multi-head attention or self-attention, to find the most effective configuration for a given task. Model blending combines the outputs of multiple models using techniques like weighted averaging or majority voting to improve overall performance and reduce the impact of individual model biases. For example, consider a language translation task, the platform could search through different attention mechanisms to find the one that produces the most accurate and fluent translations. This could involve comparing the performance of models with varying numbers of attention heads, different positional encoding schemes, or alternative attention formulations. As another example, consider an object detection task, the platform could blend the outputs of multiple models trained on different datasets or with different architectures. The blending process could assign weights to each model based on its performance on a validation set and combine their predictions using a weighted average or a more sophisticated ensemble method. According to an embodiment, model blending may comprise selecting from or blending outputs from multiple (optionally RAG-enhanced) models or authoritative knowledge bases (e.g., vector database, knowledge graph or composite vector knowledge graph), each trained on different resource collections or with different retrieval strategies or hyperparameters.

[0117] FIG. **1**B is a block diagram illustrating an exemplary system architecture for a distributed generative artificial intelligence reasoning and action platform **120**, according to an embodiment. According to the embodiment, platform **120** is configured as a cloud-based computing platform comprising various system or sub-system components configured to provide functionality directed to the execution of neuro-symbolic generative AI reasoning and action. Exemplary platform systems can include a distributed computational graph (DCG) computing system **121**, a curation computing system **122**, a marketplace computing system **123**, and a context computing system **124**. In some embodiments, systems **121-124** may each be implemented as standalone software applications or as a services/microservices architecture which can be deployed (via platform **120**) to perform a specific task or functionality. In such an arrangement, services can communicate with each other over an appropriate network using lightweight protocols such as HTTP, gRPC, or message queues. This allows for asynchronous and decoupled communication between services. Services may be scaled independently based on demand, which allows for better resource utilization and improved performance. Services may be deployed using containerization technologies such as Docker and orchestrated using container orchestration platforms like Kubernetes. This allows for easier deployment and management of services.

[0118] The distributed generative AI reasoning and action platform **120** can enable a more flexible approach to incorporating machine learning (ML) or artificial intelligence models into the future of the Internet and software applications; all facilitated by a DCG architecture capable of

dynamically selecting, creating, and incorporating trained models with internal and external data sources and marketplaces for data and algorithms.

[0119] According to the embodiment, DCG computing system **121** provides orchestration of complex, user-defined workflows built upon a declarative framework which can allow an enterprise user **110** to construct such workflows using modular components which can be arranged to suit the use case of the enterprise user. As a simple example, an enterprise user **110** can create a workflow such that platform **120** can extract, transform, and load enterprise-specific data to be used as contextual data for creating and training a ML or AI model. The DCG functionality can be extended such that an enterprise user can create a complex workflow directed to the creation, deployment, and ongoing refinement of a trained model (e.g., LLM). For example, in some embodiments, an enterprise user **110** can select an algorithm from which to create the trained model, and what type of data and from what source they wish to use as training data. DCG computing system **121** can take this information and automatically create the workflow, with all the requisite data pipelines, to enable the retrieval of the appropriate data from the appropriate data sources, the processing/preprocessing of the obtained data to be used as inputs into the selected algorithm(s), the training loop to iteratively train the selected algorithms including model validation and testing steps, deploying the trained model, and finally continuously refining the model over time to improve performance.

[0120] A context computing system **124** is present and configured to receive, retrieve, or otherwise obtain a plurality of context data from various sources including, but not limited to, enterprise users **110**, marketplaces **130***a-n*, third-party sources **150**, and other data sources **140***a-n*. Context computing system **124** may be configured to store obtained contextual data in a data store. For example, context data obtained from various enterprise endpoints **110***a-n* of a first enterprise may be stored separately from the context data obtained from the endpoints of a second enterprise. In some embodiments, context data may be aggregated from multiple enterprises within the same industry and stored as a single corpus of contextual data. In such embodiments, contextual data may be transformed prior to processing and storage so as to protect any potential private information or enterprise-specific secret knowledge that the enterprise does not wish to share.

[0121] A curation computing system **122** is present and configured to provide curated (or not) responses from a trained model (e.g., LLM) to received user queries. A curated response may indicate that it has been filtered, such as to remove personal identifying information or to remove extraneous information from the response, or it may indicate that the response has been augmented with additional context or information relevant to the user. In some embodiments, multiple trained models (e.g., LLMs) may each produce a response to a given prompt, which may include additional contextual data/elements, and a curation step may include selecting a single response of the multiple responses to send to a user, or the curation may involve curating the multiple responses into a single response. The curation of a response may be based on rules or policies that can set an individual user level, an enterprise level, or at a department level for enterprises with multiple departments (e.g., sales, marketing, research, product development, etc.).

[0122] According to the embodiment, an enterprise user **110** may refer to a business organization or company. An enterprise may wish to incorporate a trained ML model into their business processes. An enterprise may comprise a plurality of enterprise endpoints **110***a-n* which can include, but are not limited to, mobile devices, workstations, laptops, personal computers, servers, switches, routers, industrial equipment, gateways, smart wearables, Internet-of-Things (IoT) devices, sensors, and/or the like. An enterprise may engage with platform **120** to create a trained model to integrate with its business processes via one or more enterprise endpoints. To facilitate the creation of purpose-built, trained models, enterprise user **110** can provide a plurality of enterprise knowledge **111** which can be leveraged to build enterprise specific (or even specific to certain departments within the enterprise) ML/AI models. Enterprise knowledge **111** may refer to documents or other information important for the operation and success of an enterprise. Data from internal systems and databases, such as customer relationship management (CRM) systems, enterprise resource planning (ERP) systems, rules and policies databases, and transactional databases, can provide information about the operational context of an enterprise. For example, product knowledge, market knowledge, industry trends, regulatory knowledge, business processes, customer knowledge, technology knowledge, financial knowledge, organization knowledge, and risk management knowledge may be included in enterprise knowledge base **111**.

[0123] According to the embodiment, platform **120** is configured to retrieve, receive, or otherwise obtain a plurality of data from various sources. A plurality of marketplaces **130***a-n* may be present and configured to provide centralized repositories for data, algorithms, and expert judgment, which can be purchased, sold, or traded on an open marketplace. External data sourced from various marketplaces **130***a-n* can be used as a training data source for creating trained models for a particular use case or in output validation or safety checks. Expert characterization of content may also be used in subjective areas undergoing technical, legal, or cultural change. A marketplace computing system **123** is present and configured to develop and integrate various marketplaces **130***a-n*. Marketplace computing system **123** can provide functionality directed to the registration of experts or entities. An expert may be someone who has a deep understanding and knowledge of a specific industry, including its trends, challenges, technologies, regulations, and best practices. Industry experts often have many years of experience working in the industry and have developed a reputation for their expertise and insights. Examples of experts can include, but are not limited to, consultants, analysts, researchers, academics, or professionals working in the industry. In some embodiments, experts and/or entities can register with platform **120** so that they may become verified experts/entities. In such an embodiment, an expert/entity profile may be created which can provide information about expert judgment, scored data and algorithms, and comparisons/statistics about the expert's/entity's scores and judgment with respect to other expert/entities. Marketplace computing system **123** may further provide functionality directed to the management of the various marketplaces and the data/algorithms provided therein.

[0124] According to some embodiments, platform **120** can communicate with and obtain data from various third-party services **150**. For example, third-party services can include

LLM services such as APIs and LLM hosting platforms, which platform **120** can interface with to obtain algorithms or models to use as starting points for training a neuro-symbolic generative AI reasoning and action model to be deployed at the enterprise or individual level. As another example, social media platforms can provide data about trends, events, and public sentiment, which can be useful for understanding the social context of a situation. Exemplary data sources **140***a-n* can include, but are not limited to, sensors, web data, environmental data, and survey and interviews.

[0125] FIG. **2** is a block diagram illustrating an exemplary aspect of a distributed generative AI reasoning and action platform incorporating various additional contextual data. According to the aspect, a plurality of contextual data from various data sources may be integrated into platform **120**. A simple exemplary directed computational graph **200** is illustrated within the cloud and utilizing the plurality of contextual data to create and train a model. Various marketplaces **130***a-n* are shown which can provide contextual data to platform **120** including an expert judgment marketplace **260** and a model and retrieval augmented generation (RAG) marketplace **220**. According to the aspect, DCG **200** orchestrates model (and model weight) selection **204**, including multi-model usage in series or parallel (i.e., feed output of one model into another, or compare and choose outputs across multiple models), based on multiple data sources (both trained and external), input from crowdsourced expert judgment, training or tuning data set corpora, and RAG libraries.

[0126] Expert judgment will become increasingly important in the world of proprietary or otherwise blackbox ML or AI models where hallucinations and training data quality may produce misleading or otherwise incorrect results. The expert judgment marketplace **260** provides a way for experts **230** to weigh-in on the correctness of data whether that is training data or model output, and can be facilitated by a browser extension **240**, for example, to score things like data sources during their daily "trip around web". This trip report scoring **250** concept allows experts to score data sources. In an implementation, a browser extension **240** is developed with an accuracy score input where the user can rank a news article they are reading as they consume it. Expert judgment marketplace **260** allows for consumers to pick and rank "experts" based on how well their judgment helps or hinders their overall consumption of model output. Formal Structured Expert Judgment model or output scoring adjustments may also be constructed and applied to specific inputs, outputs, RAGs, knowledge bases or data corpora. For example, experts that routinely highly rank data sources, like news sites, that are known to spread false information should likewise be less trusted over time compared to their peers, and any models trained on that data similarly less trusted. Ultimately a database **270** of data sources and schemas scored by algorithms or experts could be used as input into the DCG **200** for more accurate and real-time inference based on ongoing rating of preferred data set and data format combinations (e.g. the same data might be purchased in unstructured, structured, schematized, normalized, or semantified formats) which may introduce different types of bias or impacts on performance, results, or processing costs.

[0127] Accordingly, a RAG marketplace **220** may be implemented to further refine model output. RAG information may be included as additional context which can be supplied to a GenAI model in addition to a prompt (engineered, or otherwise). This is especially important where companies may want to sell access to their proprietary dataset through the form of a RAG. For example, a medical research company may have valuable information they could sell to other institutions in the form of a RAG to augment related research without specifically providing access to the raw training data. Retrieval-augmented generation is a framework that combines elements of retrieval-based and generative models to improve the performance of natural language processing tasks. In RAG, a retriever component is used to select relevant information from a large corpus, and a generator component is used to produce a final output based on both the retrieved information and the input query. RAG marketplace **220** may be scored by experts for accuracy and effectiveness across domains.

[0128] According to the aspect, a user experience curation engine **210** is needed that is able to curate output whether that is in the form of filtering out sensitive data or simply customizing results in a way the user prefers (which may be based on user-/entity-defined rules or policies). A user can submit a query to experience curation engine **210** which can send the query to the DCG trained model to obtain a response. Experience curation **210** may then process the received response to curate it (or not) to meet the preferences of the user.

[0129] As illustrated, DCG **200** shows a simple example of a directed computational graph which can be used to create a complex workflow to create and train an MI/AI model (e.g., variations of or standard transformer architecture). A shown, the DCG comprises multiple sources of information for training the selected models(s) including multiple data sources **201***a-n* which may or may not be scored by experts, expert judgment **202**, and one or more RAGs **203** which may be obtained from RAG marketplace **220** or may be obtained directly from enterprise knowledge. DCG may have access to stored models or variants thereof. In the illustration, LLAMA (Learned Layer-wise Attention Metric for Transformers), PALM (Permuted Adaptive Lateral Modulation), and HYENA (Hyperbolic Encoder for Efficient Attention) are shown as possible examples of the types of models which can be selected by the DCG to create and train a GenAI model. Furthermore, the "model parameters" and mathematical techniques or assumptions used in each model may be cataloged and included in a model-specific template which may be stored in cloud-based storage on platform **120**. In some embodiments, platform **120** may store a hierarchical representation of transformer models (e.g., as a graph), which may represent a lineage of the evolution of transformer models. In an implementation, model selection or exploration involves selections based on the evolutionary tree of one or more model types and use said tree (e.g., graph) for selections in heuristic search for best algorithm/data combinations, licensing costs/explorations, etc. It should be appreciated that certain aspects of the invention may be tailored based on what kind of mathematical approach underpins a specific model.

[0130] In operation, DCG **200** obtains the various contextual data from the connected data sources, creates training, validation, and test datasets from the obtained data, and uses the various datasets to train, validate, and test the model as it undergoes a model training loop that iteratively trains the model to generate responses based on the plurality of contextual data.

[0131] FIG. **3** is a diagram illustrating incorporating symbolic reasoning in support of a LLM-based generative AI embodiment, according to an aspect of a neuro-symbolic generative AI reasoning and action platform. According to the aspect, platform **120** can incorporate symbolic reasoning and in-context learning to create and train off the shelf models (e.g., an LLM foundational model or narrow model) through clever prompting and conditioning on private data or very situation specific "contextual" data. Platform **120** can obtain contextual data **301** and preprocess the data for storage. Contextual data **301** may refer to data obtained from marketplaces **130***a-n*, third-party services **150**, and enterprise knowledge **111**, as well as other types of contextual data that may be obtained from other internal, Internet, or exogenous sources. DCG **330** is responsible for orchestrating the entire process and can create data pipelines **310** as needed to facilitate the ingestion of contextual data **301**. Contextual data can include text documents, PDFs, and even structure formats like CSV (comma-separated values) or SQL tables or other common generic data formats like OWL or RDF or domain specific content such as the Financial Industry Business Ontology (FIBO) or Open Graph of Information Technology (OGIT). This stage involves storing private data (e.g., context data) to be retrieved later.

[0132] Typically, the context data **301** is broken into chunks, passed through and embedding model **315**, then stored in a specialized database called a vector database **320**. Embedding models are a class of models used in many tasks such as natural language processing (NLP) to convert words, phrases, or documents into numerical representations (embeddings) that capture similarity which often correlates semantic meaning. Exemplary embedding models can include, but are not limited to, text-embedding-ada-002 model (i.e., OpenAI API), bidirectional encoder representations form transformers, Word2Vec, FastText, transformer-based models, and/or the like. The vector database **315** is responsible for efficiently storing, comparing, and retrieving a large plurality of embeddings (i.e., vectors). Vector database **315** may be any suitable vector database system known to those with skill in the art including, but not limited to, open source systems like Pinecone, Weaviate, Vespa, and Qdrant. According to the embodiment, embedding model **315** may also receive a user query from experience curation **340** and vectorize it where it may be stored in vector database **320**. This provides another useful datapoint to provide deeper context when comparing received queries against stored query embeddings.

[0133] A user may submit a query **303** to an experience curation engine **340** which starts the prompt construction and retrieval process. The query is sent to DCG **330** which can send the query to various components such as prompt engineering **325** and embedding model **315**. Embedding model **315** receives the query and vectorizes it and stores it in vector database **320**. The vector database **320** can send contextual data (via vectors) to DCG **330** and to various APIs/plugins **335**. Prompt engineering **325** can receive prompts **302** from developers to train the model on. These can include some sample outputs such as in few-shot prompting. The addition of prompts via prompt engineering **325** is designed to ground model responses in some source of truth and provide external context the model wasn't trained on. Other examples of prompt engineering that may be implemented in various embodiments include, but are not limited to, chain-of-thought, self-consistency, generated knowledge, tree of thoughts, directional stimulus, and/or the like.

[0134] During a prompt execution process, experience curation **340** can send user query to DCG **330** which can orchestrate the retrieval of context and a response. Using its declarative roots, DCG **330** can abstract away many of the details of prompt chaining; interfacing with external APIs **335** (including determining when an API call is needed); retrieving contextual data from vector databases **330**; and maintaining memory across multiple LLM calls. The DCG output may be a prompt, or series of prompts, to submit to a language model via LLM services **360** (which may be potentially prompt tuned). In turn, the LLM processes the prompts, contextual data, and user query to generate a contextually aware response which can be sent to experience curation **340** where the response may be curated, or not, and returned to the user as output **304**.

[0135] FIG. **4** is a block diagram illustrating an exemplary architecture for a neuro-symbolic generative AI reasoning and action platform **400** configured for federated learning at a plurality of edge devices **410***a-n*, according to an embodiment. According to the embodiment, platform **400** comprises DCH computing system **421**, curation computing system **422**, marketplace computing system **423**, and context computing system **424**. According to an embodiment, edge devices **410***a-n* may represent various enterprise endpoints. In other embodiments, edge devices **410***a-n* may represent various endpoints from two or more separate enterprises. In an embodiment, an edge device **410***a-n* may be a computing device associated with a platform user, such as someone who engages with the platform for experience curation or an expert who provides expert judgment scores to platform **400** via, for example, expert judgment marketplace **260** or some other mechanism.

[0136] As shown, each edge device **410***a-n* may comprise instances of local models **411***a-n*, context classification processes **412**-*n*, and experience curation processes **413***a* operating on the device. Each edge device may have access to a local data or knowledge base **420***a-n* and which is only accessible by its associated edge device. Edge devices **410***a-n* may utilize these components to perform various computations wherein the processing of data and execution of algorithms happens locally on the device, rather than relying on the systems and services provided by platform **400**. In some embodiments, a plurality of edge devices **410***a-n* may be implemented as individual computing nodes in a decentralized federated system, wherein tasks and data may be distributed across multiple nodes, allowing for parallel processing and potentially faster computation. Federated systems are often used in scenarios where data privacy and security are important, as data can remain on local nodes and only aggregated or processed results are shared more widely.

[0137] In some implementations, the platform **400** may leverage federated learning, where machine learning models **411***a-n* are trained across multiple decentralized edge devices **410***a-n*, with the models' updates being aggregated centrally. This approach allows for the training of models without the need to centrally store sensitive data from individual devices. For example, each edge device **410***a-n* could train local instances of neuro-symbolic GenAI reasoning and action models and local instances of context classification models **412***a-n*. According to an embodiment,

context classification models **412***a-n* may be configured to select relevant passages from a knowledge base **420***a-n* or corpus given a query. This can be done using various techniques such as BM25, TF-IDF, or neural retrieval models like dense passage retrieval. The retrieved passages serve as context or input to a generator (e.g., a transformer-based model).

[0138] Federated learning can occur at the edge device wherein the context classification model **412***a* is trained locally. Periodically, (e.g., hourly, daily, weekly, etc.) platform **400** may collect (e.g., aggregate) model parameters, encrypted data, and/or the like from all of, or a subset of, edge devices **410***a-n* and apply the aggregated model parameters as an update to a master or global model (e.g., context classification, neuro-symbolic GenAI model, etc.). The updated global model or just its parameters, may be transmitted to all of, or a subset of, the edge devices **410***a-n* where they may be applied to the local models operating thereon. Similarly, platform **400** can aggregate obtained training data, which may or may not be encrypted, and apply the training data to global models. These updated models may be transmitted to edge devices as described above.

[0139] As shown, edge devices **410***a-n* may further comprise a curation application **413***a-n* operating on the device. Curation application **413***a* may be configured to act as an intermediary between a user who can submit a query and models **411***a* which receive the query and generate a response back. Curation **413***a-n* may receive a response from a locally stored model and curate the response based on user (or entity) defined rules or preferences. For example, a response may first be filtered of any personal information by curation **413***a* prior to the being relayed back to the user. As another example, curation **413***a* may transform the response into specific format, style, or language based on user defined preferences. This allows the edge device **410***a* user to have their experience with the local models curated to fit any criteria they deem important.

[0140] FIG. **5** is a block diagram illustrating an exemplary architecture for a neuro-symbolic generative AI reasoning and action platform **500** configured to utilize a midserver **530** to act as a computing intermediary between a plurality of edge devices **510***a-n* and the platform. According to the embodiment, midserver **530** facilitates communication between edge devices **510***a-n* and the backend systems **521**, **522**, **523**, **524** provided by platform **500**. According to the embodiment, midserver **530** may have stored and operating on it one or more neuro-symbolic GenAI reasoning and action models **531**, context classification processes **532**, and curation processes **533**. Midserver **530** can be configured to periodically receive data (e.g., context data) and state information from each of the connected edge devices **510***a-n*. Midserver **530** may use this information to train/update the models **531**, **532**. Additionally, midserver **530** can be configured to receive user-submitted queries from edge devices via curation **533**, obtain relevant context associated with the received query via context classification **532**, and use a neuro-symbolic GenAI model **531** to process the query and context data to generate a response to the user. The generated response may be curated (or not) and transmitted back to the user of the edge device.

[0141] In some implementations, edge devices **510***a-n* may have stored upon them local models as described in FIG. **4**, and midserver **530** may store global models or even mid-tier models associated with the local models. In such an implementation, midserver can aggregate model parameters and update the global/mid-tier models accordingly.

[0142] FIG. **6** is a block diagram illustrating an exemplary mobile device **610***a-n* configured for experience curation using embedded capabilities and functionality provided by a neuro-symbolic generative AI reasoning and action platform **600**, according to an embodiment. According to the embodiment, a mobile device **610***a* may comprise an operating system **611**, various software applications **612** (e.g., text messaging application, social media application, mobile games, music streaming applications, etc.), a local instance of a neuro-symbolic GenAI model **613**, a context classification model **614**, and an experience curation application **615**. Mobile devices **610***a-n* may further comprise a processor, memory, sensors, storage, wireless communication modules, a display, audio components, and various other components to enable the functionality of a mobile computing device. Mobile devices **610***a-n* may connect to platform **600** via a suitable communication network such as the Internet. In some embodiments, mobile device may utilize the systems and services **621**, **622**, **623**, **624** provided by platform to facilitate query-response interactions with a neuro-symbolic GenAI model.

[0143] According to the embodiment, mobile device **610***a* stores and operates local models **613**, **614** and a curation application **615** which can be leveraged during instances when mobile device **610***a* is unable to connect with platform **600** or otherwise has an intermittent connection thereby making data transmission difficult, slow, or impossible. In such situations, mobile device **610***a* can leverage the local components to perform computation at the edge. A user of mobile device **610***a* can use curation application **615** to submit a query to the local neuro-symbolic GenAI model **613**, along with any aggregated context retrieved via context classification **614**. The model **613** can generate a response and send it to curation application **615** where it may be curated (or not) based on the mobile device user's preferences or rules.

[0144] In some embodiments, when there is only an intermittent connection to platform **600**, such as when a mobile device is in an area with poor network coverage, various strategies may be implemented to provide functionality to the mobile device user. For example, data (e.g., a user submitted query or prompt) can be temporarily stored in a buffer on the device until a connection to platform **600** is available. Once the connection is reestablished, the buffered data can be transmitted. Likewise, frequently accessed data or recently transmitted data can be cached on the device. This allows the device to access the data locally when a connection to platform **600** is not available. In some implementations, data can be compressed before transmission to reduce the amount of data that needs to be transmitted. This can help to minimize the impact of intermittent connections on data transmission. In some embodiments, mobile device **610***a-n* may use protocols that are designed to handle intermittent connections, such as MQTT (Message Queuing Telemetry Transport) or CoAP (Constrained Application Protocol), can help to ensure that data is successfully transmitted even in challenging network conditions. Finally, some use cases may implement an offline mode that allows users to continue using the application (or local instances) and storing data locally until a connection to platform **600** is available again.

[0145] FIG. **7** is a block diagram illustrating an exemplary aspect of a distributed generative artificial intelligence reasoning and action platform, a curation computing system **700**. According to the aspect, curation computing system **700** is configured to provide curated (or not) responses from a trained model (e.g., transformer-based model) to received user queries. A curated response may indicate that the response has been filtered, such as to remove personal identifying information or to remove extraneous information from the response, or it may indicate that the response has been augmented with additional context or information relevant to the user. The curation of a response may be based on rules or policies that can be set at an individual user level, an enterprise level, or at a department level for enterprises with multiple departments (e.g., sales, marketing, research, product development, etc.). User/entity rules and/or preferences may be stored in a data storage system of platform **120** and retrieved by a rules management component **740** during experience curation processes.

[0146] In operation, curation computing **700** receives a user query **701** directed to a neuro-symbolic GenAI model. A query portal **710** may be present and configured to receive a query **701** and prepare it for processing by a GenAI model. For example, a query may be split into tokens, (e.g., words or sub words) which are basic units of the language model. As another example, a text-based query may undergo normalization (e.g., converting to lowercase, removing punctuation, handling special characters, etc.) to ensure consistency and improve model performance. As yet another example, for models that use attention mechanisms, an attention mask may be applied to the input to indicate which tokens should be attended to and which should be ignored. In some implementations, a query portal **710** may be configured to send received queries to an embedding model which can vectorize the received query and store it in a vector database. In such embodiments, stored query embeddings may be used as a form of contextual data which may be retrieved and transmitted with the query to a GenAI model which generates a response based on the received query and contextual data.

[0147] According to the aspect, a response portal **720** is present and configured to receive a response from one a GenAI model and a response management system **730** determines if the received response needs to be curated or not. If the response does not need to be curated, then it may be sent as an uncrated response **702** to the user who submitted the query. Response management **730** can determine if there are any user/entity defined rules or preferences available such as stored in a user/entity profile in a data storage system of platform **120**. Rules management **740** can retrieve said rules and response management can curate or otherwise augment the received response based on the user/entity rules or preferences. The result is a curated response **702** which can be transmitted back to the user who submitted the query.

[0148] FIG. **8** is a block diagram illustrating an exemplary aspect of a distributed generative artificial intelligence reasoning and action platform, a marketplace computing system **800**. According to the aspect, marketplace computing system **800** is present and configured to develop and integrate various marketplaces **130***a-n* for data, algorithms, and RAGs into platform **120**. Marketplace computing system **800** can provide functionality directed to the registration of experts **810** or entities. An expert may be someone who has a deep understanding and knowledge of a specific industry, including its trends, challenges, technologies, regulations, and best practices. Industry experts often have many years of experience working in the industry and have developed a reputation for their expertise and insights. An expert may be registered by providing proof of identity and qualifications, and creating an expert profile which can store a variety of information about the expert such as their name, industry, credentials, scores (e.g., scores that the expert has assigned to data sources, models/algorithms, model outputs, and/or the like), and reputation. For example, a university professor who specializes in transformer-based algorithms can register as an expert in the realm of generative algorithms. As another example, a virologist could register as an expert and provide scores for academic papers which disclose a new methodology for viral spread modelling. Marketplace computing system **800** may further comprise a market management component **820** which can interface with a plurality of markets **130***a-n* to integrate information contained therein. A scored data management component **830** may be configured to interface with a browser extension **240** or expert judgment marketplace **260** to retrieve expert scores and store them in an expert judgment score database **270**. According to the aspect, an algorithm management component **840** is present and configured to acquire algorithms from algorithm marketplaces to be used in the construction and configuration of neuro-symbolic GenAI models.

[0149] FIG. **9** is a block diagram illustrating a simple example of a distributed computational graph **900** representation for providing neuro-symbolic artificial intelligence capabilities, including generative AI, according to an aspect. According to the aspect, the DCG may be represented as a series of nodes which represent discrete computational or data processing functions, and a series of edges connecting the nodes which represent information or data messages being sent between processing nodes. A DCG can be used to acquire a plurality of context data in the form of an enterprise knowledge base **910**. A data transformation node **920** is created to handle the ingestion and transformation of acquired context data. Obtained data may then be sent to a data embedding node **930** which can vectorize the received context data. The vectorized data may flow from the embedding node **930** to a data storage node **950**. Data storage node **950** may select the appropriate vector database **980** in which to store the vectorized context data. An input node **940** may allow for a user to submit a query to the workflow. The user query can be sent to data embedding node **930** where it may be vectorized and sent to data storage node **950** for storage in the vector database. The user query can also be sent to a model node **960** which contains the selected model(s) which will process the user query along with any relevant context data obtained from data storage node vector database **980**. Model node **960** then processes this information to generate a response which can be sent to output node **970**. In some instances, output node **970** may output the response directly to the user. In other instances, output node **970** may be configured to transform the response into a curated response based on user/entity defined rules or preferences.

[0150] FIGS. **10-14** illustrate various exemplary aspects of system architectures of distributed computational graph computing environments. For more detailed information regarding the operation of the various components and aspects described herein with respect to FIGS. **10-14**, please

refer to U.S. patent application Ser. No. 15/931,534 which is incorporated herein by reference.

[0151] FIG. **10** is a block diagram illustrating an exemplary aspect of an embodiment of a distributed computational graph computing system utilizing an advanced cyber decision platform (ACDP) for external network reconnaissance and contextual data collection. Client access to the system **1005** for specific data entry, system control and for interaction with system output such as automated predictive decision making and planning and alternate pathway simulations, occurs through the system's distributed, extensible high bandwidth cloud interface **1010** which uses a versatile, robust web application driven interface for both input and display of client-facing information via network **1007** and operates a data store **1012** such as, but not limited to MONGODB™, COUCHDB™, CASSANDRA™ or REDIS™ or DynamoDB or Neptune or DocumentDB according to various arrangements. Much of the enterprise knowledge/context data analyzed by the system both from sources within the confines of the enterprise business, and from cloud based sources, also enter the system through the cloud interface **1010**, data being passed to the connector module **1035** which may possess the API routines **1035***a* needed to accept and convert the external data and then pass the normalized information to other analysis and transformation components of the system, the directed computational graph module **1055**, high volume web crawler module **1015**, multidimensional time series database (MDTSDB) **1020** and the graph stack service **1045**. The directed computational graph module **1055** retrieves one or more streams of data from a plurality of sources, which includes, but is in no way not limited to, enterprise knowledge, RAGs, expert judgment/scores (including expertise of the crowd from samplings of a general population of interest through surveys or engagement with advertisements, media or other content), a plurality of physical sensors, network service providers, web based questionnaires and surveys, monitoring of electronic infrastructure, crowdsourcing campaigns, and human input device information. Within the directed computational graph module **1055**, data may be split into two identical streams in a specialized pre-programmed data pipeline **1055***a*, wherein one sub-stream may be sent for batch processing and storage while the other sub-stream may be reformatted for transformation pipeline analysis. The data is then transferred to the general transformer service module **1060** for linear data transformation as part of analysis or the decomposable transformer service module **1050** for branching or iterative transformations that are part of analysis. The directed computational graph module **1055** can represent all data as directed graphs where the transformations are nodes and the result messages between transformations edges of the graph. The high volume web crawling module **1015** uses multiple server hosted preprogrammed web spiders, which while autonomously configured are deployed within a web scraping framework **1015***a* of which the Internet Archive, Common Crawl, or SCRAPY™ are examples. This crawling framework may also leverage headless browsing tools such as Selenium, Puppeteer, or Undetected ChromeDriver to identify and retrieve data of interest from web based sources that are not well tagged by conventional web crawling technology. Data persistence stores such as the multiple dimension time series data store module **1020** may receive streaming data from a large plurality of sensors that may be of several different types. The multiple dimension time series data store module may also store any time series data encountered by the system such as but not limited to enterprise network usage data, component and system logs, environmental context, edge device state information, performance data, network service information captures such as, but not limited to news and financial feeds, and sales and service related customer data. The module is designed to accommodate irregular and high volume surges by dynamically allocating network bandwidth and server processing channels to process the incoming data. Inclusion of programming wrappers **1020***a* for languages examples of which are, but not limited to C++, PERL, PYTHON, Rust, GoLang, and ERLANG™ allows sophisticated programming logic to be added to the default function of the multidimensional time series database **1020** without intimate knowledge of the core programming, greatly extending breadth of function. Data retrieved by various data stores such as SQL, graph, key-value, or the multidimensional time series database (MDTSDB) **1020** and the high volume web crawling module **1015** may be further analyzed and transformed into task optimized results by the directed computational graph **1055** and associated general transformer service **1050** and decomposable transformer service **1060** modules. Alternately, data from the multidimensional time series database and high volume web crawling modules may be sent, often with scripted cuing information determining important vertexes **1045***a*, to the graph stack service module **1045** which, employing standardized protocols for converting streams of information into graph representations of that data, for example, open graph internet technology although the invention is not reliant on any one standard. Through the steps, the graph stack service module **1045** represents data in graphical form influenced by any predetermined scripted modifications **1045***a* and stores it in a graph-based data store **1045***b* such as GIRAPH™ or a key value pair type data store REDIS™, or RIAK™, among others, all of which are suitable for storing graph-based information.

[0152] Results of the transformative analysis process may then be combined with further client directives, and additional business rules and practices relevant to the analysis and situational information external to the already available data in the automated planning service module **1030** which also runs powerful information theory **1030***a* based predictive statistics functions and machine learning algorithms to allow future trends and outcomes to be rapidly forecast based upon the current system derived results and choosing each a plurality of possible business decisions. Using all available data, the automated planning service module **1030** may propose business decisions most likely to result in the most favorable business outcome with a usably high level of certainty. Closely related to the automated planning service module in the use of system derived results in conjunction with possible externally supplied additional information (i.e., context) in the assistance of end user business decision making, the action outcome simulation module **1025** with its discrete event simulator programming module **1025***a* coupled with the end user facing observation and state estimation service **1040** which is highly scriptable **1040***b* as circumstances require and has a game engine **1040***a* to more realistically stage possible outcomes of business decisions under consideration, allows business decision makers to investigate the probable outcomes of choosing one pending course of action over another based upon analysis of the current available data.

[0153] FIG. **11** is a block diagram illustrating another exemplary aspect of an embodiment **1100** of a distributed computational graph computing system utilizing an advanced cyber decision platform. According to the aspect the integrated platform **1100**, is very well suited to perform advanced predictive analytics and predictive simulations to produce investment predictions. Much of the trading specific programming functions are added to the automated planning service module **1030** of the modified advanced cyber decision platform **1100** to specialize it to perform trading analytics. Specialized purpose libraries may include but are not limited to financial markets functions libraries **1151**, Monte-Carlo risk routines **1152**, numeric analysis libraries **1153**, deep learning libraries **1154**, contract manipulation functions **1155**, money handling functions **1156**, Monte-Carlo search libraries **1157**, and quant approach securities routines **1158**. Pre-existing deep learning routines including information theory statistics engine **1159** may also be used. The invention may also make use of other libraries and capabilities that are known to those skilled in the art as instrumental in the regulated trade of items of worth. Data from a plurality of sources used in trade analysis are retrieved, much of it from remote, cloud resident **1101** servers through the system's distributed, extensible high bandwidth cloud interface **110** using the system's connector module **135** which is specifically designed to accept data from a number of information services both public and private through interfaces to those service's applications using its messaging service **135***a* routines, due to ease of programming, are augmented with interactive broker functions **1135**, market data source plugins **1136**, e-commerce messaging interpreters **1137**, business-practice aware email reader **1138** and programming libraries to extract information from video data sources **1139**.

[0154] Other modules that make up the advanced cyber decision platform may also perform significant analytical transformations on trade related data. These may include the multidimensional time series data store **1020** with its robust scripting features which may include a distributive friendly, fault-tolerant, real-time, continuous run prioritizing, programming platform such as, but not limited to Erlang/OTP **1121** and a compatible but comprehensive and proven library of math functions of which the C++ math libraries are an example **1122**, data formalization and ability to capture time series data including irregularly transmitted, burst data; the GraphStack service **145** which transforms data into graphical representations for relational analysis and may use packages for graph format data storage such as used by Titan or Neptune or Neo4j **1145** or the like and a highly interface accessible programming interface an example of which may be a RESTful API implemented in a technology like Scala's Akka and Spray libraries, although other, similar, combinations may equally serve the same purpose in this role **1146** to facilitate optimal data handling; the directed computational graph module **155** and its distributed data pipeline **155***a* supplying related general transformer service module **160** and decomposable transformer module **150** which may efficiently carry out linear, branched, and recursive transformation pipelines during trading data analysis may be programmed with multiple trade related functions involved in predictive analytics of the received trade data. Both possibly during and following predictive analyses carried out by the system, results must be presented to clients **1005** in formats best suited to convey both important results for analysts to make highly informed decisions and, when needed, interim or final data in summary and potentially raw for direct human analysis. Simulations which may use data from a plurality of field spanning sources to predict future trade conditions are accomplished within the action outcome simulation module **1025**. Data and simulation formatting may be completed or performed by the observation and state estimation service or massively multiplayer online gaming engine or simulation modeling system **1040** using its ease of scripting and gaming engine to produce optimal presentation results.

[0155] In cases where there are both large amounts of data to be ingested, schematized, normalized, semantified or otherwise cleansed, enriched or formalized and then intricate transformations such as those that may be associated with deep machine learning, predictive analytics and predictive simulations, distribution of computer resources to a plurality of systems may be routinely required to accomplish these tasks due to the volume of data being handled and acted upon. The advanced cyber decision platform employs a distributed architecture that is highly extensible to meet these needs. A number of the tasks carried out by the system are extremely processor intensive and for these, the highly integrated process of hardware clustering of systems, possibly of a specific hardware architecture particularly suited to the calculations inherent in the task, is desirable, if not required for timely completion. The system includes a computational clustering module **1180** to allow the configuration and management of such clusters during application of the AI enabled reasoning platform. While the computational clustering module is drawn directly connected to specific co-modules of the AI enabled reasoning platform these connections, while logical, are for ease of illustration and those skilled in the art will realize that the functions attributed to specific modules of an embodiment may require clustered computing under one use case and not under others. Similarly, the functions designated to a clustered configuration may be role, if not run, dictated. Further, not all use cases or data runs may use clustering.

[0156] FIG. **12** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph **1200**, according to one aspect. In an embodiments, the DCG may be implemented as a self-similar DCG which can be executed in whole or in part across cloud, content delivery networks, at the edge, and across various devices. According to the aspect, a DCG **1200** may comprise a pipeline orchestrator **1201** that may be used to perform a variety of data transformation functions on data within a processing pipeline, and may be used with a messaging system **1210** that enables communication with any number of various services and protocols, relaying messages and translating them as needed into protocol-specific API system calls for interoperability with external systems (rather than requiring a particular protocol or service to be integrated into a DCG **1200**).

[0157] Pipeline orchestrator **1201** may spawn a plurality of child pipeline clusters **1202***a-b*, which may be used as dedicated workers for streamlining parallel processing. In some arrangements, an entire data processing pipeline may be passed to a child cluster **1202***a* for handling, rather than individual processing tasks, enabling each child cluster **1202***a-b* to handle an entire data pipeline in a dedicated fashion to maintain isolated processing of different pipelines

using different cluster nodes **1202***a-b*. Pipeline orchestrator **1201** may provide a software API for starting, stopping, submitting, or saving pipelines. When a pipeline is started, pipeline orchestrator **1201** may send the pipeline information to an available worker node **1202***a-b*, for example using Akka™ clustering. For each pipeline initialized by pipeline orchestrator **1201**, a reporting object with status information may be maintained. Streaming activities may report the last time an event was processed, and the number of events processed. Batch activities may report status messages as they occur. Pipeline orchestrator **1201** may perform batch caching using, for example, an IGFS™ caching filesystem. This allows activities **1212***a-d* within a pipeline **1202***a-b* to pass data contexts to one another, with any necessary parameter configurations.

[0158] A pipeline manager **1211***a-b* may be spawned for every new running pipeline, and may be used to send activity, status, lifecycle, and event count information to the pipeline orchestrator **1201**. Within a particular pipeline, a plurality of activity actors **1212***a-d* may be created by a pipeline manager **1211***a-b* to handle individual tasks, and provide output to data services **1222***a-d*. Data models used in a given pipeline may be determined by the specific pipeline and activities, as directed by a pipeline manager **1211***a-b*. Each pipeline manager **1211***a-b* controls and directs the operation of any activity actors **1212***a-d* spawned by it. A pipeline process may need to coordinate streaming data between tasks. For this, a pipeline manager **1211***a-b* may spawn service connectors to dynamically create TCP connections between activity instances **1212***a-d*. Data contexts may be maintained for each individual activity **1212***a-d*, and may be cached for provision to other activities **1212***a-d* as needed. A data context defines how an activity accesses information, and an activity **1212***a-d* may process data or simply forward it to a next step. Forwarding data between pipeline steps may route data through a streaming context or batch context.

[0159] A client service cluster **1230** may operate a plurality of service actors **1221***a-d* to serve the requests of activity actors **1212***a-d*, ideally maintaining enough service actors **1221***a-d* to support each activity per the service type. These may also be arranged within service clusters **1220***a-d*, in a manner similar to the logical organization of activity actors **1212***a-d* within clusters **1202***a-b* in a data pipeline. A logging service **1230** may be used to log and sample DCG requests and messages during operation while notification service **1240** may be used to receive alerts and other notifications during operation (for example to alert on errors, which may then be diagnosed by reviewing records from logging service **1230**), and by being connected externally to messaging system **1210**, logging and notification services can be added, removed, or modified during operation without impacting DCG **1200**. A plurality of DCG protocols **1250***a-b* may be used to provide structured messaging between a DCG **1200** and messaging system **1210**, or to enable messaging system **1210** to distribute DCG messages across service clusters **1220***a-d* as shown. A service protocol **1260** may be used to define service interactions so that a DCG **1200** may be modified without impacting service implementations. In this manner it can be appreciated that the overall structure of a system using an actor-driven DCG **1200** operates in a modular fashion, enabling modification and substitution of various components without impacting other operations or requiring additional reconfiguration.

[0160] FIG. **13** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph **1200**, according to one aspect. According to the aspect, a variant messaging arrangement may utilize messaging system **1210** as a messaging broker using a streaming protocol **1310**, transmitting and receiving messages immediately using messaging system **1210** as a message broker to bridge communication between service actors **1221***a-b* as needed. Alternately, individual services **1222***a-b* may communicate directly in a batch context **1320**, using a data context service **1330** as a broker to batch-process and relay messages between services **1222***a-b*.

[0161] FIG. **14** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an optional, actor-driven distributed computational graph **1200**, according to one aspect. According to the aspect, a variant messaging arrangement may utilize a service connector **1410** as a central message broker between a plurality of service actors **1221***a-b*, bridging messages in a streaming context **1310** while a data context service **1330** continues to provide direct peer-to-peer messaging between individual services **1222***a-b* in a batch or streaming context **1320**.

[0162] It should be appreciated that various combinations and arrangements of the system variants described above (referring to FIGS. **10-14**) may be possible, for example using one particular messaging arrangement for one data pipeline directed by a pipeline manager **1211***a-b*, while another pipeline may utilize a different messaging arrangement (or may not utilize messaging at all). In this manner, a single DCG **1200** and pipeline orchestrator **1201** may operate individual pipelines in the manner that is most suited to their particular needs, with dynamic arrangements being made possible through design modularity as described above in FIG. **12**.

[0163] FIGS. **15-17** illustrate various exemplary aspects of system architectures and methods of distributed computational graph computing environments. For more detailed information regarding the operation of the various components and aspects described herein with respect to FIGS. **15-17**, please refer to U.S. patent application Ser. No. 15/616,427 which is incorporated herein by reference.

[0164] FIG. **15** is a block diagram of an architecture for a transformation pipeline within a system for predictive analysis of very large data sets using a distributed computational graph computing system **1500** which can coordinate primary, alternate, contingent and emergency configurations (i.e., resilient logic and data persistent specifications relying on different cyber physical graph states or dependencies) . . . . According to the aspect, streaming input from a data filter software module, **1505** serves as input to the first transformation node **1510** of the transformation pipeline. Each transformation node's function **1510**, **1520**, **1530**, **1540**, **1550** is performed on input data stream and transformed output message **1515**, **1525**, **1535**, **1545**, **1555**, **1565** is sent to the next step. In this aspect, transformation node **2 1520** has a second input stream **1560**. The specific source of this input is inconsequential to the operation of the invention and could be another transformation pipeline software module, a data store, human interaction, physical sensors, monitoring equipment for other electronic systems or a stream from the internet as from a crowdsourcing campaign, just to name a few possibilities **1560**. For example, a first input stream may

comprise enterprise knowledge and a second input stream may comprise RAG data from a RAG marketplace. Functional integration of a second input stream into one transformation node requires the two input stream events be serialized. The illustrated system can perform this serialization using a decomposable transformation software module. While transformation nodes are described according to various aspects as uniform shape, such uniformity is used for presentation simplicity and clarity and does not reflect necessary operational similarity between transformations within the pipeline. It should be appreciated that one knowledgeable in the field will realize that certain transformations in a pipeline may be entirely self-contained; certain transformations may involve direct human interaction, such as selection via dial or dials, positioning of switch or switches, or parameters set on control display, all of which may change during analysis; other transformations may require external aggregation or correlation services or may rely on remote procedure calls to synchronous or asynchronous analysis engines as might occur in simulations among a plurality of other possibilities. For example, engines may be singletons (composed of a single activity or transformation). Furthermore, leveraging the architecture in this way allows for versioning and functional decomposition (i.e. embedding entire saved workflows as single nodes in other workflows). Further according to the aspect, individual transformation nodes in one pipeline may represent function of another transformation pipeline. It should be appreciated that the node length of transformation pipelines depicted in no way confines the transformation pipelines employed by the invention to an arbitrary maximum length **1510**, **1520**, **1530**, **1540**, **1550**, as, being distributed, the number of transformations would be limited by the resources made available to each implementation of the invention. It should be further appreciated that there need be no limits on transform pipeline length. Output of the last transformation node and by extension, the transform pipeline, **1550** may be sent back to messaging software module **562** for pre-decided action dissemination or to another pipeline for action determination and execution.

[0165] FIG. **21** is a block diagram illustrating an exemplary system architecture for a distributed, composite symbolic and non-symbolic AI platform for advanced reasoning **2120**, according to an embodiment. According to the embodiment, the platform **2120** aims to enable vast automation of modeling/analysis workflows by exploring large potential parameter combinations. Platform **2120** can be configured for extracting and curating knowledge into structured ontologies to complement neuro-symbolic AI capabilities. Platform **2120** can provide an iterative multi-dimensional optimization and evaluation process to explore the relative performance of the different techniques, datasets, and "fitness of purpose" definitions (e.g., security, licenses, traceability/provenance, etc.) associated with a plurality of AI models.

[0166] According to the embodiment, platform **2120** is configured as a cloud-based computing platform comprising various system or sub-system components configured to provide functionality directed to the execution of composite symbolic generative AI reasoning and action. Exemplary platform systems can include a distributed computational graph (DCG) computing system **121**, a curation computing system **122**, a marketplace computing system **123**, and a context computing system **124**, a hierarchical process manager computing system **2121**, an embedding refinement computing system **2122**, a multi-modal alignment computing system **2123**, an ontology extraction computing system **2124**, a model blending computing system **2125**, and a hyperparameter optimization computing system **2126**. Platform **2120** may further comprise various databases for storing a plurality of models **2127**, vectors/embeddings **2128**, and knowledge graphs **2129**. In some embodiments, systems **121**-**124** and **2121**-**2126** may each be implemented as standalone software applications or as a services/microservices architecture which can be deployed (via platform **120** or **2120**) to perform a specific task or functionality. In such an arrangement, services can communicate with each other over an appropriate network using lightweight protocols such as HTTP, gRPC, or message queues. This allows for asynchronous and decoupled communication between services. Services may be scaled independently based on demand, which allows for better resource utilization and improved performance. Services may be deployed using containerization technologies such as Docker and orchestrated using container orchestration platforms like Kubernetes. This allows for easier deployment and management of services.

[0167] The composite symbolic AI reasoning and action platform **2120** can enable a more flexible approach to incorporating machine learning (ML) models into the future of the Internet and software applications; all facilitated by a distributed computational graph (DCG) architecture capable of dynamically selecting, creating, and incorporating trained models with external data sources and marketplaces for data and algorithms.

[0168] The platform **2120** emphasizes the importance of considering various types of semantics, including, but not limited to, symbolic, distributional, compositional distributional, and information-theoretic compositional distributional semantics. This consideration allows the platform to capture and represent meaning at different levels of abstraction and compositionality, enabling more comprehensive and nuanced understanding of the input data. By explicitly addressing these different types of semantics, the platform **2120** can leverage the strengths of each approach and combine them in a unified framework.

[0169] In some cases, the platform may be configured to label non-textual data (e.g., images or scenes) with textual descriptions before computing embeddings. This labeling step converts the non-textual data into textual representations, which can then be processed using language-based techniques that are more well-developed and understood. By bridging the gap between non-textual and textual data through labeling, the platform can take advantage of the rich semantic information captured by language models and embeddings. After labeling non-textual data (if applicable), the platform computes numerical embedding representations of the input data. These embeddings capture the semantic properties and relationships of the data in a dense vector format, enabling efficient storage, retrieval, and comparison. The computed embeddings may then be persisted in a vector database, which allows for fast and scalable similarity search (e.g., cosine, dot product, Euclidean, etc.) and other vector operations. The persisted embeddings serve as input features for downstream AI models, such as neural networks or symbolic reasoning engines. By incorporating the embeddings into these models, the platform can leverage the semantic information captured by the embeddings to

improve the performance and generalization of the AI system. The integration of embeddings with downstream models allows for seamless knowledge transfer and enables the AI system to make informed decisions based on the semantic understanding of the input data.

[0170] According to the embodiment, platform **2120** utilizes a plurality of neural network models that generate vector embeddings representing input data. The plurality of neural network models may be stored in model database **2126**. Each of the plurality of neural network models may be associated with a specific type of AI system (e.g., gaming, medical diagnosis, sentiment analysis, LLM, recommendation system, virtual reality, autonomous vehicle, robotics, etc.). As such, models and AI systems may be used interchangeably throughout this specification. Platform can use various neural network architectures such as Transformers, Long Short-Term Memory (LSTM), or convolutional neural networks (CNNs) to process different types of input data (text, images, audio, etc.). In some implementations, the platform can train these models on large datasets to learn meaningful vector representations (i.e., embeddings) that capture the semantic properties and relationships of the input data. Platform may leverage techniques like transfer learning, fine-tuning, or multi-task learning to improve the quality and generalizability of the embeddings. For example, a text classification system that uses a BERT model to generate embeddings for input documents, and a CNN model to generate embeddings for images associated with the documents. The embeddings may then be concatenated and fed into a final classification layer.

[0171] Embeddings are dense vector representations that capture the semantic meaning and relationships of data points. Vector databases **2128** store and index these embeddings for efficient retrieval and similarity search. Platform **2120** can facilitate iterative refinement which updates the embeddings based on new data or feedback to improve their quality and representational power. For example, a recommendation AI system uses embeddings to represent user preferences and item characteristics. As users interact with the system, their feedback is used to iteratively refine the embeddings, making them more accurate predictors of user interests. The refined embeddings are stored in a vector database for fast retrieval during recommendation generation.

[0172] According to the embodiment, a knowledge graph database **2129** is present comprising symbolic facts, entities, and relations. Platform may use an ontology or schema for the knowledge graph that defines the types of entities, relationships, and attributes relevant to a given AI system's domain. Platform populates the knowledge graph with data from structured sources (e.g., databases) and unstructured sources (e.g., text documents) using information extraction techniques like named entity recognition, relation extraction, and/or co-reference resolution. Knowledge graph database **2129** may be implemented as a graph database (e.g., Neo4j, ArangoDB) or a triple store (e.g., Apache Jena) to efficiently store and query the knowledge graph. Knowledge graph database **2129** may comprise a plurality of knowledge graphs, wherein knowledge graphs may be associated with a specific domain. For example, a biomedical knowledge graph that contains entities such as drugs, diseases, and genes, and relationships like "treats", "causes", and "interacts with". This exemplary knowledge graph is populated from structured databases like DrugBank and UniProt, as well as from unstructured sources like publications.

[0173] According to the embodiment, hierarchical process manager computing system **2121** is present and configured to route processing based on certainty thresholds (e.g., certification) and challenge-based verification. Platform may define a hierarchy of reasoning tasks and subtasks that break down the AI system's (e.g., models) decision-making process into manageable steps. Process manager **2121** orchestrates the execution of these tasks and routes data to the appropriate models or knowledge sources based on predefined rules or learned policies. Process manager **2121** or an administrator may set certainty thresholds for each task to determine when the system should proceed to the next step or seek additional information/verification. Process manager **2121** can design and leverage challenge-based verification mechanisms (e.g., adversarial examples, counterfactual reasoning, etc.) to test the robustness and reliability of the AI system's decisions. For example, a fraud detection system that first uses a rule-based model to flag potentially fraudulent transactions based on simple heuristics. If the certainty of the rule-based model is below a threshold, the transaction is routed to a more complex machine learning model for further analysis. The final decision is then verified through a challenge-response mechanism that asks the user to provide additional authentication.

[0174] Hierarchical process definitions break down complex reasoning tasks into smaller, more manageable steps. Specialized routing dynamically selects the most appropriate AI models or knowledge sources for each subtask based on their capabilities and performance. For example, an autonomous vehicle AI system uses a hierarchical process to handle different driving situations. At a top level, the platform decides whether to use models specialized for highway driving, city navigation, or parking. Within each specialization, further routing occurs to handle specific challenges like merging, pedestrian detection, or parallel parking.

[0175] Certification involves validating the performance and reliability of AI models through rigorous testing and evaluation. Challenge-based verification sets up specific test cases or benchmarks that models must pass to be considered certified for a given task. Model blending combines the outputs of multiple models using weighted averaging or more sophisticated methods to improve overall performance. For example, a financial forecasting AI system blends the predictions of several certified models, each specializing in different asset classes or market conditions. The blending weights are adjusted based on each model's historical performance and current market challenges.

[0176] According to the embodiment, embedding refinement computing system **2122** is present and configured to incorporate data from one or more knowledge graphs. Embedding refinement **2122** may utilize algorithms that can query the knowledge graph to retrieve relevant facts, entities, and relationships based on the input data and the current reasoning context. Retrieved knowledge may be used to refine the vector embeddings generated by the neural networks models, incorporating symbolic information into the distributed representations (embeddings). In some implementations, techniques like attention mechanisms, graph convolutions, and/or knowledge-aware language models to effectively combine the embeddings with the knowledge graph data. For example, consider a recommendation system

that generates initial embeddings for users and items based on their interaction history. The platform then queries a knowledge graph of user demographics, item categories, and contextual factors (e.g., time, location) to retrieve relevant information. This information can be used to refine the user and item embeddings through, for example, a graph attention network, incorporating the contextual knowledge into the recommendations.

[0177] A Graph Attention Network (GAT) is a type of neural network architecture designed to operate on graph-structured data. It leverages the concept of self-attention to compute the importance of neighboring nodes in a graph, allowing the network to focus on the most relevant information when making predictions or generating representations. The key advantage of GATs is their ability to capture the importance of neighboring nodes based on their feature compatibility, allowing the network to focus on the most relevant information. This attention mechanism enables GATs to effectively handle graph-structured data and learn meaningful representations of nodes and their relationships.

[0178] According to the embodiment, model blending computing system **2125** is present and configured to apply expressive weighting schemes to model combinations. Platform may leverage a model blending architecture that can combine the outputs of multiple neural network models based on their individual strengths and weaknesses. Such a system may use weighting schemes that can dynamically adjust the contribution of each model based on factors like uncertainty, task complexity, or domain relevance. Techniques such as Bayesian model averaging, mixture of experts, and/or ensemble learning may be implemented to optimally blend the model outputs. For example, consider a sentiment analysis system that combines the outputs of three models: a Naive Bayes model, an LSTM model, and a BERT model. Model blending **2125** assigns weights to each model based on their confidence scores and the complexity of the input text. The weights are learned through a reinforcement learning approach that optimizes the overall sentiment classification performance.

[0179] According to the embodiment, platform **2120** implements feedback loops considering security, licensing, provenance, and collaborative development. Feedback loops allow the AI system to learn and adapt based on real-world performance and user feedback. Security considerations ensure that the AI system is protected against malicious attacks or misuse. For example, implementing secure communication protocols and access controls mechanisms to protect sensitive data and prevent unauthorized access to the AI system. Economic factors optimize the cost-benefit trade-offs of different model configuration and deployment strategies. Licensing takes into account the legal rights and restrictions associated with using certain datasets or model components. Platform **2120** can monitor and ensure compliance with the terms and conditions of licensing of datasets, models, and tools used by the platform. Traceability/provenance keeps track of the lineage of data sources, training processes, and model versions used in each output. Model collaboration enables different teams or organizations to jointly develop, test, deploy, and improve AI models while maintaining security and provenance. For example, a healthcare AI system incorporates feedback from doctors and patients to continually refine its diagnosis and treatment recommendations. The system logs each decision's provenance and securely shares performance data with research partners under appropriate licensing terms. As another example, consider a federated learning system for medical image analysis that allows multiple hospitals to collaboratively train a deep learning model without sharing raw patient data. The system uses secure multi-party computation and differential privacy techniques to protect patient privacy. The model's provenance is tracked using a blockchain-based ledger, ensuring transparency and accountability. The system also includes a licensing management component that enforces usage restrictions based on each hospital's data sharing agreements.

[0180] According to the embodiment, multi-modal computing system **2123** is present and configured to align and synchronize representations across different data modalities (e.g., text, images, audio, etc.) to create a unified and consistent representation of the input data. Multi-modal system **2123** may implement techniques such as cross-modal attention, multi-modal fusion, and/or joint embedding spaces to effectively combine information from different modalities. Platform can utilize domain-specific knowledge (e.g., physics, psychology) (from knowledge graphs) to ensure the generated representations are consistent and realistic across modalities. For example, consider a virtual assistant that can process user queries in the form of text, speech, and images. The multi-modal system **2123** uses cross-modal attention to align the representations of the different input modalities, creating a unified query representation. For example, if the user asks, "What is the breed of the dog in this picture?", the engine aligns the image embedding with the relevant parts of the text embedding to understand that the query is about identifying the dog breed.

[0181] According to the embodiment, hyperparameter optimization computing system **2126** is present and configured to use information theoretic guidance for optimization tasks. System **2126** may implement an automated hyperparameter optimization framework (e.g., Bayesian optimization, evolutionary algorithms, etc.) to search for the best combination of model architectures, training settings, and embedding techniques. System **2126** can use information-theoretic measures (e.g., mutual information, Kullback-Leibler divergence) to guide the optimization process and select hyperparameters that maximize the information content and generalization ability of the learned representations. In some implementations, platform **2120** may develop efficient parallel computing strategies to speed up the hyperparameter search process and explore a larger space of configurations. For example, consider a natural language generation system that uses a variational autoencoder (VAE) to generate diverse and coherent sentences. The hyperparameter optimization system **2126** uses Bayesian optimization to search for the best combination of latent space dimensionality, regularization strength, and decoder architecture. The optimization is guided by an information-theoretic objective that maximizes the mutual information between the latent space and the generated sentences, ensuring that the VAE captures meaningful and interpretable representations.

[0182] Embedding generation techniques convert raw data into dense vector representations. Different techniques (e.g., Word2Vec, GloVe, BERT, etc.) have different strengths and weaknesses. Training data selection and processing impact the quality and generalizability of the learned embeddings. Model type (e.g., feedforward, recurrent, convolutional, etc.) and architecture (e.g., number of hidden layers, hidden

units, etc.) influence the embedding learning process. Hyperparameter optimization searches for the best combination of embedding generation technique, training data, model type, and architecture to maximize the embedding quality and downstream task performance. For example, a sentiment analysis AI system experiments with different embedding generation techniques (Word2Vec, GloVe) and model architectures (long short-term memory, convolutional neural network) to find the best combination for the specific domain and language. The platform also tunes hyperparameters such as, for example, embedding dimensionality, context window size, and learning rate to further improve performance.

[0183] Information theory provides a mathematical framework for quantifying and understanding the properties of embeddings, such as their information content, compression, and generalization ability. Theoretical analysis applies information-theoretic concepts and measures to study the effectiveness of different embedding methods and guide their development. For example, platform **2120** analyzes the mutual information between word embeddings and their context to quantify the amount of semantic information captured. Platform may then use this analysis to propose a new embedding method that maximizes mutual information while minimizing redundancy, resulting in more informative and compact representations.

[0184] According to the embodiment, ontology extraction computing system **2124** is present and configured to link embeddings to symbolic knowledge graphs with defined ontologies (e.g. in OWL or RDFS). Connectionist models (e.g., neural networks) learn distributed representations that capture patterns and relationships in data, but these representations are not directly interpretable as symbolic knowledge. Extracting symbolic representations involves techniques like rule extraction, decision tree induction, or clustering to distill the learned knowledge into a symbolic form that allows for additional forms of inference and deduction and simulation modeling not possible with connectionist approaches. Many scientific theories, proofs, equations, and principles become accessible for exploration, refinement, or incorporation when symbolic knowledge formulation is completed and ongoing knowledge corpora curation is engaged in. Linking the extracted symbolic representations to existing knowledge graphs enables the integration of the learned knowledge with prior domain expertise, facilitating more comprehensive and explainable reasoning. For example, a medical diagnosis AI system based on a deep neural network learns to classify diseases from patient data. The platform **2120** extracts symbolic rules from the trained network, expressing the learned decision boundaries in terms of interpretable clinical features. These rules are then linked to a medical knowledge graph, allowing the system to explain its reasoning in terms of known disease mechanisms and treatment guidelines.

[0185] Ontology extraction system **2124** can leverage algorithms that can analyze the learned vector embeddings and extract symbolic representations (e.g., entities, relationships, rules, etc.) that capture the underlying semantic structure in lieu of declared ontologies or in addition to them or to refine them. Additionally, vector database content of interest and its associated links to knowledge graph data or data elements can be used iteratively to improve results. Furthermore, since system can engage in temporal tagging of terms and knowledge and ontologies, it is possible to analyze model evolution and to conduct historical searches in assembled data elements based not only on semantic similarity in vector terms but in the knowledge graph and other data stores and to do so with the benefit of additional semantic consistency in terms. This essentially aids in more direct consideration of the observer bias in both knowledge creation, curation, and searching which can reflect term and concept evolution and dampen or filter such effects for the user or AI agents or processes when directed. In some implementations, techniques such as, for example, clustering, dimensionality reduction, and/or rule mining may be used to capture the underlying semantic structure. Ontology alignment and linking methods can be used to map the extracted symbolic representations to existing concepts and relationships in the knowledge graph, enabling seamless integration of the learned knowledge with prior domain expertise. For example, consider a legal case analysis system that uses a BERT or Gemini model to generate embeddings for legal documents. The ontology extraction system can use hierarchical clustering to group the embeddings into semantically related clusters, and then apply association rule mining to discover relationships between the clusters. The extracted ontology is then linked to a vector database, traditional database of cases and personas, and a legal knowledge graph that contains concepts like laws, precedents, and jurisdictions, enabling the system to reason about legal cases and principles using both the learned embeddings and the symbolically represented knowledge as well as both structured and unstructured data. Presented reasoning may be from symbolic or connectionist processes or both. In many cases a connectionist post-processing stage to wrap content from narrow symbolic elements can enhance usability and approachability.

[0186] Symbolic knowledge represents facts, rules, and relationships using structured formalisms like ontologies or knowledge graphs. Connectionist models, such as neural networks, learn distributed representations from data with explicit symbolic structure. Retrieval augmented generation (RAGs) enhance language models by incorporating an external knowledge retrieval mechanism. During the generation process, the model queries a knowledge base to retrieve relevant information and condition its outputs on both the input context and the retrieved knowledge. Expressive weightings allow the platform to dynamically adjust the influence of different knowledge sources based on their relevance to the current context. For example, a customer support AI system uses a knowledge graph of product information and troubleshooting procedures (symbolic) alongside a neural language model trained on past support interactions (connectionist). When generating responses to customer inquiries, the system employs RAG to retrieve relevant information from the knowledge graph and the language model to condition the responses on both the customer's input and the retrieved knowledge. The system assigns higher weights to knowledge sources that are more pertinent to the specific inquiry, ensuring accurate and context-appropriate responses.

[0187] According to the embodiment, platform **2120** can implement scene generation with knowledge graph elements for contextual refinement. Scene generation creates realistic images, videos, or three-dimensional (3D) environments based on textual descriptions or other input data. Knowledge graph elements, such as object properties, relationships, and constraints, can be leveraged to guide the scene generation

process to ensure consistency and realism. Contextual refinement adjusts the generated scene based on the specific context and purpose of the AI application. For example, a virtual reality AI system generates immersive scenes and sequences for training simulations. The platform can use a knowledge graph of object properties (e.g., materials, size, physics) and relationships (e.g., spatial constraints) to ensure physically plausible layouts. The generated scenes may be refined based on the specific training scenario and user interactions. The system may also focus, for this training scenario, on states or state transitions that are particularly frequent or severe to aid a human or ai process in repetitive attempts at navigating such scenarios of interest or concern. This may be enhanced via the inclusion of frequency and severity analysis and distribution compilation from both empirical and synthetic data sets about specific system components or actors.

[0188] In addition to visual and textual data, platform **2120** incorporates other sensory modalities like sound and smell to create more immersive and realistic experiences. Harmonizing multiple senses involves aligning and synchronizing the different modalities to create a coherent and consistent output. For example, a gaming AI system generates realistic soundscapes and ambient scents to match the visual environment. The platform **2120** ensures that the sound of footsteps matches the character's movement and the smell of a forest scene includes the scent of pine trees and damp moss.

[0189] According to some embodiments, platform **2120** can be leveraged to develop enterprise-specific or domain-specific models, which can be "small models" that are more efficient, accurate, or predictable in specific contexts and prompts. These small models can be integrated into platform **2120** as specialized components that are selected and deployed based on the specific domain or task at hand. Hierarchical process manager **2121** can route the input data to the appropriate small model based on the context, ensuring optimal performance and efficiency.

[0190] Furthermore, platform **2120** can provide effective orchestration, selection, and management of small models, particularly in restricted or regulated domains such as medicine, investing, law, insurance, and banking. Platform's model blending system **2125** and feedback loops can be extended to incorporate the orchestration and management of small models, taking into account factors such as data nutrition labels, model labels, and administrative processes. The system can leverage existing system/platforms, and ML ops to facilitate the effective deployment and governance of small models.

[0191] In some implementations, the platform can train and deploy hybrid models that combine foundational models with additional datasets and training processes to generate explanations, estimations, and specialized models with different performance characteristics. The platform can incorporate these hybrid models as part of its model blending and composition capabilities, leveraging the strengths of different models for tasks such as explainability, auditing, and ML ops training/supervision. The ontology extraction system **2124** can help in generating explanations and traces from these hybrid models, enhancing the interpretability and transparency of the system's reasoning process.

[0192] The platform addresses the security and intellectual property concerns associated with foundational models, which are considered core IP and may be less likely to be exposed due to their immense cost, time, and sensitivity. The platform can utilize small models as a means of model obfuscation, where the sensitive foundational models are distilled into smaller, more focused models that can be deployed with less risk of information leakage. The platform can also incorporate techniques for model theft detection, such as using vector similarity scoring and hash-based functions to identify potential infringement of small models derived from foundational models.

[0193] The platform can leverage the use of ML ops optimization routines for model selection, training, classification, and dynamic deployment based on fitness for purpose. The platform can integrate these optimization techniques to dynamically select and deploy the most suitable small models based on the specific task, context, and performance requirements. The platform can also optimize model hyperparameters, such as temperature and token length, to balance performance, efficiency, and the generation of hallucinations or other undesired outputs.

[0194] By integrating the concepts and techniques related to small models, the platform can achieve greater efficiency, specialization, explainability, security, and adaptability. The use of domain-specific small models allows the system to tailor its reasoning and decision-making processes to specific contexts, while the orchestration and management capabilities ensure the effective deployment and governance of these models. The hybrid models and explainability techniques enhance the interpretability and transparency of the platform, enabling users to understand and trust its reasoning process. The model obfuscation and theft detection mechanisms may help protect the intellectual property and sensitive information associated with the core foundational models. Overall, the integration of small models into platform **2120** aligns with the broader goals of achieving advanced reasoning, adaptability, explainability, and security in AI systems. By leveraging the strengths of small models and incorporating them into the various components and processes of the system, the platform aims to push the boundaries of AI capabilities while addressing the practical challenges and requirements of real-world applications.

[0195] FIG. **22** is a block diagram illustrating an exemplary model architecture of the Transformer, consisting of an Encoder (the components on the left side of the illustration) and a Decoder (the components on the right side of the illustration). Transformers form the backbone of large language models. A large language model (LLM) is a type of artificial intelligence algorithm that utilizes deep learning techniques and massively large datasets to understand, summarize, generate and predict new content. The term generative AI is also closely connected to LLMs, which are a type of generative AI that has been specifically architected to help generate text-based content. All language models are first trained on a set of data, and then they make use of various techniques to infer relationships and then generate new content based on the trained data. Language models are commonly used in natural language processing (NLP) applications where a user inputs a query in natural language to generate a result.

[0196] An LLM is the evolution of the language model concept in AI that dramatically expands the data used for training and inference. In turn, it provides a massive increase in the capabilities of the AI model. While there isn't a universally accepted figure for how large the data set for training needs to be, an LLM typically has at least one

billion or more parameters. Parameters are a machine learning term for the variables present in the model on which it was trained that can be used to infer new content.

[0197] Modern LLMs that have emerged within the last decade are based on transformer models, which are neural networks commonly referred to as transformers. With a large number of parameters and the transformer model, LLMs are able to understand and generate accurate responses rapidly, which makes the AI technology broadly applicable across many different domains. Some LLMs are referred to as foundation models, a term coined by the Stanford Institute for Human-Centered Artificial Intelligence in 2021. A foundation model is so large and impactful that it serves as the foundation for further optimizations and specific use cases.

[0198] LLMs take a complex approach that involves multiple components. At the foundational layer, an LLM needs to be trained on a large volume, sometimes referred to as a corpus, of data that is typically petabytes in size. The training can take multiple steps, usually starting with an unsupervised learning approach. In that approach, the model is trained on unstructured data and unlabeled data. The benefit of training on unlabeled data is that there is often vastly more data available. At this stage, the model begins to derive relationships between different words and concepts.

[0199] The next step for some LLMs is training and fine-tuning with a form of self-supervised learning. Here, some data labeling has occurred, assisting the model to more accurately identify different concepts.

[0200] Next, the LLM undertakes deep learning as it goes through the transformer neural network process. The transformer model architecture enables the LLM to understand and recognize the relationships and connections between words and concepts using a self-attention mechanism. That mechanism is able to assign a score, commonly referred to as a weight, to a given item (called a token) in order to determine the relationship.

[0201] Once an LLM has been trained, a base exists on which the AI can be used for practical purposes. By querying the LLM with a prompt, the AI model inference can generate a response, which could be an answer to a question, newly generated text, summarized text or a sentiment analysis report.

[0202] LLMs have become increasingly popular because they have broad applicability for a range of NLP tasks, including but not limited to, text generation, translation, content summary, rewriting content, classification and categorization, sentiment analysis, and conversational AI and chatbots.

[0203] There are numerous advantages that LLMs provide to organizations and users including, for example, extensibility and adaptability, flexibility, performance, accuracy, and ease of training. LLMs can serve as a foundation for customized use cases. Additional training on top of an LLM can create a finely tuned model for an organization's specific needs. One LLM can be used for many different tasks and deployments across organizations, users and applications. Modern LLMs are typically high-performing, with the ability to generate rapid, low-latency responses. As the number of parameters and the volume of trained data grow in an LLM, the transformer model is able to deliver increasing levels of accuracy. Many LLMs are trained on unlabeled data, which helps to accelerate the training process.

[0204] While there are many advantages to using LLMs, there are also several challenges and limitations such as, development costs (e.g., LLMs generally require large quantities of expensive graphics processing unit hardware and massive data sets), operational costs, bias, hallucination (e.g., AI hallucination occurs when an LLM provides an inaccurate response that is not based on trained data), complexity (e.g., with billions, or more, of parameters, modern LLMs are exceptionally complicated technologies that can be particularly complex to troubleshoot), and glitch tokens which are maliciously designed prompts to cause the LLM to malfunction.

[0205] There is an evolving set of terms to describe the different types of large language models. Among the common types are zero-shot model, fine-tuned or domain-specific models, language representation models, and multimodal model. A zero-shot model is a large, generalized model trained on a generic corpus of data that is able to give a fairly accurate result for general use cases, without the need for additional training. GPT-3 is often considered a zero-shot model. Fine-tuned/domain-specific models require additional training on top of a zero-shot model and can lead to a fine-tuned, domain-specific model. One example is OpenAI Codex, a domain-specific LLM for programming based on GPT-3. One example of a language representation model is Bidirectional Encoder Representations from Transformers (BERT), which makes use of deep learning and transformers well suited for NLP. Originally LLMs were specifically tuned just for text, but with the multimodal approach it is possible to handle both text and images. GPT-4 is an example of this type of model.

[0206] There are multiple important components significantly influencing the architecture of LLMs. The size of an LLM, often quantified by the number of parameters, greatly impacts its performance. Larger models tend to capture more intricate language patterns but require increased computational resources for training and inference. Effective input representations, like tokenization, are vital as they convert text into formats that the model can process. Special tokens, like [CLS] and [September] in BERT, enable the model to understand sentence relationships and structure. Pre-training objectives define how a model learns from unlabeled data. For instance, predicting masked words in BERT helps the model learn contextual word relationships, while autoregressive language modeling in GPT-3 teaches coherent text generation. The computational demands of LLMs can be mitigated through techniques like knowledge distillation, model pruning, and quantization. These methods maintain model efficiency without sacrificing performance. How a model generates output is essential. Greedy decoding, beam search, and nucleus sampling are techniques used in LLMs for coherent and diverse output generation. These methods balance between accuracy & creativity, while creating a significant difference between LLMs and traditional language models.

[0207] The illustrated Transformer comprises an Encoder and a Decoder. The Encoder takes input embeddings and processes them through a stack of layers (represented as dashed box **2210**). Each layer consists of: positional encoding, which adds position information to the input embeddings; multi-head attention, which allows the model to attend to different parts of the input sequence; add and norm, which applies residual connection and layer normalization; feed forward, which is a fully connected feed-forward network; and add and norm which is another residual connection and layer normalization.

[0208] The power of the transformer model lies in the self-attention mechanism. This mechanism contributes to accelerated learning compared to traditional models such as long short-term memory models. Self-attention empowers the transformer model with the remarkable capability to meticulously scrutinize distinct segments of a given sequence or even encompass the entire contextual essence of a sentence. This profound contextual awareness enables the model to make predictions with an elevated degree of accuracy and relevance.

[0209] The input embedding **2201** to the Encoder is a sequence of tokens, typically represented as integers. Each token is mapped to a learnable embedding vector of a fixed size. The embedding layer is a lookup table that converts each token into its corresponding dense vector representation. The embeddings are learned during training and capture semantic and syntactic relationships between tokens.

[0210] A dense vector representation, also known as a dense embedding or a continuous vector representation, is a way of representing data, particularly words or tokens, as dense vectors in a high-dimensional continuous space. In the context of natural language processing (NLP) and language models, dense vector representations are used to capture semantic and syntactic information about words or tokens. Each word or token is mapped to a fixed-size vector of real numbers, typically with hundreds or thousands of dimensions. Each word or token is represented by a vector of a fixed size, regardless of the length of the input sequence. The size of the vector is a hyperparameter that is determined during model design. The vectors exist in a continuous high-dimensional space, where each dimension represents a latent feature or aspect of the word or token. The continuous nature allows for capturing fine-grained relationships and similarities between words. The dense vector representations are learned during the training process of the model. The model learns to assign similar vectors to words that have similar meanings or occur in similar contexts. The dense vector representations aim to capture semantic and syntactic relationships between words. Words that have similar meanings or are used in similar contexts tend to have similar vector representations. Dense vector representations allow for performing algebraic operations on words, such as addition and subtraction. These operations can capture analogies and relationships between words, such as "prince"−"man"+"woman"≈"princess". Dense vector representations serve as input features for various downstream NLP tasks, such as text classification, sentiment analysis, named entity recognition, and machine translation. The dense representations provide a rich and informative input to the models, enabling them to learn patterns and make predictions. Some popular examples of dense vector representations include, but are not limited to, Word2Vec, Global Vectors for Word Representations (GloVe), FastText, and BERT.

[0211] After the input embedding layer, positional encoding **2202** is added to the input embedding to provide position information to the model. Since the Transformer architecture doesn't have inherent recurrence or convolution, positional encodings help capture the order and relative positions of tokens. The positional encodings are typically sine and cosine functions of different frequencies, allowing the model to learn relative positions. The positional encodings have the same dimensionality as the input embeddings and are summed with them.

[0212] The Encoder utilizes a multi-head attention mechanism **2203** which is a key component of the Transformer architecture. It allows the Encoder to attend to different parts of the input sequence and capture dependencies between tokens. The attention mechanism computes three matrices: Query (Q), Key (K), and Value (V). The Query, Key, and Value matrices are obtained by linearly projecting the input embeddings using learned weight matrices. The attention scores are computed by taking the dot product of the Query matrix with the transpose of the Key matrix, followed by scaling and applying a softmax function. The attention scores determine the importance of each token in the input sequence for a given position. The Value matrix is then multiplied with the attention scores to obtain the weighted sum of the values, which forms the output of the attention mechanism. Multi-Head Attention splits the Query, Key, and Value matrices into multiple heads, allowing the model to attend to different aspects of the input simultaneously. The outputs from each head are concatenated and linearly projected to obtain the final output of the Multi-Head Attention layer **2203**.

[0213] After the Multi-Head Attention layer, a residual connection is applied, followed by Layer Normalization at add and norm **2204**. The residual connection adds the input embeddings to the output of the attention layer, helping the model learn faster and deeper. Layer Normalization normalizes the activations across the features, stabilizing the training process.

[0214] The Feed Forward layer **2205** is a fully connected neural network applied to each position of the Encoder's hidden states. It consists of two linear transformations with a Rectified Linear Unit (ReLU) activation function in between. The purpose of the Feed Forward layer is to introduce non-linearity and increase the model's capacity to learn complex representations. The output of the Feed Forward layer has the same dimensionality as the input embeddings. A residual connection and Layer Normalization **2204** are applied after the Feed Forward layer.

[0215] The Encoder layers **2210** are stacked Nx times, where N is a hyperparameter that determines the depth of the Encoder. Each layer follows the same structure: Multi-Head Attention, Add & Norm, Feed Forward, and Add & Norm. By stacking multiple Encoder layers, the model can capture hierarchical and long-range dependencies in the input sequence. The output of the final Encoder layer represents the encoded input sequence, which is then passed to the Decoder for generating the output sequence.

[0216] The Decoder generates the output probabilities. It has a similar structure to the Encoder, with a few additions. The Decoder takes output embeddings and processes them through a stack of layers (represented as dashed box **2220**). The output embedding layer **2206** takes the previous output tokens (shifted right by one position) and converts them into dense vectors. Each token is mapped to a learnable embedding vector of a fixed size. The embedding vectors capture semantic and syntactic relationships between tokens.

[0217] Positional encoding **2207** is added to the output embedding to provide position information to the model. Since the Transformer architecture does not have inherent recurrence or convolution, positional encodings help capture the order and relative positions of tokens. The positional encodings are typically sine and cosine functions of different frequencies, allowing the model to learn relative positions.

[0218] The masked multi-head attention **2208** mechanism prevents the model form attending to future tokens. This layer performs self-attention on the Decoder's input sequence. It allows the Decoder to attend to different parts of its own input sequence. The attention is "masked" to prevent the Decoder from attending to future tokens, ensuring that the predictions are based only on the previously generated tokens. Multi-head attention splits the input into multiple heads, allowing the model to attend to different aspects of the input simultaneously.

[0219] After the masked multi-head attention, a residual connection is applied follows by layer normalization via add and norm **2204**. The residual connection adds the input to the output of the attention layer, helping the model learn faster and deeper. Layer normalization normalizes the activations across the features, stabilizing the training process.

[0220] The multi-head attention **2209** layer performs attention between the Decoder's hidden states and the Encoder's output. It allows the Decoder to attend to relevant parts of the input sequence based on the Encoder's representations. The attention weights are computed based on the compatibility between the Decoder's hidden states and Encoder's outputs.

[0221] Another add and norm **2204** layer is then followed by feed forward network **2205**. This a fully connected feed-forward network applied to each position of the Decoder's hidden states. It consists of two linear transformations with a Rectified Linear Unit (ReLU) activation in between. The feed forward layer helps the model capture nonlinear interactions and increases the model's capacity.

[0222] Another add and norm **2204** layer is followed by linear **2212** and softmax **2213** layers. The final hidden states of the Decoder are passed through a linear transformation to project them into the vocabulary space. Vocabulary space refers to the set of all unique tokens or words that the model can generate or predict. In the context of language models, the vocabulary is a predefined set of tokens that the model is trained on and can output. When the Decoder's final hidden states are passed through a linear transformation, they are projected into a vector space with the same dimensionality as the size of the vocabulary. Each dimension in this space corresponds to a specific token in the vocabulary. For example, the model has a vocabulary of 10,000 unique tokens. The linear transformation would project the Decoder's hidden states into a 10,000-dimensional vector space. Each element in this vector represents the model's predicted probability or score for the corresponding token in the vocabulary.

[0223] A softmax function is applied to the projected values (vectors) to generate output probabilities over the vocabulary. The softmax function normalizes the values so that they sum up to 1, representing a probability distribution over the vocabulary. Each probability indicates the likelihood of a specific token being the next output token. The token with the highest probability is selected as the next output token. During the model's training, the objective is to maximize the probability of the correct next token given the input sequence and the previously generated tokens. The model learns to assign higher probabilities to the tokens that are more likely to appear based on the context. At inference time, the token with the highest probability in the vocabulary space is selected as the next output token. This process is repeated iteratively, with the generated token being fed back into the Decoder as input for the next step, until a stopping criterion is met (e.g., reaching a maximum length or generating an end-of-sequence token). The size and composition of the vocabulary can vary depending on the specific task and the data the model is trained on. It can include words, subwords, or even characters, depending on the tokenization strategy used.

[0224] The Decoder layers **2220** can be stacked Nx times, allowing the model to capture complex dependencies and generate coherent output sequences.

[0225] This transformer architecture allows the model to process input sequences, capture long-range dependencies, and generate output sequences based on the encoded input and the previously generated tokens.

[0226] There are at least three variations of transformer architecture that enable different LLMs. A first such variation comprises Auto-Encoding Models. In autoencoders, the decoder portion of the transformer is discarded after pre-training and only the encoder is used to generate the output. The popular BERT and ROBERTa models are examples of models based on this architecture and perform well on sentiment analysis and text classification. These types of models may be trained using a process called masked language modeling (MLM).

[0227] The primary goal of an autoencoder is to learn efficient representations of input data by encoding the data into a lower-dimensional space and then reconstructing the original data from the encoded representation. Autoencoders are trained in an unsupervised manner, meaning they don't require labeled data. They learn to capture the underlying structure and patterns in the input data without explicit guidance. An autoencoder consists of two main components: an encoder and a decoder. The encoder takes the input data and maps it to a lower-dimensional representation, often referred to as the latent space or bottleneck. The decoder takes the latent representation and tries to reconstruct the original input data. Autoencoders can be used for dimensionality reduction by learning a compressed representation of the input data in the latent space. The latent space has a lower dimensionality than the input data, capturing the most salient features or patterns. The training objective of an autoencoder is to minimize the reconstruction error between the original input and the reconstructed output. The model learns to encode and decode the data in a way that preserves the essential information needed for reconstruction. Variants and extensions of autoencoders can include denoising autoencoders, variational autoencoders (VAEs) which introduce a probabilistic approach to autoencoders wherein they learn a probabilistic encoder and decoder, allowing for generating new samples from the learned latent space, and conditional autoencoders which incorporate additional conditions or labels as input to the encoder and decoder, enabling the generation of samples conditioned on specific attributes.

[0228] Autoencoders can have various applications. Autoencoders can be used to detect anomalies by measuring the reconstruction error. Anomalous samples tend to have higher reconstruction errors compared to normal samples. Autoencoders can be used as a pre-training step to learn meaningful features from unlabeled data. The learned features can then be used for downstream tasks like classification or clustering. Additionally, or alternatively, autoencoders, particularly VAEs, can be used as generative models to generate new samples similar to the training data by sampling from the learned latent space. It's worth noting that while autoencoders can be effective for certain tasks, they have some

limitations. They may struggle to capture complex dependencies and may generate blurry or less sharp reconstructions compared to other generative models like Generative Adversarial Networks (GANs).

[0229] Another type of variation is the auto-regressive model which features the use of only the decoder portion of the transformer architecture. In autoregressive architectures, the decoder portion of the transformer is retained and the encoder portion is not used after model pre-training. Auto-regressive models are a class of models that generate outputs by predicting the next element based on the previously generated elements. In the context of the Transformer architecture and language modeling, auto-regressive models are commonly used for tasks such as text generation, machine translation, and language understanding.

[0230] Auto-regressive models generate outputs sequentially, one element at a time. In the case of language modeling, the model predicts the next word or token based on the previous words or tokens in the sequence. The prediction of the next element is conditioned on the previously generated elements. The model learns the conditional probability distribution $P(x_t|x_1, x_2, \ldots, x_{t-1})$, where x_t is the element at position t, and $x_1, x_2, \ldots, x_{t-1}$ are the previously generated elements. The Transformer architecture, particularly the Decoder component, is well-suited for auto-regressive modeling. The Decoder generates the output sequence one element at a time, conditioned on the previously generated elements and the encoded input sequence from the Encoder. In the Transformer Decoder, the self-attention mechanism is masked to prevent the model from attending to future positions during training. This masking ensures that the model relies only on the previously generated elements to make predictions, following the auto-regressive property. During training, the Transformer Decoder uses a technique called teacher forcing. Instead of feeding the model's own predictions as input for the next step, the ground truth target sequence is used. This helps the model learn to generate the correct output sequence based on the input sequence and the previous target tokens. During inference or generation, the Transformer Decoder generates the output sequence one element at a time. At each step, the model takes the previously generated elements as input and predicts the next element. This process continues until a stopping criterion is met, such as reaching a maximum sequence length or generating an end-of-sequence token. Auto-regressive models, including the Transformer, have achieved state-of-the-art performance in language modeling tasks. They excel at capturing the statistical properties and dependencies in sequential data, making them effective for generating coherent and fluent text.

[0231] While text generation is the most suitable use case of auto-regressors, they perform exceptionally well on a wide variety of tasks. Most modern LLMs are auto-regressors including, for example, the popular GPT series of LLMs, BERT, and XLNet.

[0232] The third variation of the transformer model is the sequence-to-sequence model which utilizes both the encoder and decoder portions of the transformer and can be trained in multiple ways. One of the methods is span corruption and reconstruction. These models are, generally, best suited for language translation. The T5 and BART family of models are examples of sequence-to-sequence models.

[0233] FIG. **23** is a block diagram illustrating an exemplary basic embedding layer generation process, according to an embodiment. The illustration shows the basic structure of an embedding layer, which is commonly used in natural language processing tasks to convert input words into dense vector representations. The diagram shows an input word **2301**, an input word layer **2302**, an embedding layer **2303**, and an output layer **2304**. As shown, the input word **2301** is represented as one-hot encoded vectors, where each word is represented by a vector of size 10,000 (i.e., the vocabulary size). One-hot encoding is a common technique used to represent categorical variables, such as words in a vocabulary, as binary vectors. In one-hot encoding, each word is represented by a vector with a length equal to the size of the vocabulary. The vector consists of zeros in all positions except for a single position, which is set to one, indicating the presence of the corresponding word. The input word is one-hot encoded with a 1 at the corresponding word index and 0s elsewhere. For example, if a vocabulary of 10,000 words exists, each word will be represented by a vector of size 10,000. If the input word is the 5th word in the vocabulary, its one-hot encoded vector will have a 1 at the 5th position and 0s everywhere else. It is important to note that the one-hot encoding is just one way to represent input words. Other techniques, such as integer encoding or using pre-trained word embeddings (e.g., Word2Vec or GloVe), can also be used depending on the specific requirements of the task and the available resources.

[0234] The input layer **2302** takes the one-hot encoded input word vectors and passes them to the embedding layer **2303**. The input layer in the embedding generation process is responsible for handling the initial representation of the input words before they are passed to the embedding layer. The one-hot encoding ensures that each word has a unique representation, but it also results in sparse and high-dimensional vectors. The embedding layer **2303** then transforms these sparse vectors into dense, lower-dimensional representations (embeddings) that capture semantic and syntactic relationships between words. The embedding layer **2303** is a fully connected layer without an activation function. It maps the one-hot encoded input vectors to dense vector representations of a specified dimension (in this case, **300**). The embedding layer has a weight matrix of size (vocabulary_size, embedding_dimension), which is learned during training. In the given example, the vocabulary size is 10,000, and the embedding dimension is 300. Each row in the weight matrix corresponds to a word in the vocabulary, and the columns represent the dimensions of the embedding space. When a one-hot encoded vector is passed to the embedding layer, it performs an embedding lookup. Since the one-hot vector has a single 1 at the position corresponding to the input word, the embedding lookup effectively selects the corresponding row from the weight matrix, which represents the embedding vector for that word.

[0235] The embedding size (dimension) is a hyperparameter that determines the size of the dense vector representations. In the example, the embedding size is 300, meaning each word is represented by a vector of length 300. The choice of embedding size depends on the complexity of the task, the size of the vocabulary, and the available computational resources. Larger embedding sizes can capture more fine-grained semantic information but also require more memory and computation. The embedding layer's weights (the embedding vectors) are learned during the training

process through backpropagation. The model adjusts these weights based on the downstream task's objective, such as minimizing a loss function. As a result, the learned embeddings capture semantic and syntactic relationships between words, with similar words having similar vector representations. Once the embeddings are learned, they can be reused for various downstream tasks. The learned embeddings can be used as input features for other models, such as recurrent neural networks (RNNs) or convolutional neural networks (CNNs), in tasks like text classification, sentiment analysis, or language translation.

[0236] The output layer **2304** consists of the dense word embeddings generated by the embedding layer. In this example, there are four output embedding vectors, each of size 300, corresponding to different words in the vocabulary. The embedding layer allows the model to learn meaningful representations of words in a lower-dimensional space, capturing semantic and syntactic relationships between words. These embeddings can then be used as input to downstream tasks such as text classification, sentiment analysis, or language modeling.

DETAILED DESCRIPTION OF EXEMPLARY ASPECTS

[0237] FIG. **16** is a process flow diagram of a method **1600** for predictive analysis of very large data sets using the distributed computational graph. One or more streams of data from a plurality of sources, which includes, but is in no way not limited to, a number of physical sensors, web-based questionnaires and surveys, monitoring of electronic infrastructure, crowdsourcing campaigns, and direct human interaction, may be received by system **1601**. The received stream is filtered **1602** to exclude data that has been corrupted, data that is incomplete or misconfigured and therefore unusable, data that may be intact but nonsensical within the context of the analyses being run, as well as a plurality of predetermined analysis related and unrelated criteria set by the authors. Filtered data may be split into two identical streams at this point (second stream not depicted for simplicity), wherein one substream may be sent for batch processing **1600** while another substream may be formalized **1603** for transformation pipeline analysis **1604**, **1500**, and retraining **1605**. Data formalization for transformation pipeline analysis acts to reformat the stream data for optimal, reliable use during analysis. Reformatting might entail, but is not limited to: setting data field order, standardizing measurement units if choices are given, splitting complex information into multiple simpler fields, and stripping unwanted characters, again, just to name a few simple examples. The formalized data stream may be subjected to one or more transformations. Each transformation acts as a function on the data and may or may not change the data. Within the invention, transformations working on the same data stream where the output of one transformation acts as the input to the next are represented as transformation pipelines. While the great majority of transformations in transformation pipelines receive a single stream of input, modify the data within the stream in some way and then pass the modified data as output to the next transformation in the pipeline, the invention does not require these characteristics. According to the aspect, individual transformations can receive input of expected form from more than one source or receive no input at all as would a transformation acting as a timestamp. According to the aspect, individual transformations may not modify the data as would be encountered with a data store acting as a queue for downstream transformations. According to the aspect, individual transformations may provide output to more than one downstream transformations. This ability lends itself to simulations where multiple possible choices might be made at a single step of a procedure all of which need to be analyzed. While only a single, simple use case has been offered for each example, in each case, that example was chosen for simplicity of description from a plurality of possibilities, the examples given should not be considered to limit the invention to only simplistic applications. Last, according to the invention, transformations in a transformation pipeline backbone may form a linear, a quasi-linear arrangement or may be cyclical, where the output of one of the internal transformations serves as the input of one of its antecedents allowing recursive analysis to be run. The result of transformation pipeline analysis may then be modified by results from batch analysis of the data stream and output **1606** in format predesigned by the authors of the analysis with could be human readable summary printout, human readable instruction printout, human-readable raw printout, data store, or machine encoded information of any format known to the art to be used in further automated analysis or action schema.

[0238] FIG. **17** is a process flow diagram of a method **1700** for an aspect of modeling the transformation pipeline module as a directed graph using graph theory. According to the aspect, the individual transformations **17102**, **17104**, **17106** of the transformation pipeline $t_1 \ldots t_n$ such that each t_i T are represented as graph nodes. Transformations belonging to T are discrete transformations over individual datasets d_i, consistent with classical functions. As such, each individual transformation t_j, receives a set of inputs and produces a single output. The input of an individual transformation t_i is defined with the function in: $t_i\ d_1 \ldots d_k$ such that $in(t_i)=\{d_1 \ldots d_k)$ and describes a transformation with k inputs. Similarly, the output of an individual transformation is defined as the function out: $t_i\ [ld_1]$ to describe transformations that produce a single output (usable by other transformations). A dependency function can now be defined such that $dep(t_a,t_b)\ out(t_a)in(t_b)$ The messages carrying the data stream through the transformation pipeline **1701**,**1703**, **1705** make up the graph edges. Using the above definitions, then, a transformation pipeline within the invention can be defined as G=(V,E) where message $(t_1, t_2 \ldots t_{(n-1)}, t_n)$V and all transformations $t_1 \ldots t_n$ and all dependencies $dep(t_i,t_j)$E **1707**.

[0239] FIG. **18** is a flow diagram illustrating an exemplary method for providing experience curation, according to an aspect of an embodiment. According to the aspect, the process begins at step **1801** when a distributed generative AI reasoning and action platform receives a user query directed to a generative AI system. The query may comprise a request for information, a summary, a request for a document, or some other action. The user may submit their query to the platform via an experience curation portal such as through a web app or website accessed via an Internet browser operating on a computer (e.g., personal computer, laptop), or through an associated curation application which can be operated on a mobile computing device (e.g., smart phone, tablet, smart wearable, IoT device, etc.). In some implementations, the received user query may be sent to a data embedding system which can vectorize the query and store

it in a vector database where it may be retrieved to be used as contextual data included in a query/prompt sent to a generative AI system.

[0240] At step **1802** the query is sent to the generative AI system which processes the query and returns a generated response which is received by the platform at step **1803**. At step **1804** curation system locates and retrieves any available user-defined rules or preferences. In some embodiments, the user-defined rules/preferences may be defined by an entity (e.g., a company). Exemplary rules or preferences can include, but are not limited to, conditional generation preferences, formatting rules, language rules, style rules, geographic rules, environmental rules, and timing rules. With respect to conditional generation rules, the model can be conditioned on specific input data related to the individual, such as preferences, behavior, and characteristics. For example, in text generation, the model could be conditioned on a user's previous messages or writing style to generate more personalized responses. Formatting, style, and language rules are closely related and may be used to curate a response in a specific format (e.g., bullet points, paragraph, single sentence, numbered outline, CSV, etc.), response style (e.g., formal, informal, academic, accessible, abstract, casual, etc.), and the language in which a response is translated, respectively. At step **1805** curation system can curate the response based on the retrieved user-defined rules or preferences. For example, the system may filter out extraneous data, or personal information. As a last step **1806**, curation system returns the curated response to the user, thereby providing experience curation to a platform user.

[0241] FIG. **19** is a flow diagram illustrating an exemplary method for providing experience curation with using rich contextual data, according to an aspect of an embodiment. According to the aspect, the process begins at step **1901** when a distributed generative AI reasoning and action platform receives a user query directed to a generative AI system. The query may comprise a request for information, a summary, a request for a document, or some other action. The user may submit their query to the platform via an experience curation portal such as through a webapp or website accessed via an Internet browser operating on a computer (e.g., personal computer, laptop), or through an associated curation application which can be operated on a mobile computing device (e.g., smart phone, tablet, smart wearable, IoT device, etc.). In some implementations, the received user query may be sent to a data embedding system which can vectorize the query and store it in a vector database where it may be retrieved to be used as contextual data included in a query/prompt sent to an ML, AI, generative AI, planning, or automation/action orchestration system.

[0242] A DCG orchestrated model which employs a hierarchical classification and model selection regime for content (either in whole or in part) can enable much more accurate ultimate semantic performance. For example, a query/prompt can be submitted to the generative AI system with additional metadata associated with the context of the prompt itself as well as additional broader information about the user and the user's ongoing behavior and/or activities. At step **1902** the system obtains a plurality of rich context data associated with the user, the query, or both. A subset of the plurality of context data information may be obtained from a vector database, the vector database comprising a plurality of embedded contextual data. Embedded contextual data can comprise (but is not limited to) information obtained from an enterprise knowledge base and embedded queries/prompts. Context data associated with the user may comprise information obtained from or related to one or more of a computing device on which the user is accessing the curation system/platform, the geographic location the user is located, an action the user is performing during interaction with the curation system/platform, and timing data associated with the user, and/or the like. A subset of the plurality of obtained context data may be obtained from one or more marketplaces such as a data marketplace and/or an expert judgment marketplace. In some embodiments, the selection of context data may be based on one or more expert judgment scores assigned to an information source or dataset.

[0243] As an example, if a user is asking a generative AI enhanced search engine for "the best pizza" on her cell phone while driving at 55 mph on the road and not near her home (e.g. on vacation) this is massively different from the user being at home, on her couch, connected on her laptop, from her normal IP address, having just ran a series of searches for airline tickets to Italy and Neapolitan Pizza recipes. The additional device, user, recent behavior, etc. content can be used by a classifier alongside a prompt to help focus results on things that are not only relevant (e.g. pizza places near the user that are open now) but likely to be consistent with her broader needs/persona (e.g. if available, the suggestions could be looked at based on other budget, dining, etc. preferences like outdoor seating and meals below $20 per person). The same principle applies to more complicated and complex topics like medicine or finance or law.

[0244] At step **1903** the obtained plurality of context data may be processed into vectors by an embedding model and stored in the vector database.

[0245] At step **1904** the user query and the vectorized context data is sent to the generative AI system which processes the query and returns a generated response which accounts for the information contained in the vectorized context data and which is received by the platform at step **1905**. At step **1906** the curation system locates and retrieves any available user-defined rules or preferences. In some embodiments, the user-defined rules/preferences may be defined by an entity (e.g., a company). Exemplary rules or preferences can include, but are not limited to, conditional generation preferences, formatting rules, language rules, style rules, geographic rules, environmental rules, and timing rules. With respect to conditional generation rules, the model can be conditioned on specific input data related to the individual, such as preferences, behavior, and characteristics. For example, in text generation, the model could be conditioned on a user's previous messages or writing style to generate more personalized responses. Formatting, style, and language rules are closely related and may be used to curate a response in a specific format (e.g., bullet points, paragraph, single sentence, numbered outline, CSV, etc.), response style (e.g., formal, informal, academic, accessible, abstract, casual, etc.), and the language in which a response is translated, respectively. At step **1907** curation system can curate the response based on the retrieved user-defined rules or preferences. For example, the system may filter out extraneous data, or personal information. As a last step **1908**, curation system returns the curated response to the user, thereby providing experience curation to a platform user.

[0246] FIG. **20** is a flow diagram illustrating an exemplary method for using a distributed computation graph system for creating structured representations or knowledge graphs from various data sources, and setting up a pipeline for continuous processing and monitoring of that data, according to an embodiment. According to the embodiment, the process begins at step **2001** when the platform receives a plurality of input data of interest from structured (e.g., databases, spreadsheets, etc.) and unstructured (e.g., documents, websites, social media, etc.) data sources. Data may be obtained using data extraction techniques such as, for example, web scraping, APIs, natural language processing, etc.). Additionally, or alternatively, the data may be obtained from a data marketplace (e.g., expert judgment, RAGs, models, datasets, etc.). At step **2002** the platform creates a knowledge graph or structured representation from data of interest. This may comprise applying information extraction methods (e.g., named entity recognition, relation extraction, etc.) to extract entities and relationships from unstructured data and integrating the extracted information with structured data sources. Further, a knowledge graph representation can be built by creating nodes for entities and edges for relationships. Optionally, platform can be configured to create vector representations of entities/relationships using techniques like word embeddings.

[0247] At step **2003**, platform selects data of interest, knowledge graph of interest, vector database of interest, embedding of interest, simulation model of interest, crowd or individual or expert of interest, model of interest or simulation of interest from the marketplace and procures it on either a one-time, periodic or ongoing basis. Platform can search/browse a marketplace or repository for relevant data sources, knowledge graphs, vector databases, models, simulations, simulation elements, etc., and evaluate the potential options based on factors like relevance, quality, usage limitations, provenance, certifications, insurance, bonding, operating costs, and licensure costs. This step may further include purchasing or licensing selected assets for use in a pipeline and filing or obtaining necessary privacy, usage, or regulatory disclosures with customers, partners, or regulators. As a next step **2004**, platform creates a new pipeline which will continue to process target of interest data on a continuous or periodic or aperiodic basis going forward. The pipeline may be designed (e.g., batch, streaming, etc.) based on the processing needs and can integrate components for data ingestion, knowledge graph updates, model execution and/or the like.

[0248] At step **2005**, platform can instantiate or reserve resources for the new pipeline based on estimated resource needs for storage, transport, compute, privacy, regulation/laws, safety, and prices for relevant services needed to handle future pipeline via a probabilistic representation of it. Platform may estimate pipeline resource requirements (storage, compute, networking, etc.) and also consider privacy, regulatory, and safety constraints that impact resource needs. Platform may use probabilistic modeling to forecast future resource demands for the pipeline in whole or in part over time horizons of interest. This step may further comprise provisioning cloud, edge, CDN, on-premise, host, wearable, mobile, et cetera resources (e.g., virtual machines, containers, databases, etc.) accordingly. It may also involve participating in spot markets or reservation markets for such resources on a forward basis within a limited time horizon (e.g., a day or 3 years). Such probabilistic forward looking resource estimation may allow system to distribute elements of the DCG specified process to different cloud vs CDN vs edge vs device resources for at least a portion of the considered time period via publication and dissemination of DCG specifications across such devices with distributed execution and coordination of the globally specified process. As a last step **2006**, platform monitors and adjusts the pipeline going forward based on uncertainty quantification methods looking at model expectations versus empirical observations and expected future "exogenous" zone of interest. A pipeline may be monitored for performance, data drift, model accuracy, etc. and by tracking metrics like data volumes, processing times, error rates, and model accuracies. The platform may use techniques such as, for example, Bayesian modeling to quantify uncertainties in model parameters and propagate input/parameter uncertainties through the model(s) to get prediction uncertainties. Techniques such as bootstrap, cross-validation can also quantify model uncertainties. Platform can identify external variables (e.g., new regulations, market shifts, technology changes, etc.) that may impact the "zone of interest" and quantify potential impacts on pipeline performance/relevance. As an example, platform could implement monitoring for these variables using web scraping, news feeds, log data, APM information, etc.

[0249] FIG. **24** is a flow diagram illustrating an exemplary method **2400** for routing processing based on certainty threshold and/or challenge-based verification, according to an embodiment. According to the embodiment, the process begins at step **2401** by defining a hierarchy of reasoning tasks and subtasks that break down decision-making processes into manageable steps. Examples of reasoning tasks could include "Gather relevant information," "Analyze data," "Generate potential solutions," "Evaluate alternatives," and "Select the best option." For each identified reasoning task, break it down further into smaller, more manageable subtasks. For example, the reasoning task "Gather relevant information" could be decomposed into subtasks such as "Identify information sources," "Extract relevant data," "Preprocess and clean data," and "Integrate data from multiple sources." Determine which tasks or subtasks need to be completed before others can be started (prerequisites) and establish the flow of information and outputs between tasks and subtasks, specifying how the results of one task feed into the inputs of another. This can be orchestrated by the DCG computing system. For each subtask, assign the appropriate AI models, algorithms, or knowledge sources that will be used to perform the required processing. This could include machine learning models, rule-based systems, knowledge bases, or external APIs.

[0250] At step **2402** platform **2120** orchestrates the execution of these tasks and routes data to the appropriate models or knowledge sources based on predefined rules or learned policies. Platform **2120** or an administrator can set certainty thresholds for each task to determine when the system should proceed to the next step or seek additional information/verification at step **2403**. Certainty thresholds can be predetermined levels of confidence or probability that an AI system uses to make decisions or trigger specific actions. As a last step **2404**, the platform may use challenge-based verification mechanisms to test the robustness and reliability of a given AI system's decisions by subjecting the system to various challenges or adversarial scenarios. These mechanisms help identify potential weaknesses, biases, or failure

points in the decision-making process. Some examples of challenge-based verification mechanisms can include, adversarial examples, edge case testing, counterfactual reasoning, stress testing, robustness to noise and outliers, and fairness and bias testing, to name a few.

[0251] Adversarial examples are carefully crafted inputs that are designed to fool or mislead the AI system into making incorrect predictions or decisions. For example, in an image classification system, an adversarial example could be an image that has been slightly perturbed or modified in a way that is imperceptible to humans but causes the system to misclassify the image. By testing the system's performance on a range of adversarial examples, platform **2120** can assess its robustness against manipulated or deceptive inputs.

[0252] Edge case testing involves evaluating the system's performance on rare, extreme, or unusual scenarios that may not be well-represented in the training data. For example, in a self-driving car system, an edge case could be a scenario where a pedestrian suddenly appears from behind a parked vehicle or a situation with complex road construction and detours. By subjecting the system to a variety of edge cases, platform **2120** can assess its ability to handle unexpected or challenging situations gracefully.

[0253] Counterfactual reasoning involves analyzing how the system's decisions would change if certain input features or conditions were different. As an example, in a loan approval system, counterfactual reasoning could involve examining how the system's decision would differ if an applicant's income or credit score were slightly modified. By exploring counterfactual scenarios, platform **2120** can identify the sensitivity of the system's decisions to specific input features and ensure that the decisions remain consistent and fair.

[0254] Robustness to noise and outliers tests the system's resilience to noisy or outlier data points that may be present in real-world scenarios. As an example, in a sentiment analysis system, robustness testing could involve evaluating the system's performance on reviews with spelling errors, grammatical mistakes, or unconventional language patterns. By assessing the system's performance on noisy and outlier data, platform **2120** can ensure that it remains reliable and accurate in the presence of imperfect or unexpected inputs.

[0255] Fairness and bias testing aim to identify and mitigate any biases or discriminatory behavior in the system's decision-making process. For example, in a hiring recommendation system, fairness testing could involve analyzing the system's predictions for any systematic biases based on protected attributes such as gender, race, or age. By conducting fairness and bias tests, the platform can improve the system's decisions from an equitable evaluation perspective and not perpetuate or amplify societal biases that might be reflected in historical data, to include "what if" analysis with alternative models or training data for comparative purposes or model blends/consensus approaches.

[0256] These challenge-based verification mechanisms help assess the robustness, reliability, fairness, and transparency of an AI system's decisions. By subjecting the system to various challenges and adversarial scenarios, platform **2120** can identify potential weaknesses, biases, or failure modes and take appropriate measures to mitigate them. It's important to note that the specific challenges and verification mechanisms used will depend on the domain, the nature of the AI system, and the potential consequences of its decisions. A comprehensive verification strategy should encompass a diverse set of challenges to thoroughly test the system's performance and ensure its reliability in real-world deployment.

[0257] FIG. **25** is a flow diagram illustrating an exemplary method **2500** for retrieving relevant contextual data from a knowledge graph database and enriching vector embeddings with the contextual data, according to an embodiment. According to an aspect of an embodiment, this process may be conducted by embedding refinement computing system **2122**. According to the embodiment, the process begins at step **2501** when platform **2120** queries a knowledge graph to retrieve symbolic information comprising relevant facts, entities, and relationships based on input data and the current reasoning context. At step **2502**, the retrieved knowledge is used to refine vector embeddings generated by neural network models, incorporating symbolic information into the distributed representations (i.e., embeddings). As a last step **2503**, the platform **2120** can implement techniques to effectively combine the embeddings with the knowledge graph data. One or more techniques may be used to combine the embeddings and the symbolic information. A first technique may leverage knowledge graph embedding alignment wherein platform **2120** generates vector embeddings for the entities and relationships in the knowledge graph using techniques such as TransE, TransR, or DistMult, for example, and aligning the vector embeddings generated by the neural network models with the knowledge graph embeddings using techniques such as embedding space transformation or joint embedding learning. Then the platform can update the neural network embeddings by incorporating the aligned knowledge graph embeddings, allowing the symbolic information to influence the distributed representations.

[0258] Another approach may utilize attention mechanisms to compute the relevance or importance of the retrieved knowledge for each input instance and then modify the neural network architecture to incorporate attention layers that take the retrieved knowledge as additional input. During the attention computation, higher weights may be assigned to the retrieved knowledge that is most relevant to the current input and task. Platform can update the vector embeddings generated by the neural network models by incorporating the attention-weighted knowledge representations.

[0259] Another technique may leverage knowledge-aware language models wherein the language model architecture is modified to incorporate knowledge-aware layers or components and the retrieved knowledge is injected into the language model during the encoding or decoding process. For example, platform **2120** can use techniques like knowledge-aware self-attention, where the attention computation is conditioned on the retrieved knowledge. Additional techniques can include the use of graph convolutional networks, and/or knowledge distillation.

[0260] It's important to note that the retrieved knowledge should be relevant and complementary to the input data and the task at hand. The symbolic information should provide additional context or constraints that can guide the refinement of the vector embeddings and improve the overall performance of the AI system.

[0261] FIG. **26** is a flow diagram illustrating an exemplary method **2600** for applying expressive weighting schemes to model combinations, according to an embodiment. Accord-

ing to an aspect of an embodiment, the process may be performed by model blending computing system **2125**.

[0262] According to the embodiment, the process begins at step **2601** by combining the outputs of multiple neural network models based on their individual strengths and weaknesses. At step **2602** weighting schemes dynamically adjust the contribution of each model based on factors such as uncertainty, task complexity, and domain relevance. As a last step **2603**, platform **2120** may implement techniques like Bayesian model averaging, mixture of experts, and/or ensemble learning to optimally blend model outputs. When combining the outputs of multiple neural network models based on their individual strengths and weaknesses, and developing weighting schemes to dynamically adjust the contribution of each model, the goal is to create an ensemble of models that can leverage the diverse capabilities of each individual model to improve overall performance and robustness.

[0263] Multiple neural network models, each trained on the same task or dataset, can have different strengths and weaknesses. Some models may excel at capturing certain patterns or features, while others may be more robust to noise or better at handling specific types of inputs. By combining the outputs of these models, platform **2120** can harness their complementary strengths and mitigate their individual weaknesses. Common approaches for combining model outputs include (but are not limited to) averaging (e.g., taking the average of the outputs from all models), voting (e.g., assigning the final output based on the majority vote of the model), and weighted averaging (e.g., assigning different weights to the outputs of each model based on their perceived importance or performance).

[0264] Weighting schemes determine how much influence each individual model has on the final combined output. Instead of using fixed weights, platform **2120** can develop dynamic weighting schemes that adjust the contribution of each model based on various factors. A first such factor is uncertainty wherein models that exhibit higher uncertainty or lower confidence in their predictions can be given lower weights, while models with higher confidence can have higher weights. Another factor is task complexity wherein for tasks with varying levels of complexity, the platform can assign higher weights to models that specialize in handling specific types of complexity. A domain relevance factor determines if the input data belongs to different domains or categories, wherein the platform can assign higher weights to models that are more relevant or perform better in that particular domain.

[0265] Combining the outputs of multiple models and dynamically adjusting their contributions based on relevant factors allows for more robust, accurate, and adaptable AI systems. By leveraging the strengths of different models and adapting to the characteristics of the input data, the ensemble can provide improved performance and handle a wider range of scenarios compared to individual models.

[0266] FIG. **27** is a flow diagram illustrating an exemplary method **2700** for using feedback loops considering security, licensing, provenance, and collaborative development, according to an embodiment. According to the embodiment, the process begins at step **2701** by implementing secure communication protocols and access control mechanisms to protect sensitive data and prevent unauthorized access. Platform **2120** may be configured to ensure compliance with licensing terms and conditions of datasets, models, and tools used therein at step **2702**. For example, platform **2120** may use governance frameworks and policies that define the roles, responsibilities, and processes for collaborative AI development and implement compliance checks and validation processes to ensure adherence to legal, ethical, and regulatory requirements. Furthermore, the platform can record the lineage of data, models, and decisions made by the various AI systems through the lifecycle of said systems at step **2703**. As a last step **2704**, the platform may create and use collaborative development tools and workflows that allow multiple teams or organizations to jointly develop, test, and deploy AI models while maintaining security and provenance.

[0267] To perform data lineage tracking the platform **2120** can leverage a data versioning and tracking system that captures the source, transformations, and dependencies of the data used for training and inference. This may involve the use of metadata standards and schemas to describe properties, origins, and relationships of the data. Platform may maintain a historical record of data updates, modifications, and deletions to ensure traceability, as well as utilize data cataloging and discovery tools to facilitate easy searching and understanding of the data lineage.

[0268] To perform model lineage tracking the platform **2120** can establish a model versioning and tracking system that captures the evolution of the AI models throughout their lifecycle. This may involve recording information such as model architectures, hyperparameters, training configurations, and performance metrics for each version of the model. Platform can maintain a repository of model artifacts, including trained weights, configuration files, and associated documentation to track the dependencies between models, including any transfer learning or fine-tuning relationships.

[0269] To perform decision lineage tracking the platform **2120** can implement a decision tracking system that captures the inputs, outputs, and intermediate steps involved in each decision made by an AI system. This may involve recording the specific model versions, data inputs, and any external factors that influenced each decision and maintaining a log of decision outcomes, along with their associated confidence scores or uncertainty measures. This may further comprise a mechanism to link decisions back to the corresponding models and data used for inference. In some implementations, the platform may leverage auditing and reporting capabilities to analyze decision patterns, identify anomalies, and support accountability.

[0270] Collaborative development tools can include version control systems (e.g., Git) to manage the codebase, models, and configurations collaboratively. The platform **2120** can use access control mechanisms to ensure that only authorized individuals or teams can contribute to the development process and establish code review workflows and pull request processes to maintain code quality and security standards. In some implementations, platform may leverage federated learning techniques to enable collaborative model training without directly sharing raw data.

[0271] FIG. **28** is a flow diagram illustrating an exemplary method **2800** for multi-modal alignment for consistent representations across data types, according to an embodiment. According to an aspect of an embodiment, the process may be performed by multi-modal alignment computing system **2123**. According to the embodiment, the process begins at step **2801** when platform **2120** aligns and synchronizes

representations across different data modalities (e.g., text, images, audio, smell, etc.) to create a unified and consistent representation of input data. At step **2802** one or more techniques such cross-modal attention, multi-modal fusion, and/or joint embedding spaces are used to combine information from different modalities. At step **2803** the platform uses domain-specific knowledge (e.g., knowledge graph) to ensure the generated representations (embeddings) are consistent and realistic across modalities.

[0272] Multimodal embedding space alignment is performed by learning a shared embedding space where representations from different modalities can be projected and aligned. This may utilize techniques like canonical correlation analysis (CCA) or adversarial learning to map the representations from each modality into a common space. Platform may then train the embedding space alignment model using paired or aligned data from different modalities. Once the alignment model is trained, it can be used to project the representations from each modality into the shared space, creating a unified representation.

[0273] Cross-modal attention mechanisms utilize attention mechanisms to attend to relevant information from one modality based on the representations from another modality. For example, in a visual-textual alignment task, use the textual representations to guide the attention over the visual features, or vice versa. Platform can train the attention mechanism to learn the cross-modal dependencies and alignments wherein the attended representations from different modalities can be combined or fused to create a unified representation.

[0274] In some implementations, platform can train a joint embedding model that learns to map the representations from different modalities into a shared embedding space. This may involve the use of techniques like contrastive loss or triplet loss to bring the representations of aligned or similar instances from different modalities closer together in the embedding space.

[0275] FIG. **29** is a flow diagram illustrating an exemplary method **2900** for hyperparameter optimization using information-theoretic guidance, according to an embodiment. According to an aspect of an embodiment, this process may be performed by hyperparameter optimization computing system **2126**. According to the embodiment, the process begins at step **2901** with the implementation of a hyperparameter optimization framework which searches for the best combination of model architectures, training settings, and embedding techniques. Developing such a framework may begin by defining the hyperparameter search space. This can include identifying the hyperparameters to optimize, such as model architectures, learning rates, batch sizes, embedding dimensions, etc., and specifying the range or possible values for each hyperparameter, defining the search space. This may further involve using appropriate data types and ranges for each hyperparameter (e.g., categorical variables for model architectures, continuous variables for learning rates). Some exemplary hyperparameter optimization algorithms which may be implemented can include, but are not limited to, gird search, random search, Bayesian optimization, and evolutionary algorithms. Platform may create an optimization loop that iteratively generates hyperparameter configurations, evaluates them using the objective function, and updates the search process based on the results. For grid search or random search, platform can generate all the configurations upfront and evaluate them in parallel or sequentially. For Bayesian optimization or evolutionary algorithms, the platform may need to implement the specific update rules and sampling strategies based on the chosen algorithm.

[0276] At step **2902** information-theoretic measures are incorporated into the hyperparameter optimization to guide the optimization process and select hyperparameters that maximize the information content and generalization ability of learned representations. Information content refers to the amount of meaningful or relevant information captured by the learned representations (embeddings). Representations with high information content are able to capture and encode the salient features, patterns, and relationships present in the input data. Maximizing the information content ensures that the learned representations are rich, expressive, and informative. Representations with good generalization ability can effectively capture the underlying patterns and structures in the data, rather than merely memorizing the training examples. Maximizing the generalization ability ensures that the learned representations are robust, transferable, and applicable to a wide range of tasks and datasets.

[0277] Information-theoretic measures quantify the information content and relationships between variables or representations. Common information-theoretic measures, which may be implemented in various aspects of platform **2120**, can include: Shannon entropy which measures the average amount of information contained in a random variable or representation; mutual information which quantifies the amount of information shared between two variables or representations; or Kullback-Leibler (KL) divergence which measures the difference between two probability distributions, often used to assess the dissimilarity between learned representations and a reference distribution. During the hyperparameter optimization process, information-theoretic measures can be used as objective functions or regularization terms to guide the search towards hyperparameters that maximize the information content and generalization ability. For example, platform **2120** or an administrator can define an objective function that combines the performance metric (e.g., accuracy) with an information-theoretic measure (e.g., mutual information between learned representations and class labels). By optimizing this objective function, the hyperparameter search will favor configurations that not only achieve high performance but also learn representations with high information content and generalization ability.

[0278] Information-theoretic measures can be used to evaluate and compare different hyperparameter configurations based on the quality of the learned representations. For each hyperparameter configuration, the platform can compute the relevant information-theoretic measures on the learned representations and assess their information content and generalization ability. Hyperparameter configurations that yield representations with higher information content and better generalization ability are considered more desirable and are selected as the optimal choices.

[0279] Information-theoretic measures can also be used as regularization terms or constraints during the model training process itself. For example, the platform can add a regularization term that encourages the learned representations to have high mutual information with the target variables or to minimize the KL divergence between the learned representations and a desired prior distribution. These regularization

techniques help guide the model towards learning representations that are informative, generalize well, and align with the desired properties.

[0280] Hyperparameter optimization can be computationally expensive, especially when training and evaluating complex models. As such, the platform may leverage parallel computing techniques to distribute the evaluation of hyperparameter configurations across multiple cores, machines, or clusters. Additionally, or alternatively, the platform can incorporate early stopping mechanisms to terminate the evaluation of poorly performing hyperparameter configurations early, saving computational resources and allocate more resources (e.g., training iterations, computational budget) to promising configurations based on their intermediate performance. For example, techniques like successive halving or Hyperband can dynamically allocate resources based on the relative performance of configurations.

[0281] FIG. **30** is a flow diagram illustrating an exemplary method **3000** for linking embeddings to knowledge graphs, according to an embodiment. According to an aspect of an embodiment, the process may be performed by ontology extraction computing system **2124**. According to the embodiment, the process begins at step **3001** by analyzing learned vector embeddings (produced by one or more neural network models) and extracting symbolic representations that capture the underlying semantic structure. At step **3002** the platform may use clustering, dimensionality reduction, and/or rule mining to distill the embeddings into interpretable symbolic forms.

[0282] Platform **2120** may apply clustering algorithms, such as k-means or hierarchical clustering, to group similar embeddings together based on their spatial proximity in the vector space. Each cluster can be considered as a symbolic representation or concept that captures a group of semantically related embeddings. Platform may analyze the clusters to identify common themes, attributes, or relationships among the embeddings within each cluster and then assign meaningful labels or descriptions to the clusters based on their content or representative embeddings.

[0283] In embodiments where dimension reduction techniques are used, platform **2120** may implement Principal Component Analysis (PCA) or t-SNE (t-Distributed Stochastic Neighbor Embedding), to reduce the high-dimensional embedding space to a lower-dimensional representation and then visualize the reduced-dimensional space to identify patterns, clusters, or separations among the embeddings. Platform can analyze the principal components or dimensions to understand the most significant factors contributing to the variance in the embedding space in order to interpret the dimensions or components in terms of their semantic meaning or the attributes they capture.

[0284] In other implementations, platform **2120** may use semantic similarity analysis to compute pairwise similarities or distances between embeddings using metrics such as cosine similarity, Euclidean distance, or dot product to identify pairs or groups of embeddings that have high semantic similarity, indicating their close relationship or shared attributes. The most similar embeddings may be analyzed to understand the semantic connections and relationships captured by the embedding space and to extract symbolic representations or rules based on the observed semantic similarities, such as synonyms, antonyms, or analogies.

[0285] At step **3002**, the platform may utilize ontology alignment techniques that align the learned embeddings with existing ontologies or knowledge bases (e.g., knowledge graphs) that provide a structured symbolic representation of the domain. This may involve the use of ontology matching techniques, such as string similarity, semantic similarity, or structural similarity, to establish correspondences between embeddings and ontology concepts. Leverage the aligned ontology to assign symbolic labels or categories to the embeddings based on their semantic similarity to ontology concepts and enrich the ontology with new concepts or relationships discovered from the embedding space.

[0286] FIG. **31** is a flow diagram illustrating an exemplary method for advanced reasoning using a composite artificial intelligence platform, according to an embodiment. According to the embodiment, the process begins at step **3101** by generating vector embeddings (i.e., learned representations) of input data using a plurality of neural network models trained on large datasets. This may be accomplished by applying transfer learning, fine-tuning, and/or multi-task learning techniques to improve the quality and generalizability of the embeddings. At step **3102** platform **2120** can store and retrieve symbolic facts, entities, and relations using an ontology or schema that defines the types of entities, relationships, and attributes relevant to a given system's (AI model) domain, populating the system with data from structured and unstructured sources using information extraction techniques. Symbolic information can be stored in one or more knowledge graph databases **2129**. At step **3103** platform **2120**, via DCG computing system **121** and hierarchical process system **2121** manages and routes processing tasks based on certainty thresholds and/or challenge based verification, selecting the appropriate models and data sources to complete the tasks.

[0287] As a next step **3104** platform can refine vector embeddings using contextual information by retrieving relevant facts, entities, and relationships from the knowledge base (e.g., knowledge graphs), updating the embeddings by incorporating the retrieved contextual information. At steep **3105** platform **2120** combines the outputs of multiple models using expressive weighting schemes which dynamically adjust the contribution of each model based on various factors. Platform can implement secure communication protocols and access control mechanisms to ensure security, licensing compliance, and provenance tracking with respect to models, data sources, and decision making in a collaborative development environment at step **3106**.

[0288] At step **3107** platform **2120** may align and harmonize representations across different data modalities and then optimize hyperparameters using information theoretic guidance at step **3108**. As a last step **3109**, platform **2120** extracts symbolic knowledge from the vector embeddings by analyzing the learned embeddings to extract symbolic representations and map the extracted symbolic representations to existing concepts and relationships in a knowledge graph.

[0289] In this way, platform **2120** can provide an end-to-end process of advanced reasoning in an artificial intelligence system, starting from the generation of vector embeddings using neural network models, progressing through the storage and retrieval of symbolic knowledge, managing and routing processing tasks, refining embeddings with contextual information, combining outputs of multiple models, ensuring security and compliance, aligning representations

across modalities, optimizing hyperparameters, and finally extracting symbolic knowledge from the learned embeddings.

[0290] FIG. **32** is a flow diagram illustrating an exemplary method **3200** for fitness for purpose optimization of a generative AI model, according to an embodiment. According to an aspect, the process may be performed by model optimization computing system **171** of advanced model management platform **170**. According to the embodiment, the process begins at step **3201** by collecting a diverse dataset representative of a target task and domain. The diverse dataset should cover various aspects and challenges of the identified target task which are representative of the real-world scenarios the model will encounter. This step may further involve preprocessing and cleaning the dataset, handling missing values, outliers, and inconsistencies. As a next step **3202** the platform defines a suitable reward function that measures the model's performance on the target task. This may involve identifying the key metrics that measure the model's performance on the task (e.g., accuracy, F1 score, BLEU score, etc.) and defining a mathematical formula that combines these metrics into a single scalar value. The choice of reward function should be selected to ensure the reward function aligns with the desired behavior and objectives of the model.

[0291] At step **3203**, the platform implements a reinforcement learning algorithm (e.g., PPO, A3C) to optimize the model settings. The selection of the reinforcement learning algorithm may be based on, for example, the task requirements and computational resources available. The chosen algorithm may be implemented using a deep learning framework such as, for example, TensorFlow or PyTorch. Platform may define the model architecture and hyperparameters for the reinforcement learning agent. At step **3204**, the platform trains the model using the reinforcement learning algorithm, iteratively updating the settings based on the reward function. This may involve initializing the model with random weights or using pretrained weights if available. The dataset may be split into training and validation subsets. Platform can monitor the model's performance on the validation subset and adjust hyperparameters as needed.

[0292] As a last step the platform evaluates the optimized model on a held-out test set to assess its performance **3205**. This can involve computing the relevant performance metrics (e.g., accuracy, F1 score, BLEU score, etc.) on the test set and analyzing the model's performance across different subsets of the test set to identify strengths and weaknesses of the optimized model. The optimized model's performance may be compared to baseline models or state-of-the-art approaches.

[0293] FIG. **33** is a flow diagram illustrating an exemplary method **3300** for hallucination mitigation of a generative AI model, according to an embodiment. According to an aspect, the process may be performed by hallucination mitigation computing system **172** of advanced model management platform **170**. According to the embodiment, the process begins at step **3301** by preprocessing training data to identify and link named entities to a knowledge graph or base. This may be performed by using named entity recognition techniques provided by natural language processing libraries such as spaCy or NLTK for named entity recognition and entity linking. Platform can store the linked entities and their corresponding knowledge graph IDs in a knowledge graph database **2129** for retrieval during training and inference. At step **3302**, the platform implements a retrieval mechanism (e.g., dense retrieval, sparse retrieval) to fetch relevant information from the knowledge graph based on an input query. The selection of the retrieval mechanisms may be based on the knowledge graph structure and query types. The retrieval mechanism may be implemented using efficient data structures and algorithms (e.g., inverted index, FAISS, etc.). Platform may define similarity metrics and thresholds for retrieving relevant information from the knowledge graph.

[0294] At step **3303**, the platform modifies the model architecture to incorporate the retrieved information into the generation process. This can involve implementing techniques such as cross-attention or concatenation to condition the model's output on the retrieved information. It should be noted that the modified architecture should be compatible with the retrieval mechanism and knowledge graph structure. At step **3304**, the platform trains the model using a RAG objective, which encourages the model to generate output that is consistent with the retrieved information. In some aspects, platform may implement the RAG objective function using a deep learning framework's loss modules and tensor operations. By training the model using the RAG objective, platform can jointly optimize the retrieval and generation components. During this step platform monitors the model's performance on a validation subset and adjust the hyperparameters as needed.

[0295] As a last step **3305**, the model's performance is evaluated on a test set, measuring the factual accuracy and consistency of the generated output (e.g., text). This may comprise using metrics like precision, recall, and/or F1 score, and comparing the generated output to the ground truth information in the knowledge graph. Additionally, the platform may analyze the model's performance on different types of queries and entities to identify areas for improvement. In some implementations, the platform may conduct human evaluation to assess the quality and coherence of the generated output.

[0296] FIG. **34** is a flow diagram illustrating an exemplary method **3400** for model validation of a generative AI model, according to an embodiment. According to an aspect, the process may be performed by model validation computing system **173** of advanced model management platform **170**. According to the embodiment, the process begins at step **3401** by collecting a dataset of domain-specific questions and answers curated by experts or sourced from authoritative databases. The dataset may be sourced from, in part, an expert judgment marketplace **260** or expert judgment database **270**, trip report scoring system **250**, enterprise knowledge base **111**, and/or other data sources and third-party services **150**. This step can include identifying a target domain or task for validation (e.g., medical diagnosis, legal reasoning, etc.). The collected dataset should cover a wide range of question types, difficulty levels, and edge cases. The collected dataset may be preprocessed and cleaned, handling formatting issues and inconsistencies.

[0297] At step **3402**, the platform implements a cross-validation procedure to split the collected dataset into training and validation subsets. Examples of cross-validation that may be implemented can include, but are not limited to, k-fold and stratified k-fold. It is important to ensure that the selected splitting procedure maintains the distribution of question types and difficulty levels across the subsets. In some implementations, platform may use techniques like

stratified sampling to handle imbalanced datasets. Platform trains the model on the training subset and evaluates its performance (e.g., accuracy, F1 score, BLEU, etc.) on the validation subset at step **3403**. The training and evaluation process may be repeated for each fold of the cross-validation procedure.

[0298] At step **3404**, the platform compares the model's answers to the expert-provided answers, using metrics such as accuracy, F1 score, and/or BLEU score. This may involve computing performance metrics for each question type and difficulty level and analyzing the model's performance across different subsets of the validation set to identify strengths and weaknesses. At step **3405**, the platform performs error analysis on the optimized model. This may comprise conducting a detailed error analysis on the model's incorrect answers and identifying common patterns or categories of errors (e.g., missing information, incorrect reasoning, inconsistent results, etc.). The platform may use the insights from the error analysis to guide further model improvements and data collection efforts.

[0299] FIG. **35** is a flow diagram illustrating an exemplary method **3500** for model training and sandboxing of a generative AI model, according to an embodiment. According to an aspect, the process may be performed by model training sandbox computing system **174** of advanced model management platform **170**. According to the embodiment, the process begins at step **3501** by generating adversarial examples by applying perturbations or transformation to the model's input data. According to some embodiments, this step may comprise using methods such as gradient-based attacks (e.g., Fast Gradient Sign Method [FGSM], Projected Gradient Descent [PGD]) or decision-based attacks (e.g., boundary attack) to create adversarial examples. Platform ensures the generated adversarial examples are diverse and cover various types of perturbations and transformations. At step **3502**, the platform augments the training data with the adversarial examples to improve the model's robustness. The appropriate ratio of adversarial examples to include in the training data may be based on the desired level of robustness and techniques to balance the distribution of adversarial and clean examples in the augmented data may be implemented, according to an embodiment.

[0300] According to the embodiment, the next step **3503** involves using input perturbation techniques to test the model's stability. Some exemplary input perturbation techniques can include, but are not limited to, adding noise, rotations, or translations. The range and intensity of perturbations may be based on the input data type and model architecture. The platform may apply the perturbations to the input data during training and evaluation to assess the model's robustness. Platform can use adversarial training objectives (e.g., PGD, FGSM) to optimize the model's performance on the adversarial examples at step **3504**. This may comprise modifying the model's loss function to incorporate the adversarial training objectives. Platform may then train the model using the adversarial training objectives, jointly optimizing for robustness and performance on clean examples. As a last step **3505**, the model's performance is evaluated on a test set of adversarial examples to assess its robustness. The test set may comprise adversarial examples generated using different attack methods and perturbation intensities. Platform can compute the model's accuracy, robustness score, and other relevant metrics on the adversarial test set. Platform can compare the model's performance on adversarial examples to its performance on clean examples to assess the effectiveness of the adversarial training. In some implementations, the platform may conduct ablation studies to understand the impact of different adversarial training techniques and hyperparameters on the model's robustness.

[0301] FIG. **36** is a flow diagram illustrating an exemplary method **3600** for providing security and defense of a generative AI model, according to an embodiment. According to an aspect, the process may be performed by security and defense computing system **175** of advanced model management platform **170**. According to the embodiment, the process begins at step **3601** by implementing model distillation by training a smaller student model to mimic the behavior of a larger teacher model. The distillation procedure may comprise training the student model to minimize the difference between its outputs and the teacher model's outputs and may use, for example, techniques such as temperature scaling or knowledge distillation loss to transfer knowledge from the teacher to the student. At step **3602**, the platform applies differential privacy techniques (e.g., adding noise to the gradients) during the distillation process to protect sensitive information. The appropriate level of privacy protection may be based on the sensitivity of the data and the desired trade-off between privacy and utility. Platform can monitor the impact of differential privacy on the student model's performance and adjust the privacy parameters as needed.

[0302] As a next step **3603**, the platform can utilize similarity scoring methods (e.g., cosine similarity, Euclidean distance, etc.) to compare the weights or outputs of the student model to the teacher model. This may involve normalizing and preprocessing the model weights or outputs to ensure a fair comparison. Platform or an administrator can define appropriate similarity thresholds for detecting potential model infringement or theft. At step **3604**, the platform provides model monitoring using a similarity threshold to detect potential model infringement or theft. The monitoring system may regularly evaluate the student model's performance and behavior and compare the student model's outputs to the teacher model's outputs on a diverse set of inputs. Platform can monitor for any sudden changes or anomalies in the student model's performance or similarity scores. As a last step **3605**, the platform regularly monitors the model's performance and behavior to identify any anomalies or signs of tampering. In some implementations, platform may comprise an automated system to compare the student model's weights or outputs to other models in the market and use the similarity scoring methods and thresholds to detect potential instances of model infringement or theft. In some implementations, the platform may establish a protocol for handling detected infringement cases, including legal and technical actions.

[0303] FIG. **37** is a flow diagram illustrating an exemplary method **3700** for model management of a generative AI model, according to an embodiment. According to an aspect, the process may be performed by model management computing system **176** of advanced model management platform **170**. According to the embodiment, the process begins at step **3701** by implementing an attention mechanism search procedure to explore different attention architectures (e.g., multi-head attention, self-attention, etc.) and hyperparameters (e.g., number of heads, hidden dimension, etc.). Additionally, or alternatively, step **3701** may comprise a model

search process. This may comprise defining a search space that covers a wide range of attention configurations and hyperparameter values. Platform may utilize techniques such as, for example, grid search, random search, or Bayesian optimization to efficiently explore the search space. At step **3702**, platform can train multiple models with different attention configurations on a target task and evaluate the performance of each model on a validation set using relevant metrics (e.g., accuracy, F1 score, BLEU score, etc.). Platform can record the performance metrics and corresponding attention configurations for each model.

[0304] At step **3703**, the platform evaluates the performance of each of the trained models on a validation set and selects the best performing attention configuration. Platform may be configured to consider the trade-off between model performance and computational efficiency when selecting the best configuration. Additionally, the platform may conduct additional fine-tuning or hyperparameter optimization on the selected configuration if necessary. At step **3704** a model blending procedure is applied to each model on a validation set and the best-performing model(s) is selected. The model blending procedure combines the outputs of multiple models. This may involve the use of techniques like weighted averaging, majority voting, or stacking to blend the model outputs to determine the optimal blending weights or meta-model architecture based on the performance on a validation set. At step **3705**, platform trains multiple models with different architectures, datasets, or retrieval strategies for a target task, and blends their outputs (using the blending procedure) to create a more robust and reliable system. Platform can evaluate the performance of the blended model on a test set and compare it to the individual models. As a last step **3706**, the platform continuously monitors the performance of the blended model over time and updates the individual models or blending weights as needed. The platform can collect user feedback, error reports, and performance metrics to identify areas for improvement and regularly update the individual models with new data or architectures based on the monitoring results. Platform may be further configured to retrain the blending weights or meta-model as new models are added or updated. In some implementations, DCG computing system **121** may be leveraged to establish a versioning and deployment pipeline to seamlessly integrate model updates into the production system.

Exemplary Computing Environment

[0305] FIG. **38** illustrates an exemplary computing environment on which an embodiment described herein may be implemented, in full or in part. This exemplary computing environment describes computer-related components and processes supporting enabling disclosure of computer-implemented embodiments. Inclusion in this exemplary computing environment of well-known processes and computer components, if any, is not a suggestion or admission that any embodiment is no more than an aggregation of such processes or components. Rather, implementation of an embodiment using processes and components described in this exemplary computing environment will involve programming or configuration of such processes and components resulting in a machine specially programmed or configured for such implementation. The exemplary computing environment described herein is only one example of such an environment and other configurations of the components and processes are possible, including other relationships between and among components, and/or absence of some processes or components described. Further, the exemplary computing environment described herein is not intended to suggest any limitation as to the scope of use or functionality of any embodiment implemented, in whole or in part, on components or processes described herein.

[0306] The exemplary computing environment described herein comprises a computing device **10** (further comprising a system bus **11**, one or more processors **20**, a system memory **30**, one or more interfaces **40**, one or more non-volatile data storage devices **50**), external peripherals and accessories **60**, external communication devices **70**, remote computing devices **80**, and cloud-based services **90**.

[0307] System bus **11** couples the various system components, coordinating operation of and data transmission between those various system components. System bus **11** represents one or more of any type or combination of types of wired or wireless bus structures including, but not limited to, memory busses or memory controllers, point-to-point connections, switching fabrics, peripheral busses, accelerated graphics ports, and local busses using any of a variety of bus architectures. By way of example, such architectures include, but are not limited to, Industry Standard Architecture (ISA) busses, Micro Channel Architecture (MCA) busses, Enhanced ISA (EISA) busses, Video Electronics Standards Association (VESA) local busses, a Peripheral Component Interconnects (PCI) busses also known as a Mezzanine busses, or any selection of, or combination of, such busses. Depending on the specific physical implementation, one or more of the processors **20**, system memory **30** and other components of the computing device **10** can be physically co-located or integrated into a single physical component, such as on a single chip. In such a case, some or all of system bus **11** can be electrical pathways within a single chip structure.

[0308] Computing device may further comprise externally-accessible data input and storage devices **12** such as compact disc read-only memory (CD-ROM) drives, digital versatile discs (DVD), or other optical disc storage for reading and/or writing optical discs **62**; magnetic cassettes, magnetic tape, magnetic disk storage, or other magnetic storage devices; or any other medium which can be used to store the desired content and which can be accessed by the computing device **10**. Computing device may further comprise externally-accessible data ports or connections **12** such as serial ports, parallel ports, universal serial bus (USB) ports, and infrared ports and/or transmitter/receivers. Computing device may further comprise hardware for wireless communication with external devices such as IEEE 1394 ("Firewire") interfaces, IEEE 802.11 wireless interfaces, BLUETOOTH® wireless interfaces, and so forth. Such ports and interfaces may be used to connect any number of external peripherals and accessories **60** such as visual displays, monitors, and touch-sensitive screens **61**, USB solid state memory data storage drives (commonly known as "flash drives" or "thumb drives") **63**, printers **64**, pointers and manipulators such as mice **65**, keyboards **66**, and other devices **67** such as joysticks and gaming pads, touchpads, additional displays and monitors, and external hard drives (whether solid state or disc-based), microphones, speakers, cameras, and optical scanners.

[0309] Processors **20** are logic circuitry capable of receiving programming instructions and processing (or executing)

those instructions to perform computer operations such as retrieving data, storing data, and performing mathematical calculations. Processors **20** are not limited by the materials from which they are formed or the processing mechanisms employed therein, but are typically comprised of semiconductor materials into which many transistors are formed together into logic gates on a chip (i.e., an integrated circuit or IC). The term processor includes any device capable of receiving and processing instructions including, but not limited to, processors operating on the basis of quantum computing, optical computing, mechanical computing (e.g., using nanotechnology entities to transfer data), and so forth. Depending on configuration, computing device **10** may comprise more than one processor. For example, computing device **10** may comprise one or more central processing units (CPUs) **21**, each of which itself has multiple processors or multiple processing cores, each capable of independently or semi-independently processing programming instructions based on technologies like complex instruction set computer (CISC) or reduced instruction set computer (RISC). Further, computing device **10** may comprise one or more specialized processors such as a graphics processing unit (GPU) **22** configured to accelerate processing of computer graphics and images via a large array of specialized processing cores arranged in parallel. Further computing device **10** may be comprised of one or more specialized processes such as Intelligent Processing Units, field-programmable gate arrays or application-specific integrated circuits for specific tasks or types of tasks. The term processor may further include: neural processing units (NPUs) or neural computing units optimized for machine learning and artificial intelligence workloads using specialized architectures and data paths; tensor processing units (TPUs) designed to efficiently perform matrix multiplication and convolution operations used heavily in neural networks and deep learning applications; application-specific integrated circuits (ASICs) implementing custom logic for domain-specific tasks; application-specific instruction set processors (ASIPs) with instruction sets tailored for particular applications; field-programmable gate arrays (FPGAs) providing reconfigurable logic fabric that can be customized for specific processing tasks; processors operating on emerging computing paradigms such as quantum computing, optical computing, mechanical computing (e.g., using nanotechnology entities to transfer data), and so forth. Depending on configuration, computing device **10** may comprise one or more of any of the above types of processors in order to efficiently handle a variety of general purpose and specialized computing tasks. The specific processor configuration may be selected based on performance, power, cost, or other design constraints relevant to the intended application of computing device **10**.

[0310] System memory **30** is processor-accessible data storage in the form of volatile and/or nonvolatile memory. System memory **30** may be either or both of two types: non-volatile memory and volatile memory. Non-volatile memory **30***a* is not erased when power to the memory is removed, and includes memory types such as read only memory (ROM), electronically-erasable programmable memory (EEPROM), and rewritable solid state memory (commonly known as "flash memory"). Non-volatile memory **30***a* is typically used for long-term storage of a basic input/output system (BIOS) **31**, containing the basic instructions, typically loaded during computer startup, for transfer of information between components within computing device, or a unified extensible firmware interface (UEFI), which is a modern replacement for BIOS that supports larger hard drives, faster boot times, more security features, and provides native support for graphics and mouse cursors. Non-volatile memory **30***a* may also be used to store firmware comprising a complete operating system **35** and applications **36** for operating computer-controlled devices. The firmware approach is often used for purpose-specific computer-controlled devices such as appliances and Internet-of-Things (IoT) devices where processing power and data storage space is limited. Volatile memory **30***b* is erased when power to the memory is removed and is typically used for short-term storage of data for processing. Volatile memory **30***b* includes memory types such as random-access memory (RAM), and is normally the primary operating memory into which the operating system **35**, applications **36**, program modules **37**, and application data **38** are loaded for execution by processors **20**. Volatile memory **30***b* is generally faster than non-volatile memory **30***a* due to its electrical characteristics and is directly accessible to processors **20** for processing of instructions and data storage and retrieval. Volatile memory **30***b* may comprise one or more smaller cache memories which operate at a higher clock speed and are typically placed on the same IC as the processors to improve performance.

[0311] There are several types of computer memory, each with its own characteristics and use cases. System memory **30** may be configured in one or more of the several types described herein, including high bandwidth memory (HBM) and advanced packaging technologies like chip-on-wafer-on-substrate (CoWoS). Static random access memory (SRAM) provides fast, low-latency memory used for cache memory in processors, but is more expensive and consumes more power compared to dynamic random access memory (DRAM). SRAM retains data as long as power is supplied. DRAM is the main memory in most computer systems and is slower than SRAM but cheaper and more dense. DRAM requires periodic refresh to retain data. NAND flash is a type of non-volatile memory used for storage in solid state drives (SSDs) and mobile devices and provides high density and lower cost per bit compared to DRAM with the trade-off of slower write speeds and limited write endurance. HBM is an emerging memory technology that provides high bandwidth and low power consumption which stacks multiple DRAM dies vertically, connected by through-silicon vias (TSVs). HBM offers much higher bandwidth (up to 1 TB/s) compared to traditional DRAM and may be used in high-performance graphics cards, AI accelerators, and edge computing devices. Advanced packaging and CoWoS are technologies that enable the integration of multiple chips or dies into a single package. CoWoS is a 2.5D packaging technology that interconnects multiple dies side-by-side on a silicon interposer and allows for higher bandwidth, lower latency, and reduced power consumption compared to traditional PCB-based packaging. This technology enables the integration of heterogeneous dies (e.g., CPU, GPU, HBM) in a single package and may be used in high-performance computing, AI accelerators, and edge computing devices.

[0312] Interfaces **40** may include, but are not limited to, storage media interfaces **41**, network interfaces **42**, display interfaces **43**, and input/output interfaces **44**. Storage media interface **41** provides the necessary hardware interface for loading data from non-volatile data storage devices **50** into system memory **30** and storage data from system memory **30**

to non-volatile data storage device **50**. Network interface **42** provides the necessary hardware interface for computing device **10** to communicate with remote computing devices **80** and cloud-based services **90** via one or more external communication devices **70**. Display interface **43** allows for connection of displays **61**, monitors, touchscreens, and other visual input/output devices. Display interface **43** may include a graphics card for processing graphics-intensive calculations and for handling demanding display requirements. Typically, a graphics card includes a graphics processing unit (GPU) and video RAM (VRAM) to accelerate display of graphics. In some high-performance computing systems, multiple GPUs may be connected using NVLink bridges, which provide high-bandwidth, low-latency interconnects between GPUs. NVLink bridges enable faster data transfer between GPUs, allowing for more efficient parallel processing and improved performance in applications such as machine learning, scientific simulations, and graphics rendering. One or more input/output (I/O) interfaces **44** provide the necessary support for communications between computing device **10** and any external peripherals and accessories **60**. For wireless communications, the necessary radio-frequency hardware and firmware may be connected to I/O interface **44** or may be integrated into I/O interface **44**.

[0313] Non-volatile data storage devices **50** are typically used for long-term storage of data. Data on non-volatile data storage devices **50** is not erased when power to the non-volatile data storage devices **50** is removed. Non-volatile data storage devices **50** may be implemented using any technology for non-volatile storage of content including, but not limited to, CD-ROM drives, digital versatile discs (DVD), or other optical disc storage; magnetic cassettes, magnetic tape, magnetic disc storage, or other magnetic storage devices; solid state memory technologies such as EEPROM or flash memory; or other memory technology or any other medium which can be used to store data without requiring power to retain the data after it is written. Non-volatile data storage devices **50** may be non-removable from computing device **10** as in the case of internal hard drives, removable from computing device **10** as in the case of external USB hard drives, or a combination thereof, but computing device will typically comprise one or more internal, non-removable hard drives using either magnetic disc or solid state memory technology. Non-volatile data storage devices **50** may store any type of data including, but not limited to, an operating system **51** for providing low-level and mid-level functionality of computing device **10**, applications **52** for providing high-level functionality of computing device **10**, program modules **53** such as containerized programs or applications, or other modular content or modular programming, application data **54**, and databases **55** such as relational databases, non-relational databases, object oriented databases, NoSQL databases, vector databases, key-value databases, document oriented data stores, and graph databases.

[0314] Applications (also known as computer software or software applications) are sets of programming instructions designed to perform specific tasks or provide specific functionality on a computer or other computing devices. Applications are typically written in high-level programming languages such as C, C++, Scala, Java, Erlang, Rust, GoLang, and Python, which are then either interpreted at runtime or compiled into low-level, binary, processor-executable instructions operable on processors **20**. Applications may be containerized so that they can be run on any computer hardware running any known operating system. Containerization of computer software is a method of packaging and deploying applications along with their operating system dependencies into self-contained, isolated units known as containers. Containers provide a lightweight and consistent runtime environment that allows applications to run reliably across different computing environments, such as development, testing, and production systems.

[0315] The memories and non-volatile data storage devices described herein do not include communication media. Communication media are means of transmission of information such as modulated electromagnetic waves or modulated data signals configured to transmit, not store, information. By way of example, and not limitation, communication media includes wired communications such as sound signals transmitted to a speaker via a speaker wire, and wireless communications such as acoustic waves, radio frequency (RF) transmissions, infrared emissions, and other wireless media.

[0316] External communication devices **70** are devices that facilitate communications between computing device and either remote computing devices **80**, or cloud-based services **90**, or both. External communication devices **70** include, but are not limited to, data modems **71** which facilitate data transmission between computing device and the Internet **75** via a common carrier such as a telephone company or internet service provider (ISP), routers **72** which facilitate data transmission between computing device and other devices, and switches **73** which provide direct data communications between devices on a network. Here, modem **71** is shown connecting computing device **10** to both remote computing devices **80** and cloud-based services **90** via the Internet **75**. While modem **71**, router **72**, and switch **73** are shown here as being connected to network interface **42**, many different network configurations using external communication devices **70** are possible. Using external communication devices **70**, networks may be configured as local area networks (LANs) for a single location, building, or campus, wide area networks (WANs) comprising data networks that extend over a larger geographical area, and virtual private networks (VPNs) which can be of any size but connect computers via encrypted communications over public networks such as the Internet **75**. As just one exemplary network configuration, network interface **42** may be connected to switch **73** which is connected to router **72** which is connected to modem **71** which provides access for computing device **10** to the Internet **75**. Further, any combination of wired **77** or wireless **76** communications between and among computing device **10**, external communication devices **70**, remote computing devices **80**, and cloud-based services **90** may be used. Remote computing devices **80**, for example, may communicate with computing device through a variety of communication channels **74** such as through switch **73** via a wired **77** connection, through router **72** via a wireless connection **76**, or through modem **71** via the Internet **75**. Furthermore, while not shown here, other hardware that is specifically designed for servers may be employed. For example, secure socket layer (SSL) acceleration cards can be used to offload SSL encryption computations, and transmission control protocol/internet protocol (TCP/IP) offload hardware and/or packet classifiers on network interfaces **42** may be installed and used at server devices.

[0317] In a networked environment, certain components of computing device **10** may be fully or partially implemented on remote computing devices **80** or cloud-based services **90**. Data stored in non-volatile data storage device **50** may be received from, shared with, duplicated on, or offloaded to a non-volatile data storage device on one or more remote computing devices **80** or in a cloud computing service **92**. Processing by processors **20** may be received from, shared with, duplicated on, or offloaded to processors of one or more remote computing devices **80** or in a distributed computing service **93**. By way of example, data may reside on a cloud computing service **92**, but may be usable or otherwise accessible for use by computing device **10**. Also, certain processing subtasks may be sent to a microservice **91** for processing with the result being transmitted to computing device **10** for incorporation into a larger processing task. Also, while components and processes of the exemplary computing environment are illustrated herein as discrete units (e.g., OS **51** being stored on non-volatile data storage device **51** and loaded into system memory **35** for use) such processes and components may reside or be processed at various times in different components of computing device **10**, remote computing devices **80**, and/or cloud-based services **90**.

[0318] In an implementation, the disclosed systems and methods may utilize, at least in part, containerization techniques to execute one or more processes and/or steps disclosed herein. Containerization is a lightweight and efficient virtualization technique that allows you to package and run applications and their dependencies in isolated environments called containers. One of the most popular containerization platforms is containerd, which is widely used in software development and deployment. Containerization, particularly with open-source technologies like Docker and container orchestration systems like Kubernetes, is a common approach for deploying and managing applications. Containers are created from images, which are lightweight, standalone, and executable packages that include application code, libraries, dependencies, and runtime. Images are often built from a Dockerfile or similar, which contains instructions for assembling the image. Dockerfiles are configuration files that specify how to build a Docker image. Systems like Kubernetes also support containerd or CRI-O. They include commands for installing dependencies, copying files, setting environment variables, and defining runtime configurations. Docker images are stored in repositories, which can be public or private. Docker Hub is an exemplary public registry, and organizations often set up private registries for security and version control using tools such as Hub, JFrog Artifactory and Bintray, Gitlab, Github Packages or Container registries. Containers can communicate with each other and the external world through networking. Docker provides a bridge network by default, but can be used with custom networks. Containers within the same network can communicate using container names or IP addresses.

[0319] Remote computing devices **80** are any computing devices not part of computing device **10**. Remote computing devices **80** include, but are not limited to, personal computers, server computers, thin clients, thick clients, personal digital assistants (PDAs), mobile telephones, watches, tablet computers, laptop computers, multiprocessor systems, microprocessor based systems, set-top boxes, programmable consumer electronics, video game machines, game consoles, portable or handheld gaming units, network terminals, desktop personal computers (PCs), minicomputers, mainframe computers, network nodes, virtual reality or augmented reality devices and wearables, and distributed or multiprocessing computing environments. While remote computing devices **80** are shown for clarity as being separate from cloud-based services **90**, cloud-based services **90** are implemented on collections of networked remote computing devices **80**.

[0320] Cloud-based services **90** are Internet-accessible services implemented on collections of networked remote computing devices **80**. Cloud-based services are typically accessed via application programming interfaces (APIs) which are software interfaces which provide access to computing services within the cloud-based service via API calls, which are pre-defined protocols for requesting a computing service and receiving the results of that computing service. While cloud-based services may comprise any type of computer processing or storage, three common categories of cloud-based services **90** are microservices **91**, cloud computing services **92**, and distributed computing services **93**.

[0321] Microservices **91** are collections of small, loosely coupled, and independently deployable computing services. Each microservice represents a specific computing functionality and runs as a separate process or container. Microservices promote the decomposition of complex applications into smaller, manageable services that can be developed, deployed, and scaled independently. These services communicate with each other through well-defined application programming interfaces (APIs), typically using lightweight protocols like HTTP, gRPC, or message queues such as Kafka. Microservices **91** can be combined to perform more complex processing tasks.

[0322] Cloud computing services **92** are delivery of computing resources and services over the Internet **75** from a remote location. Cloud computing services **92** provide additional computer hardware and storage on as-needed or subscription basis. Cloud computing services **92** can provide large amounts of scalable data storage, access to sophisticated software and powerful server-based processing, or entire computing infrastructures and platforms. For example, cloud computing services can provide virtualized computing resources such as virtual machines, storage, and networks, platforms for developing, running, and managing applications without the complexity of infrastructure management, and complete software applications over the Internet on a subscription basis.

[0323] Distributed computing services **93** provide large-scale processing using multiple interconnected computers or nodes to solve computational problems or perform tasks collectively. In distributed computing, the processing and storage capabilities of multiple machines are leveraged to work together as a unified system. Distributed computing services are designed to address problems that cannot be efficiently solved by a single computer or that require large-scale computational power. These services enable parallel processing, fault tolerance, and scalability by distributing tasks across multiple nodes.

[0324] Although described above as a physical device, computing device **10** can be a virtual computing device, in which case the functionality of the physical components herein described, such as processors **20**, system memory **30**, network interfaces **40**, and other like components can be

provided by computer-executable instructions. Such computer-executable instructions can execute on a single physical computing device, or can be distributed across multiple physical computing devices, including being distributed across multiple physical computing devices in a dynamic manner such that the specific, physical computing devices hosting such computer-executable instructions can dynamically change over time depending upon need and availability. In the situation where computing device **10** is a virtualized device, the underlying physical computing devices hosting such a virtualized computing device can, themselves, comprise physical components analogous to those described above, and operating in a like manner. Furthermore, virtual computing devices can be utilized in multiple layers with one virtual computing device executing within the construct of another virtual computing device. Thus, computing device **10** may be either a physical computing device or a virtualized computing device within which computer-executable instructions can be executed in a manner consistent with their execution by a physical computing device. Similarly, terms referring to physical components of the computing device, as utilized herein, mean either those physical components or virtualizations thereof performing the same or equivalent functions.

[0325] The skilled person will be aware of a range of possible modifications of the various aspects described above. Accordingly, the present invention is defined by the claims and their equivalents.

1. A computing system for optimizing generative AI models, the computing system comprising:

one or more hardware processors configured for:

optimizing an AI model's performance by selecting one or more settings for the AI model using reinforcement learning algorithms based on a task-specific reward function that measures the AI model's performance on a specified task;

optimizing the AI model's content by using retrieval augmented generation (RAG) to retrieve information for the AI model from a curated knowledge corpus based on contextual matching with the input query and conditioning the AI model's prompts or outputs based on content from the retrieved information;

validating the AI model's performance against one or more authorities using cross-validation, wherein the one or more authorities includes human experts, crowdsourcing, authoritative databases, rule sets, or expert judgment models that perform synthesis of multiple responses using consensus mechanisms;

optimizing the AI model's robustness using adversarial training;

optimizing the AI model's stability using input perturbation; and

optimizing the AI model's reliability for the specified task using one or more techniques measured against a fitness function, wherein the techniques include model type search, attention mechanism search, model blending with weighted consensus, expert synthesis, RAG, knowledge graph verification, or composite vectorized knowledge graphs, and wherein optimization is performed through a distributed computational graph that automatically parallelizes processing across heterogeneous computing resources.

2. The computing system of claim **1**, wherein optimizing the AI model's performance includes one or more reinforcement learning algorithms comprising Proximal Policy Optimization or Asynchronous Advantage Actor-Critic algorithms.

3. (canceled)

4. The computing system of claim **1**, wherein validating the AI model's performance comprises comparing the AI model's responses to responses provided by the one or more authorities.

5. (canceled)

6. The computing system of claim **1**, wherein the adversarial training incorporates malicious examples into training data to make the AI model more resilient against manipulated predictions.

7. (canceled)

8. The computing system of claim **1**, wherein model blending comprises selecting from or blending outputs from multiple models or authoritative knowledge bases, each trained on, or obtained from, defined resource collections or with different retrieval strategies or hyperparameters.

9. A computer-implemented method for optimizing generative AI models, the computer-implemented method comprising:

optimizing an AI model's performance by selecting one or more settings for the AI model using reinforcement learning algorithms based on a task-specific reward function that measures the AI model's performance on a specified task;

optimizing the AI model's content by using retrieval augmented generation (RAG) to retrieve information for the AI model from a curated knowledge corpus based on contextual matching with the input query and conditioning the AI model's prompts or outputs based on content from the retrieved information;

validating the AI model's performance against one or more authorities using cross-validation, wherein the one or more authorities includes human experts, crowdsourcing, authoritative databases, or rule sets, or expert judgment models that perform synthesis of multiple responses using consensus mechanisms;

optimizing the AI model's robustness using adversarial training;

optimizing the AI model's stability using and input perturbation; and

optimizing the AI model's reliability for the specified task using one or more techniques, measured against a fitness function, wherein the techniques include model type search, attention mechanisms search, model blending with weighted consensus, expert synthesis, RAG, knowledge graph verification, or composite vectorized knowledge graphs, and wherein the optimization is performed through a distributed computational graph that automatically parallelizes processing across heterogeneous computing resources.

10. The computer-implemented method of claim **9**, wherein optimizing the AI model's performance include one or more reinforcement learning algorithms comprising Proximal Policy Optimization or Asynchronous Advantage Actor-Critic algorithms.

11. (canceled)

12. The computer-implemented method of claim **9**, wherein validating the AI model's performance comprises

comparing the AI model's responses to responses provided by the one or more authorities.

13. (canceled)

14. The computer-implemented method of claim **9**, wherein the adversarial training incorporates malicious examples into training data to make the AI model more resilient against manipulated predictions.

15. (canceled)

16. The computer-implemented method of claim **9**, wherein model blending comprises selecting from or blending outputs from multiple models or authoritative knowledge bases, each trained on, or obtained from, defined resource collections or with different retrieval strategies or hyperparameters.

17-24. (canceled)

25. Non-transitory, computer-readable storage media having computer-executable instructions embodied thereon that, when executed by one or more processors of a computing system for optimizing generative AI models, cause the computing system to:

optimize an AI model's performance by selecting one or more settings for the AI model using reinforcement learning algorithms based on a task-specific reward function that measures the AI model's performance on a specified task;

optimize the AI model's content by using retrieval augmented generation (RAG) to retrieve information for the AI model from a curated knowledge corpus based on contextual matching with the input query and conditioning the AI model's prompts or outputs based on content from the retrieved information;

validate the AI model's performance against one or more authorities using cross-validation, wherein the one or more authorities includes human experts, crowdsourcing, authoritative databases, or rule sets, or expert judgment models that perform synthesis of multiple responses using consensus mechanisms;

optimize the AI model's robustness using adversarial training;

optimize the AI model's stability using input perturbation; and

optimize the AI model's reliability for the specified task using one or more techniques measured against a fitness function, wherein the techniques include model type search, attention mechanism search, model blending with weighted consensus, expert synthesis, RAG, knowledge graph verification, or composite vectorized knowledge graphs, and wherein optimization is performed through a distributed computational graph that automatically parallelizes processing across heterogeneous computing resources.

26. The non-transitory, computer-readable storage media of claim **25**, wherein optimizing the AI model's performance includes one or more reinforcement learning algorithms comprising Proximal Policy Optimization or Asynchronous Advantage Actor-Critic algorithms.

27. (canceled)

28. The non-transitory, computer-readable storage media of claim **25**, wherein validating the AI model's performance comprises comparing the AI model's responses to responses provided by the one or more authorities.

29. (canceled)

30. The non-transitory, computer-readable storage media of claim **25**, wherein the adversarial training incorporates malicious examples into training data to make the AI model more resilient against manipulated predictions.

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