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Senthivel et al.

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(54) **SERVICE ARCHITECTURE FOR ENTITY AND RELATIONSHIP DETECTION IN UNSTRUCTURED TEXT**

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(21) Appl. No.: **16/437,338**

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(51) **Int. Cl.**
G06F 16/93 (2019.01)
G06F 40/30 (2020.01)
(Continued)

(52) **U.S. Cl.**
CPC ***G06F 40/295*** (2020.01); ***G06F 16/288*** (2019.01); ***G06F 16/31*** (2019.01);
(Continued)

(58) **Field of Classification Search**
CPC G06F 40/30; G06F 16/3344; G06F 40/279; G06F 40/284; G06F 40/295;
(Continued)

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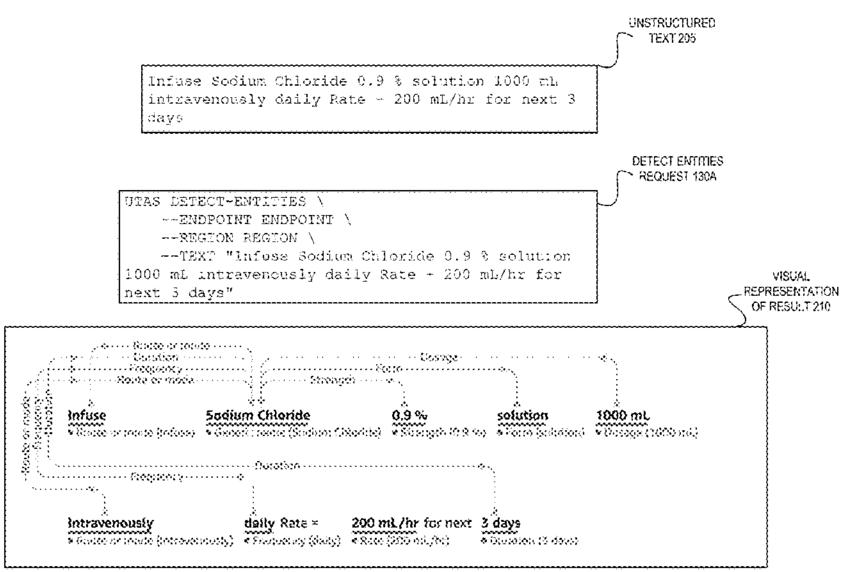
(57) **ABSTRACT**

Techniques for entity and relationship detect from unstructured text as a service are described. A service may receive a request to identify entities within a provided unstructured text element, and the service may segment and tokenize the unstructured text and send the result to multiple services implementing multiple deep machine learning models trained to identify particular entities. The service may send additional requests to an additional service or services implementing additional deep machine learning models to identify relationships between detected attributes and ones of the detected entities. The outputs from all services can be analyzed and consolidated into a single result that identifies the entities, any attributes of the entities, and confidence scores indicating the confidence in each detected entity.

20 Claims, 11 Drawing Sheets



(51) **Int. Cl.**
G06F 40/295 (2020.01)
G06F 16/28 (2019.01)
G06F 16/31 (2019.01)
G06N 3/04 (2006.01)
G06N 3/08 (2006.01)
G06F 40/284 (2020.01)

(52) **U.S. Cl.**
CPC ***G06F 40/284*** (2020.01); ***G06N 3/0454*** (2013.01); ***G06N 3/08*** (2013.01); *G06N 3/04* (2013.01); *G06N 3/0445* (2013.01)

(58) **Field of Classification Search**
CPC G06F 40/205; G06N 3/0445; G06N 5/022; G06N 20/00; G06N 5/04; G06N 3/0427; G06N 3/08; G06N 20/20; G06N 3/04
See application file for complete search history.

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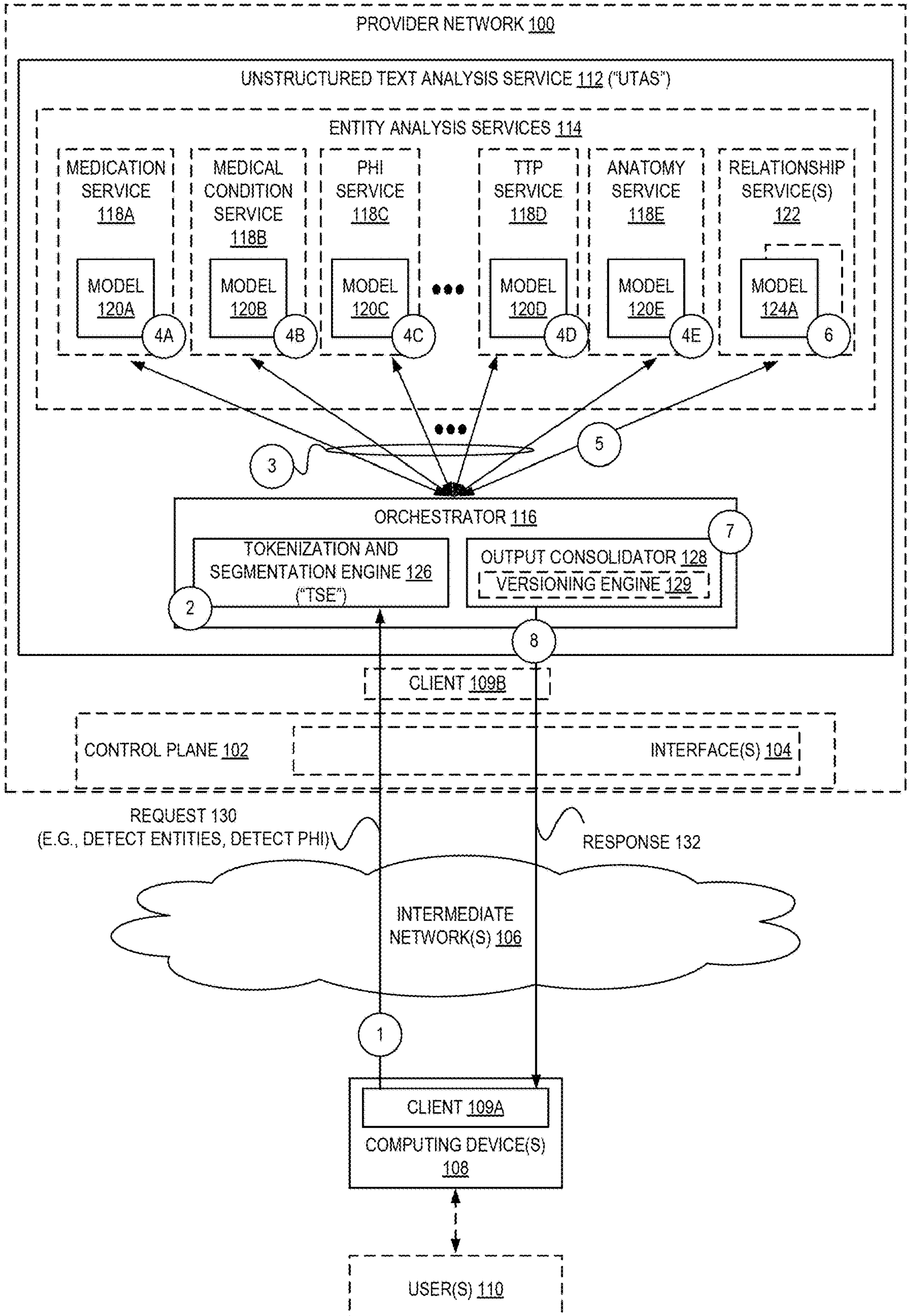
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UNSTRUCTURED TEXT ANALYSIS SERVICE 112 ("UTAS")
ENTITY ANALYSIS SERVICES 114
MEDICATION SERVICE 118A
MODEL 120A
4A
MEDICAL CONDITION SERVICE 118B
MODEL 120B
4B
PHI SERVICE 118C
MODEL 120C
4C
TTP SERVICE 118D
MODEL 120D
4D
ANATOMY SERVICE 118E
MODEL 120E
4E
RELATIONSHIP SERVICE(S) 122
MODEL 124A
6
3
5
ORCHESTRATOR 116
7
TOKENIZATION AND SEGMENTATION ENGINE 126 ("TSE")
2
OUTPUT CONSOLIDATOR 128
VERSIONING ENGINE 129
8
CLIENT 109B
CONTROL PLANE 102
INTERFACE(S) 104
REQUEST 130 (E.G., DETECT ENTITIES, DETECT PHI)
RESPONSE 132
INTERMEDIATE NETWORK(S) 106
1
CLIENT 109A
COMPUTING DEVICE(S) 108
USER(S) 110

FIG. 1

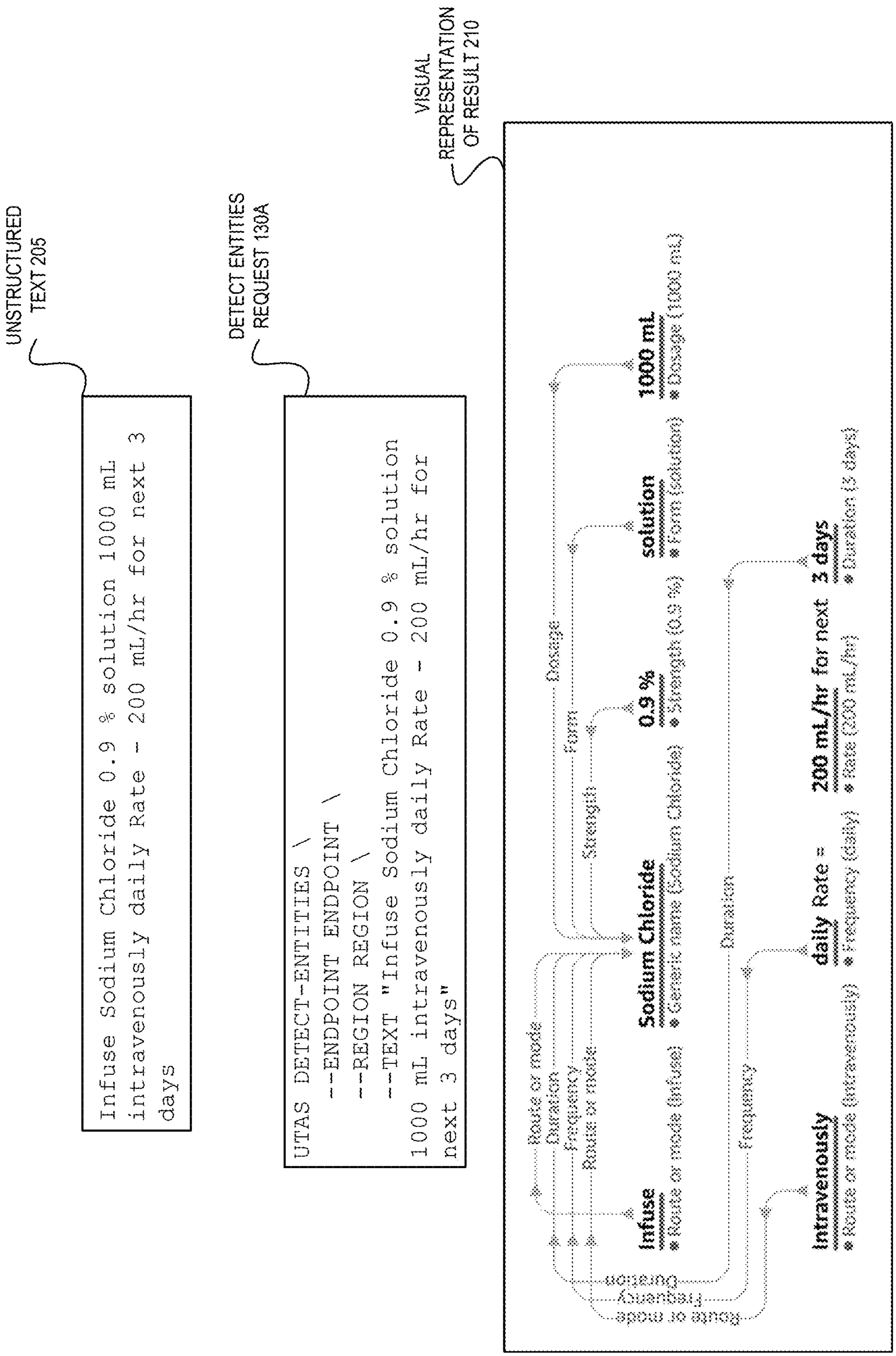
UNSTRUCTURED TEXT 205
Infuse Sodium Chloride 0.9 % solution 1000 mL intravenously daily Rate - 200 mL/hr for next 3 days
DETECT ENTITIES REQUEST 130A
UTAS DETECT-ENTITIES \
--ENDPOINT ENDPOINT \
--REGION REGION \
--TEXT "Infuse Sodium Chloride 0.9 % solution 1000 mL intravenously daily Rate - 200 mL/hr for next 3 days"
VISUAL REPRESENTATION OF RESULT 210
Infuse
Route or mode (Infuse)
Sodium Chloride
Generic name (Sodium Chloride)
0.9 %
Strength (0.9 %)
solution
Form (solution)
1000 mL
Dosage (1000 mL)
Intravenously
Route or mode (intravenously)
daily Rate =
Frequency (daily)
200 mL/hr for next
Rate (200 mL/hr)
3 days
Duration (3 days)
Route or mode
Duration
Frequency
Strength
Form
Dosage

FIG. 2

```
{
    "ENTITIES": [
        {
            "ID": 1,
            "BEGINOFFSET": 7,
            "ENDOFFSET": 22,
            "SCORE": 0.9998517036437988,
            "TEXT": "SODIUM CHLORIDE",
            "CATEGORY": "MEDICATION",
            "TYPE": "GENERIC_NAME",
            "TRAITS": [],
            "ATTRIBUTES": [
                {
                    "TYPE": "ROUTE_OR_MODE",
                    "SCORE": 0.32359644770622253,
                    "RELATIONSHIPSCORE": 0.9719992280006409,
                    "ID": 0,
                    "BEGINOFFSET": 0,
                    "ENDOFFSET": 6,
                    "TEXT": "INFUSE",
                    "TRAITS": []
                },
...
                {
                    "TYPE": "DURATION",
                    "SCORE": 0.9392423033714294,
                    "RELATIONSHIPSCORE": 0.9961885809898376,
                    "ID": 8,
                    "BEGINOFFSET": 91,
                    "ENDOFFSET": 97,
                    "TEXT": "3 DAYS",
                    "TRAITS": []
                }
            ]
        }
    ],
   "UNMAPPEDATTRIBUTES": [
        {
            "TYPE": "MEDICATION",
            "ATTRIBUTE": {
                "TYPE": "DOSAGE",
                "SCORE": 0.9922149777412415,
                "ID": 4,
                "BEGINOFFSET": 37,
                "ENDOFFSET": 44,
                "TEXT": "1000 ML",
                "TRAITS": []
            }
        },
        {
            "TYPE": "MEDICATION",
            "ATTRIBUTE": {
                "TYPE": "RATE",
                "SCORE": 0.9728594422340393,
                "ID": 7,
                "BEGINOFFSET": 72,
                "ENDOFFSET": 81,
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                "TRAITS": []
            }
        }
    ]
}
```
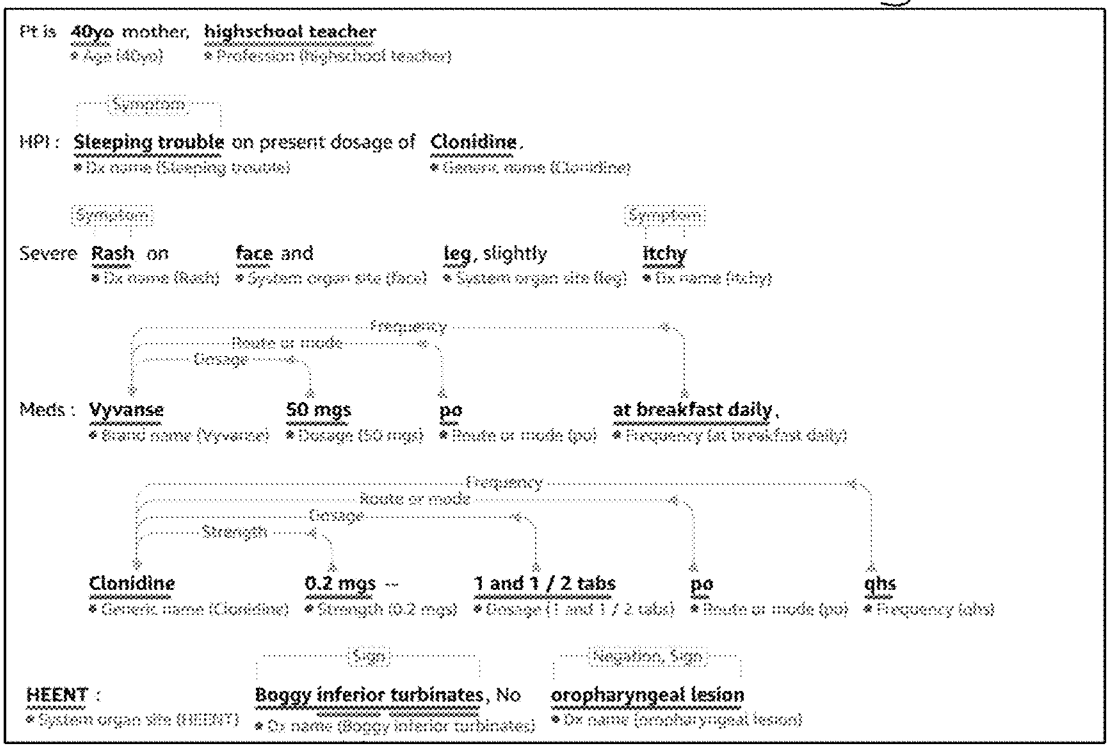


(ABBREVIATED) RESULT 300

FIG. 3

RESULT USER INTERFACE 400



RESULT USER INTERFACE 410

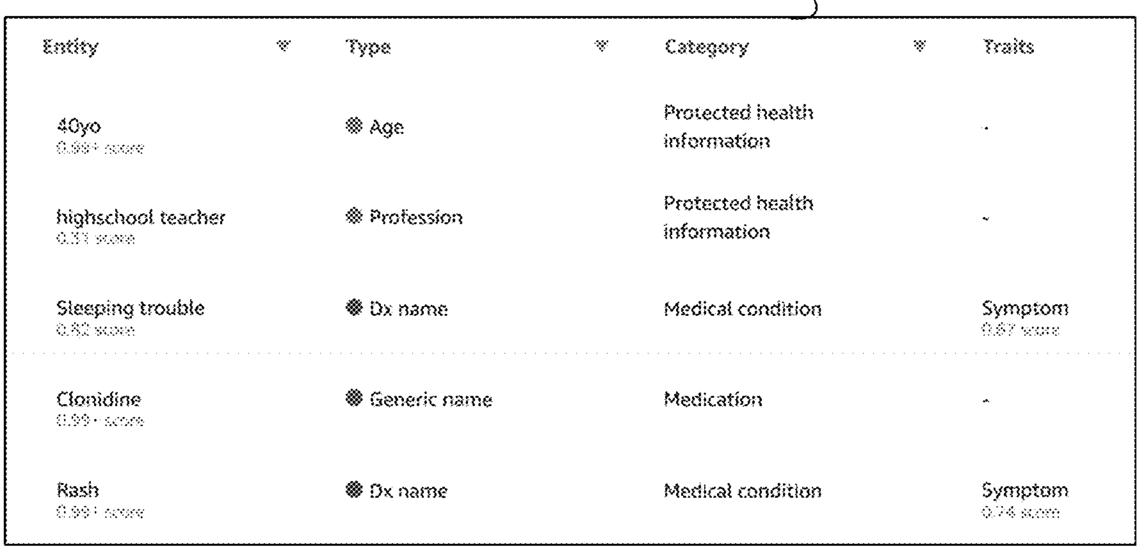
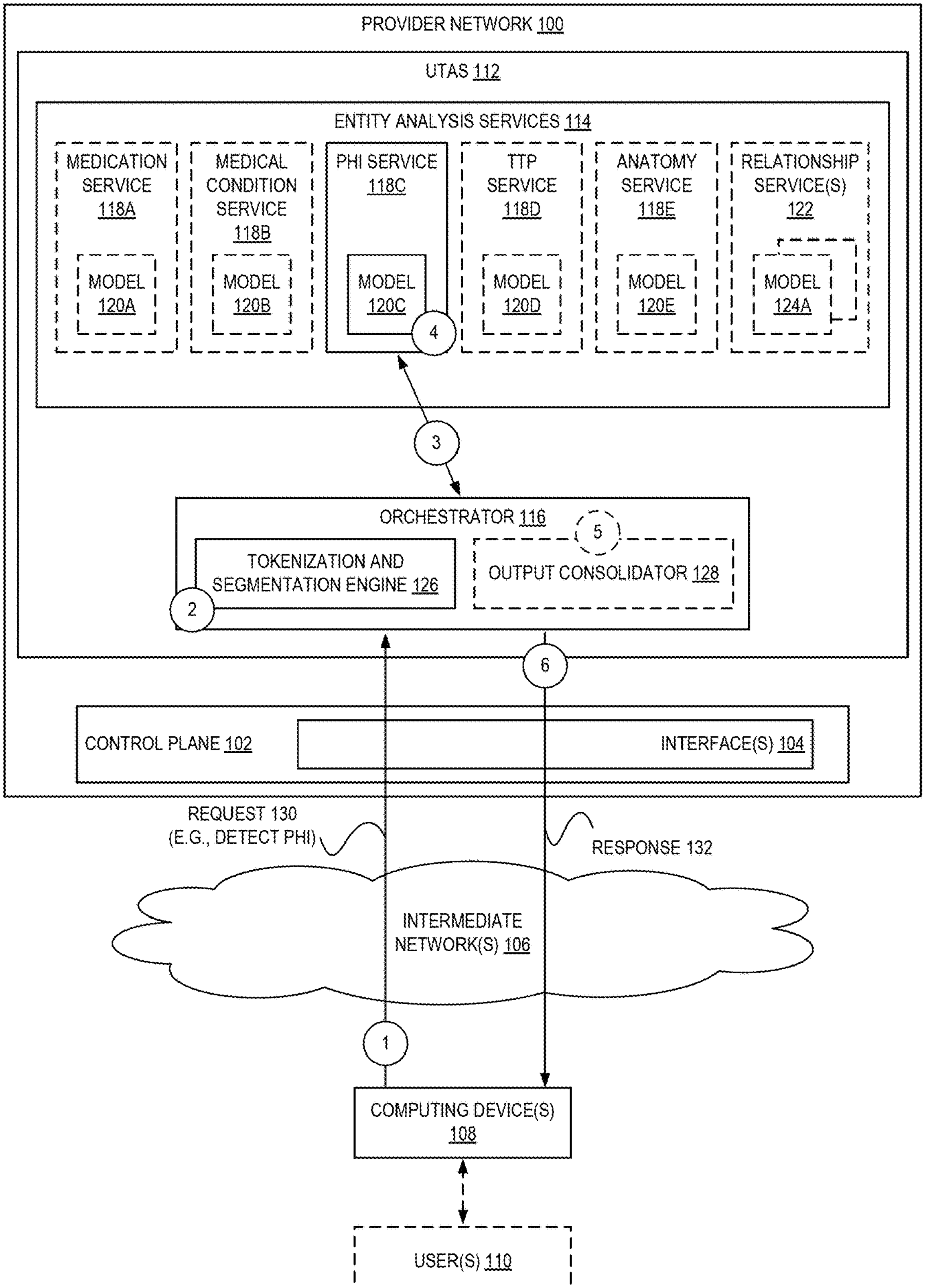


FIG. 4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MODEL 120B
PHI SERVICE 118C
MODEL 120C
TTP SERVICE 118D
MODEL 120D
ANATOMY SERVICE 118E
MODEL 120E
RELATIONSHIP SERVICE(S) 122
MODEL 124A
4
3
ORCHESTRATOR 116
5
TOKENIZATION AND SEGMENTATION ENGINE 126
OUTPUT CONSOLIDATOR 128
2
6
CONTROL PLANE 102
INTERFACE(S) 104
REQUEST 130 (E.G., DETECT PHI)
RESPONSE 132
INTERMEDIATE NETWORK(S) 106
1
COMPUTING DEVICE(S) 108
USER(S) 110

FIG. 5

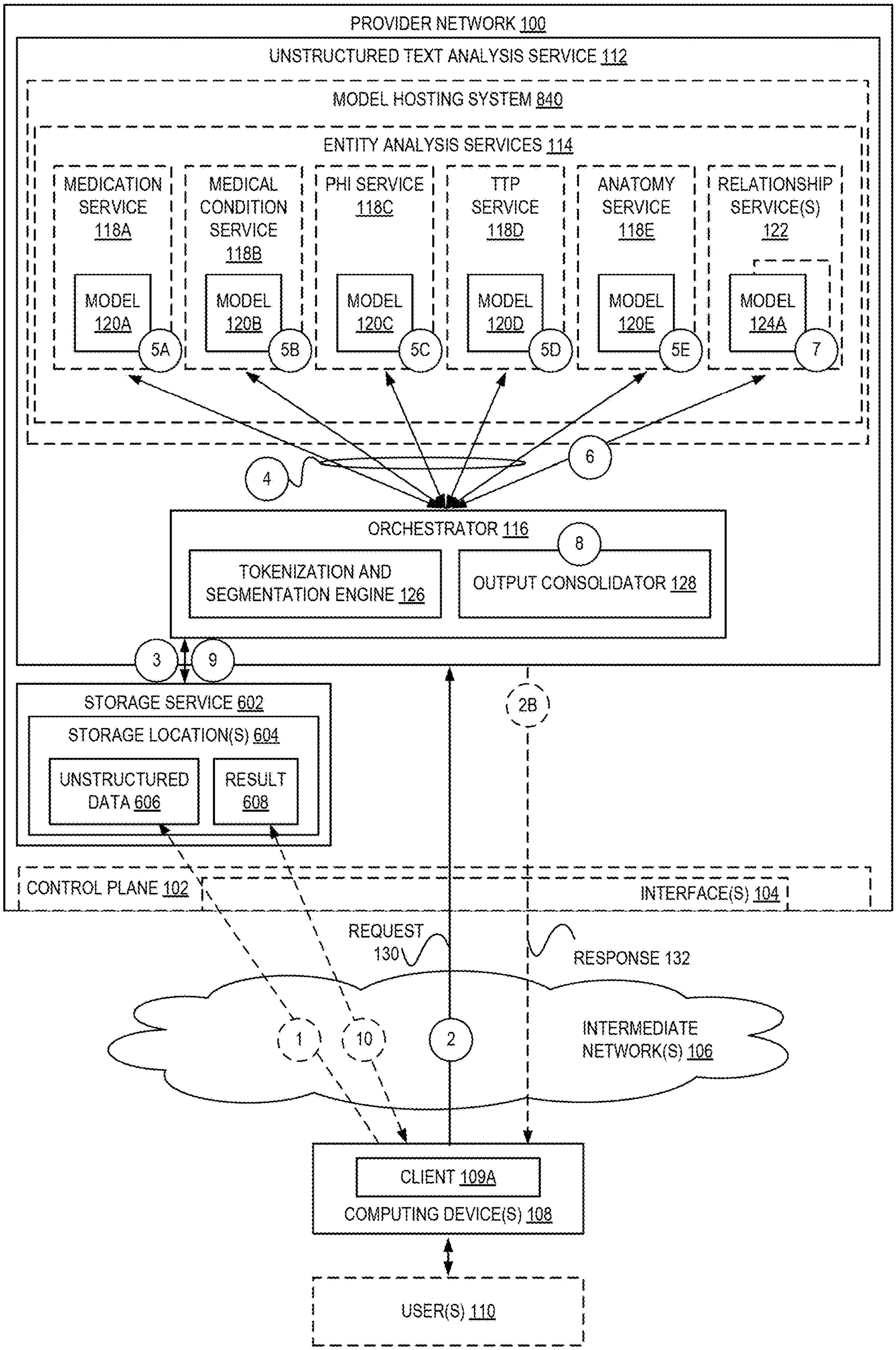

PROVIDER NETWORK 100
UNSTRUCTURED TEXT ANALYSIS SERVICE 112
MODEL HOSTING SYSTEM 840
ENTITY ANALYSIS SERVICES 114
MEDICATION SERVICE 118A
MODEL 120A
5A
MEDICAL CONDITION SERVICE 118B
MODEL 120B
5B
PHI SERVICE 118C
MODEL 120C
5C
TTP SERVICE 118D
MODEL 120D
5D
ANATOMY SERVICE 118E
MODEL 120E
5E
RELATIONSHIP SERVICE(S) 122
MODEL 124A
7
4
6
ORCHESTRATOR 116
8
TOKENIZATION AND SEGMENTATION ENGINE 126
OUTPUT CONSOLIDATOR 128
3
9
2B
STORAGE SERVICE 602
STORAGE LOCATION(S) 604
UNSTRUCTURED DATA 606
RESULT 608
CONTROL PLANE 102
INTERFACE(S) 104
REQUEST 130
RESPONSE 132
1
10
2
INTERMEDIATE NETWORK(S) 106
CLIENT 109A
COMPUTING DEVICE(S) 108
USER(S) 110

FIG. 6

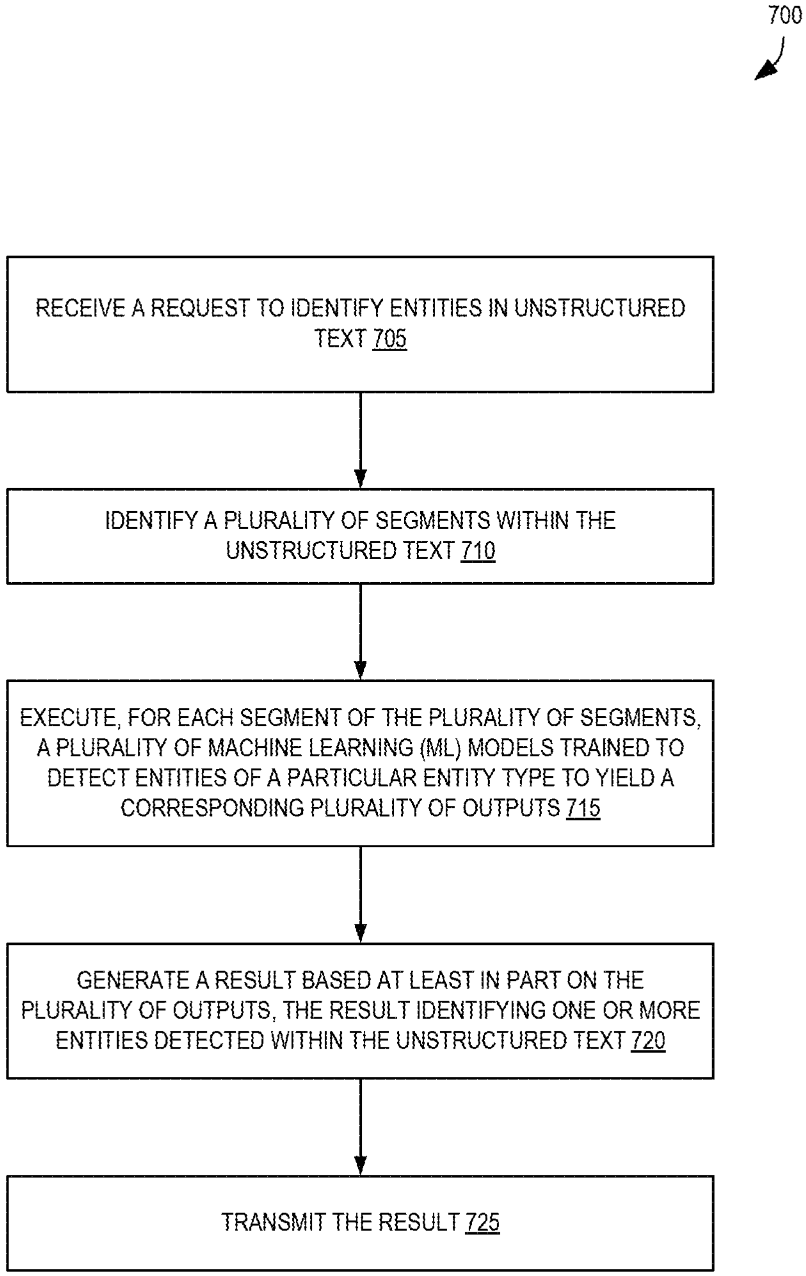

700
RECEIVE A REQUEST TO IDENTIFY ENTITIES IN UNSTRUCTURED TEXT 705
IDENTIFY A PLURALITY OF SEGMENTS WITHIN THE UNSTRUCTURED TEXT 710
EXECUTE, FOR EACH SEGMENT OF THE PLURALITY OF SEGMENTS, A PLURALITY OF MACHINE LEARNING (ML) MODELS TRAINED TO DETECT ENTITIES OF A PARTICULAR ENTITY TYPE TO YIELD A CORRESPONDING PLURALITY OF OUTPUTS 715
GENERATE A RESULT BASED AT LEAST IN PART ON THE PLURALITY OF OUTPUTS, THE RESULT IDENTIFYING ONE OR MORE ENTITIES DETECTED WITHIN THE UNSTRUCTURED TEXT 720
TRANSMIT THE RESULT 725

FIG. 7

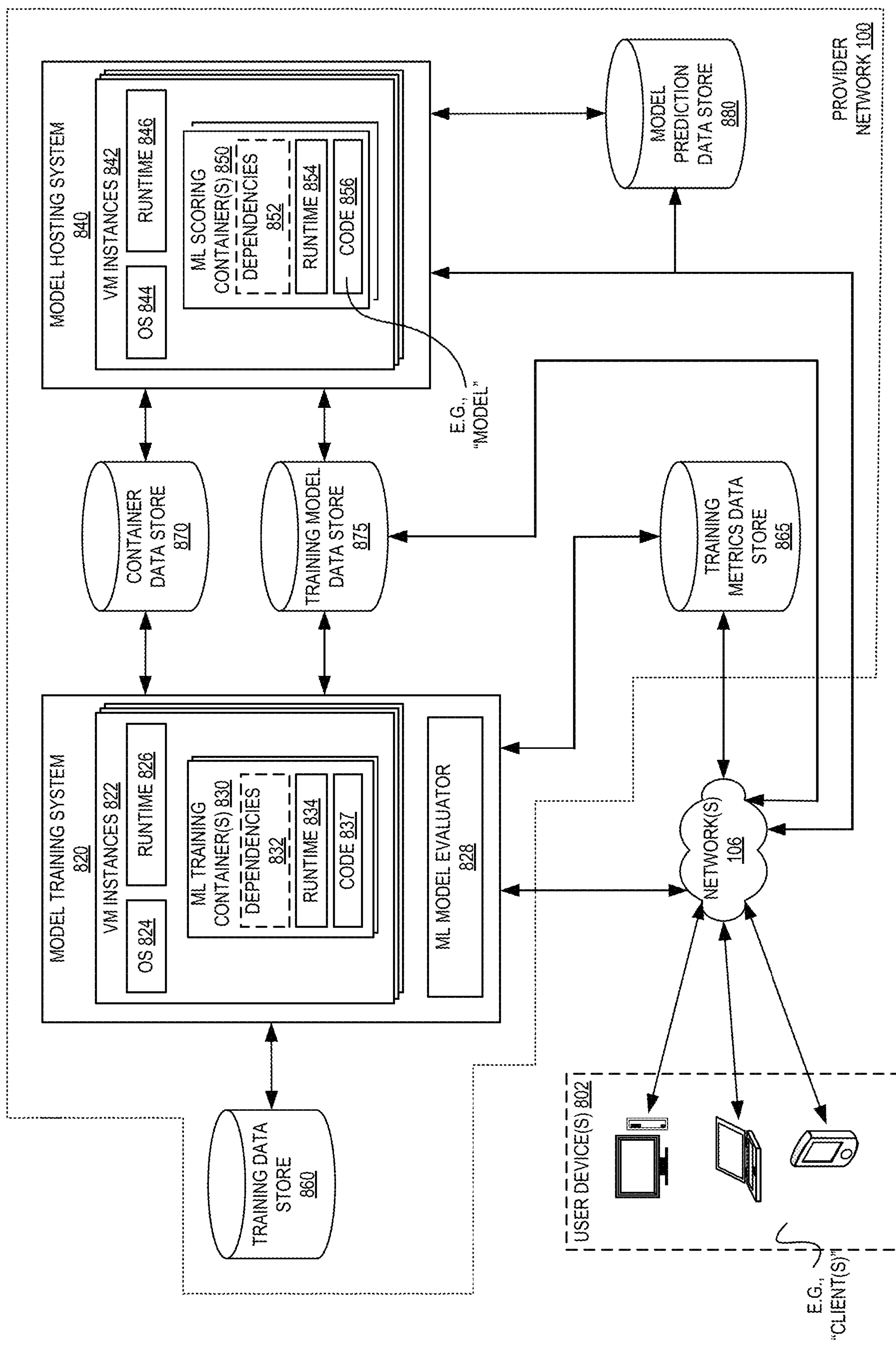

PROVIDER NETWORK 100
MODEL HOSTING SYSTEM 840
VM INSTANCES 842
OS 844
RUNTIME 846
ML SCORING CONTAINER(S) 850
DEPENDENCIES 852
RUNTIME 854
CODE 856
E.G., "MODEL"
MODEL PREDICTION DATA STORE 880
CONTAINER DATA STORE 870
TRAINING MODEL DATA STORE 875
TRAINING METRICS DATA STORE 865
MODEL TRAINING SYSTEM 820
VM INSTANCES 822
OS 824
RUNTIME 826
ML TRAINING CONTAINER(S) 830
DEPENDENCIES 832
RUNTIME 834
CODE 837
ML MODEL EVALUATOR 828
NETWORK(S) 106
TRAINING DATA STORE 860
USER DEVICE(S) 802
E.G., "CLIENT(S)"

FIG. 8

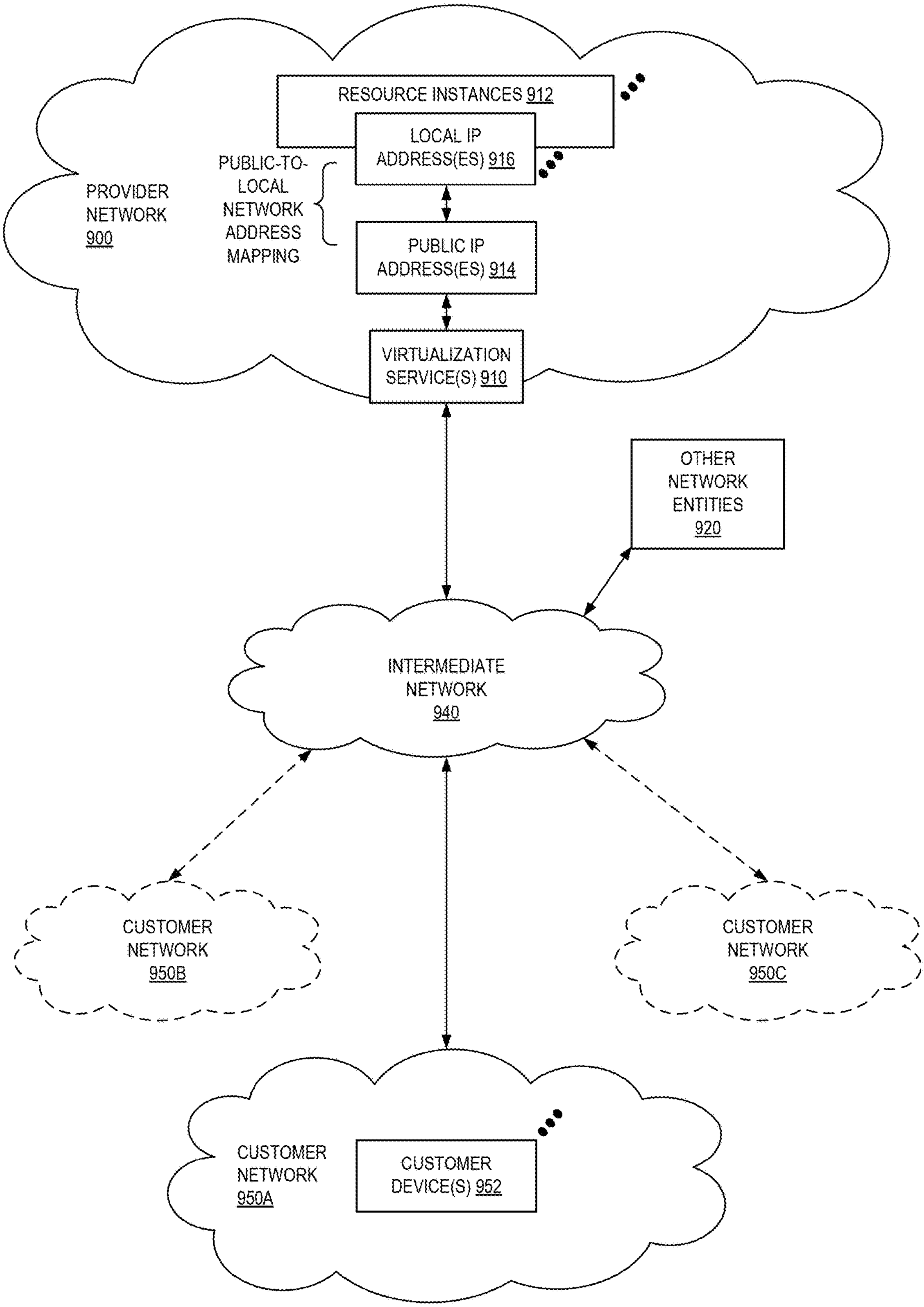
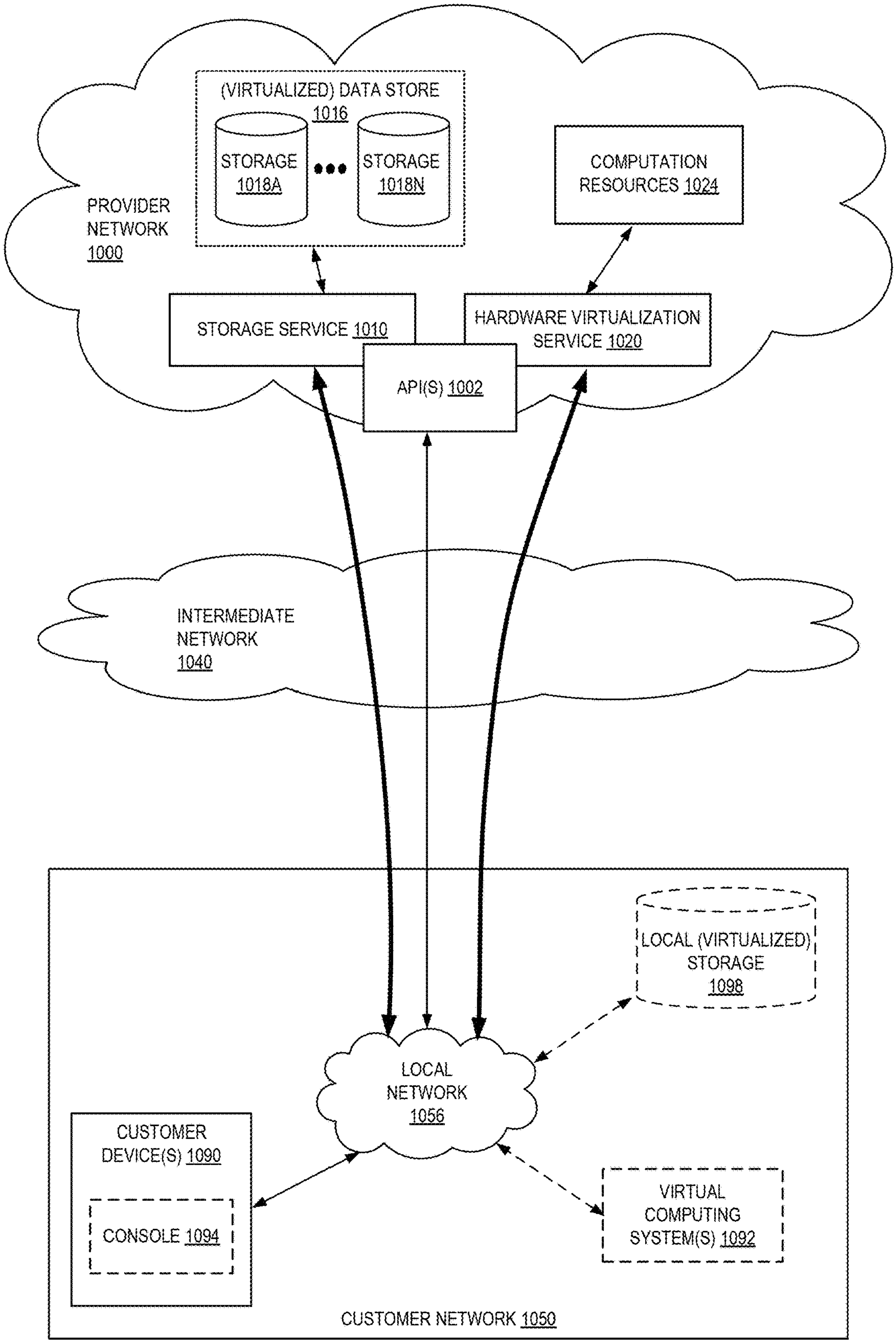

RESOURCE INSTANCES 912
LOCAL IP ADDRESS(ES) 916
PUBLIC-TO-LOCAL NETWORK ADDRESS MAPPING
PROVIDER NETWORK 900
PUBLIC IP ADDRESS(ES) 914
VIRTUALIZATION SERVICE(S) 910
OTHER NETWORK ENTITIES 920
INTERMEDIATE NETWORK 940
CUSTOMER NETWORK 950B
CUSTOMER NETWORK 950C
CUSTOMER NETWORK 950A
CUSTOMER DEVICE(S) 952

FIG. 9



(VIRTUALIZED) DATA STORE 1016
STORAGE 1018A
STORAGE 1018N
COMPUTATION RESOURCES 1024
PROVIDER NETWORK 1000
STORAGE SERVICE 1010
HARDWARE VIRTUALIZATION SERVICE 1020
API(S) 1002
INTERMEDIATE NETWORK 1040
LOCAL (VIRTUALIZED) STORAGE 1098
LOCAL NETWORK 1056
CUSTOMER DEVICE(S) 1090
CONSOLE 1094
VIRTUAL COMPUTING SYSTEM(S) 1092
CUSTOMER NETWORK 1050

FIG. 10

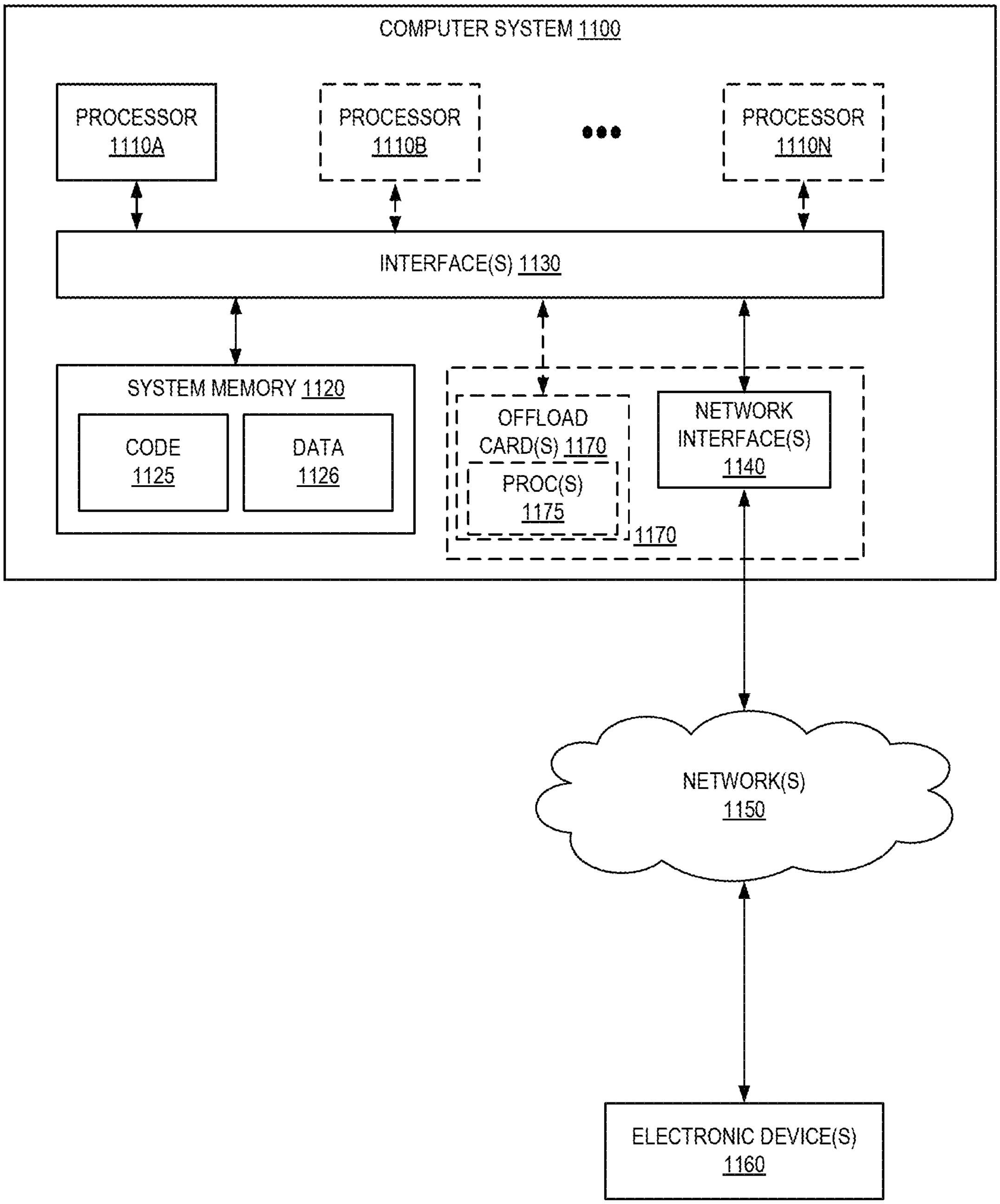

COMPUTER SYSTEM 1100
PROCESSOR 1110A
PROCESSOR 1110B
PROCESSOR 1110N
INTERFACE(S) 1130
SYSTEM MEMORY 1120
CODE 1125
DATA 1126
OFFLOAD CARD(S) 1170
PROC(S) 1175
1170
NETWORK INTERFACE(S) 1140
NETWORK(S) 1150
ELECTRONIC DEVICE(S) 1160

FIG. 11

SERVICE ARCHITECTURE FOR ENTITY AND RELATIONSHIP DETECTION IN UNSTRUCTURED TEXT

BACKGROUND

As the amount of data generated and utilized in modern computing continues to expand, a relatively new problem has arisen regarding how to effectively manage and utilize the sheer volume of data. As one example, many organizations have large amounts of unstructured alphanumeric data including textual notes or summaries. While such data is easily utilized and understood by human readers, it is incredibly difficult if not impossible for computing applications to be able to use data in this format, which may be disorganized or organized according to different people's preferences, include different word spellings or acronyms across different users, include varying amounts of detail, etc.

For example, business intelligence type applications are typically designed to provide specific analytics, and thus require a specific data schema or arrangement of data to operate upon. Thus, these applications are not able to utilize the various types of data provided by unstructured data, as unstructured data cannot provide any explicit data structure and instead may or may not provide dimensions or identification attributes, such as tags or metadata that may describe the unstructured data. Further, in the rare case that some business's unstructured data conforms to an explicit structure, it typically will not be compatible with existing business applications. As unstructured data typically does not provide a schema or other data descriptor that may be interpreted by current applications, these applications will fail to extract any base data on which analytics can be run. Finally, as unstructured data is often in different formats and structures—even within a same service area, market, type and/or content—current applications are thus unable to make assumptions about data. As a result, attempts to automate the use of current business intelligence systems on various unstructured data sources have failed.

Some methods have been developed to attempt to bring unstructured data into existing business intelligence type applications, such as via manual tagging. However, manually tagging unstructured data by human taggers to provide a well-defined structure is completely impractical in most systems having large amounts of data, and furthermore manual processes typically produce significant numbers of errors. Thus, manual tagging fails to scale as the amount of unstructured data grows, resulting in a significant number of errors being introduced into the data. Further, although some attempts have been made to create automated tagging software, these systems similarly tend to introduce many errors and typically only work for specific use cases.

BRIEF DESCRIPTION OF DRAWINGS

Various embodiments in accordance with the present disclosure will be described with reference to the drawings, in which:

FIG. **1** is a diagram illustrating an environment for synchronous entity and relationship detection from unstructured text according to some embodiments.

FIG. **2** is a diagram illustrating examples of medical unstructured data, an application programming interface call, and an illustration of detected entities and relationships according to some embodiments.

FIG. **3** is a diagram illustrating an example result including detected entities and relationships according to some embodiments.

FIG. **4** is a diagram including an illustration of detected entities and relationships from an unstructured medical text along with an exemplary graphical user interface for presenting the detected entities and relationships according to some embodiments.

FIG. **5** is a diagram illustrating an environment for synchronous specified entity detection from unstructured text according to some embodiments.

FIG. **6** is a diagram illustrating an environment for asynchronous entity and relationship detection from unstructured text according to some embodiments.

FIG. **7** is a flow diagram illustrating operations of a method for entity detection from unstructured text according to some embodiments.

FIG. **8** is a block diagram of an illustrative operating environment in which machine learning models are trained and hosted according to some embodiments.

FIG. **9** illustrates an example provider network environment according to some embodiments.

FIG. **10** is a block diagram of an example provider network that provides a storage service and a hardware virtualization service to customers according to some embodiments.

FIG. **11** is a block diagram illustrating an example computer system that may be used in some embodiments.

DETAILED DESCRIPTION

Various embodiments of methods, apparatus, systems, and non-transitory computer-readable storage media for entity and relationship detection from unstructured text are described. According to some embodiments, a service for entity and relationship detection is disclosed that upon a user's request can quickly and accurately identify various types of entities and relationships from unstructured text. The service receives unstructured data (e.g., unstructured text) from a client associated with the user, segments the unstructured data input and identifies tokens in these segments, and provides the segmented data and token information to be used with different machine learning (ML) models trained to detect different entity types within the segments. The output from ones of the models may be sent to one or more other models trained to identify relationships between detected classes of objects, such as attributes and entities. The outputs may then be consolidated and returned to the client in a unified response. In some example embodiments, the service may implement various ML models trained to detect medical-related entities from unstructured text (such as doctors' notes). Clients may call the service to request the identification of any entities that can be found, or just specific entities.

As indicated above, many organizations have large amounts of useful data stored in plaintext formats, which makes it extremely difficult to use at large scale in programmatic ways—e.g., for performing analytics. This challenge is particularly relevant in the medical field, in which there exists huge amounts of medical information—ranging from textual descriptions of symptoms, patient history, treatment plans, etc.—represented in data within plaintext fields. There remains a very strong interest in analyzing this extensive medical information to advance the field, whether for detecting optimal treatment patterns, identifying shared but unknown causes of ailments, eliminating administrative burdens, and for countless other possibilities. For example, if various notes regarding clinical trials are made in plaintext form, and a researcher seeks to identify patients who had a particular disease and took a particular medication, typically the researcher (and/or assisting workers) must examine the doctors' notes one by one and/or use search tools in complex ways, such as via crafting queries broadly enough to cover alternative spellings, abbreviations, etc., for the terms of interest, and trying to craft complex but flexible queries to search for different types of information in close proximity with other types of information, e.g., "daily" and "aspirin" and "heart attack" or "stroke" and "male" and "age 70" within some "close" amount of proximity to each other. However, this remains exceedingly difficult—for medical or administrative workers without advanced experience in information retrieval, and even for those well-versed in the field—due to the huge amount of data involved and lack of standardization in the formats of data present in these fields.

Accordingly, embodiments described herein provide a service that can be utilized in a simple and straightforward manner by clients to automatically identify entities—such as types of medications, treatments, medical conditions, etc. —and optionally, relationships involving these entities with other detected classes of objects such as attributes or traits—from unstructured text.

As used herein, unstructured data (or unstructured information) may refer to information that either does not have a pre-defined data model or is not organized in a pre-defined manner Thus, the term unstructured text may refer to alphanumeric type unstructured data such as one or more sentences, one or more sentence fragments, one or more paragraphs, etc. Such unstructured text is often generated or originated by humans, e.g., doctors or nurses may write notes regarding a patient, a salesperson may write notes regarding a sales lead, a student may write an essay, a lawyer may draft a contract, a transcript may be taken of a court proceeding or television broadcast, a businessperson may generate a vendor agreement, etc.

For further detail, FIG. **1** is a diagram illustrating an environment for synchronous entity and relationship detection from unstructured text according to some embodiments. In this exemplary environment, an unstructured text analysis service **112** (or "UTAS") includes an orchestrator **116** that receives requests **130** to detect entities within unstructured text and implements a "scatter" approach to processing utilizing multiple ML models **120**/**124** (of a set of one or more entity analysis services **114**) trained to detect particular entities and/or relationships between types of detected objects. The outputs of these models can be used to generate a consolidated result provided as a response **132** to the request **130** that identifies the various entities and optionally relationships between the entities and other detected objects from within the provided unstructured text.

In some embodiments, the UTAS **112** can operate to detect useful medical-related information in unstructured text such as clinical text. As much as 75% of all health record data is found in unstructured text, e.g., in physician's notes, discharge summaries, test results, case notes, and so on, the UTAS **112** can utilize uses Natural Language Processing (NLP) models to sort through this enormous quantity of data and retrieve valuable information that is otherwise difficult to retrieve and use without significant manual effort.

Although the UTAS **112** may not be a substitute for professional medical advice, diagnosis, or treatment, the UTAS **112** can provide confidence scores that indicate the level of confidence in the accuracy of the detected entities, which can be used to enable client systems to apply more (or less) scrutiny to its results based on the particular use case. For example, in certain use cases a client may cause the results generated by the UTAS **112** to be reviewed and verified by appropriately-trained human reviewers, though in other use cases such review and verification may be unnecessary or may be only needed for those results exhibiting less than some threshold amount of accuracy based on the confidence scores.

Components of the UTAS **112** may be implemented as software executed by one or more computing devices, as hardware, or as a combination of both hardware and software. As one example, the UTAS **112** may include an orchestrator **116** implemented as software executed by a first one or more computing devices and may further include one or more models **120**/**124** implemented as software by the first one or more computing devices or a second one or more computing devices.

In some embodiments, the UTAS **112** is implemented as a service within a provider network **100**. A provider network **100** provides users with the ability to utilize one or more of a variety of types of computing-related resources such as compute resources (e.g., executing virtual machine (VM) instances and/or containers, executing batch jobs, executing code without provisioning servers), data/storage resources (e.g., object storage, block-level storage, data archival storage, databases and database tables, etc.), network-related resources (e.g., configuring virtual networks including groups of compute resources, content delivery networks (CDNs), Domain Name Service (DNS)), application resources (e.g., databases, application build/deployment services), access policies or roles, identity policies or roles, machine images, routers and other data processing resources, etc. These and other computing resources may be provided as services, such as a hardware virtualization service that can execute compute instances, a storage service that can store data objects, the UTAS **112** described herein, etc. Users **110** (or "customers") of provider networks **100** may utilize one or more user accounts that are associated with a customer account, though these terms may be used somewhat interchangeably depending upon the context of use. Users may utilize a computing device **108** to interact with a provider network **100** across one or more intermediate networks **106** (e.g., the internal via one or more interface(s) **104**, such as through use of application programming interface (API) calls, via a console implemented as a website or application, etc. The interface(s) **104** may be part of, or serve as a front-end to, a control plane **102** of the provider network **100** that includes "backend" services supporting and enabling the services that may be more directly offered to customers.

To provide these and other computing resource services, provider networks **100** often rely upon virtualization techniques. For example, virtualization technologies may be used to provide users the ability to control or utilize compute instances (e.g., a VM using a guest operating system (O/S) that operates using a hypervisor that may or may not further operate on top of an underlying host O/S, a container that may or may not operate in a VM, an instance that can execute on "bare metal" hardware without an underlying hypervisor), where one or multiple compute instances can be implemented using a single electronic device. Thus, a user may directly utilize a compute instance hosted by the provider network to perform a variety of computing tasks or may indirectly utilize a compute instance by submitting code to be executed by the provider network, which in turn utilizes a compute instance to execute the code (typically without the user having any control of or knowledge of the underlying compute instance(s) involved).

For example, in various embodiments, a "serverless" function may include code provided by a user or other entity that can be executed on demand Serverless functions may be maintained within provider network **100** and may be associated with a particular user or account or may be generally accessible to multiple users and/or multiple accounts. Each serverless function may be associated with a URL, URI, or other reference, which may be used to call the serverless function. Each serverless function may be executed by a compute instance, such as a virtual machine, container, etc., when triggered or invoked. In some embodiments, a serverless function can be invoked through an application programming interface (API) call or a specially formatted HyperText Transport Protocol (HTTP) request message. Accordingly, users can define serverless functions that can be executed on demand, without requiring the user to maintain dedicated infrastructure to execute the serverless function. Instead, the serverless functions can be executed on demand using resources maintained by the provider network **100**. In some embodiments, these resources may be maintained in a "ready" state (e.g., having a pre-initialized runtime environment configured to execute the serverless functions), allowing the serverless functions to be executed in near real-time. In some embodiments, one or more or all of the components of the UTAS **112** may be implemented as serverless functions, e.g., the orchestrator **116**, tokenization and segmentation engine **126** ("TSE"), output consolidator **128**, ML models **120**/**124**, etc.

As indicated herein, a user **110** may with to utilize the UTAS **112** to detect entities within medical unstructured text. Thus, the user may utilize a client **109**A implemented by a computing device **108** outside the provider network **100** (e.g., as part of a medical application installed on a personal computer or server computing device, as part of a web-based console provided by the provider network **100**) or a client **109**B implemented by a computing device within the provider network **100** (e.g., as part of an application executed in the provider network **100**, such as by a hardware virtualization service, "serverless" on-demand code execution service, etc.) to issue requests **130** at circle (1) to the UTAS **112**.

These clients **109** may use the UTAS **112** for a variety of purposes. As one example, a client **109** may be part of an application allowing doctors and health care providers to manage their unstructured notes effectively and rapidly assess medical information about their patients that doesn't easily fit into the forms traditionally used. Analyzing case notes, for instance, may help providers identify candidates for early screening for certain medical conditions before the condition becomes more difficult to treat. It may also allow patients to report their health concerns in a narrative that can provide more information in a simple format, and then make those narratives easily available to providers in a more structured form, allowing more accurate diagnosis of medical conditions.

As another example, a client **109** may operate as part of a clinical research application allowing life sciences or research organizations to optimize the matching process for fitting patients into clinical trials using information from unstructured clinical texts, such as case notes and test results. For instance, for a clinical trial of a new heart medicine, use of the UTAS **112** makes it much simpler to analyze text to find specific information about heart failure patients. The client **109** may also be part of an application to improve pharmacovigilance and post-market surveillance to monitor adverse drug events by using UTAS **112** to detect pertinent information in clinical text that is otherwise difficult to access. Moreover, the client **109** may use the UTAS **112** to assess therapeutic effectiveness by easily detecting vital information in follow-up notes and other clinical texts. For example, it can be easier and more effective to monitor how patients respond to certain therapies by analyzing their narratives.

As yet another example, a client **109** may be part of a medical records application, e.g., a medical billing system payor can use the UTAS **112** to expand its analytics to include the use of unstructured documents such as clinical notes, where more information about a diagnosis as it relates to billing codes can be determined.

The request **130** (and response **132**) sent by clients **109** can utilize encrypted connections (e.g., using HTTPS over TLS), and the UTAS **112** in some embodiments does not persistently store any user/client content. Accordingly, the UTAS **112** may qualify as a HIPAA eligible service without requiring users to configure encryption-at-rest within the service.

In some embodiments, the request **130** may be one or either of a "Detect Entities" (or, "DetectEntities") request or a "Detect PHI" (or, "DetectPHI") request. A DetectEntities request may be used to indicate a client's request for the UTAS **112** to examine unstructured clinical text to detect textual references to valuable medical information related to various "entities" such as medical condition, treatment, tests and test results, medication (possibly including dosage, frequency, method of administration, etc.), treatment, Protected Health Information (PHI) data, and so on. In contrast, a DetectPHI request may be used to indicate a client's request for the UTAS **112** to detect references to only one entity—e.g., PHI data such as names, addresses, ages, etc. In other embodiments, other types of requests may be straightforwardly implemented by one of skill in the art based on this provided description to involve more, fewer, and/or different types of entities.

For the sake of illustration, we assume the request **130** sent at circle (1) is a DetectEntities request, instructing the UTAS **112** to inspect provided clinical text for a variety of medical entities and return specific information about any detected entities such as each entity's category, location, and confidence score on that information. In some embodiments, the request **130** includes an amount of unstructured text—e.g., up to 20,000 bytes of characters in some format (e.g., UTF-8).

For example, FIG. **2** is a diagram illustrating examples of medical unstructured data, an application programming interface call, and an illustration of detected entities and relationships according to some embodiments. As shown, a portion of unstructured text **205** may be submitted within the request **130** or otherwise identified by the request **130**, such as via an identifier of a storage location, database record, etc., where the text is stored. In this example, the portion of unstructured text **205** reads "Infuse Sodium Chloride 0.9% solution 1000 mL intravenously daily Rate-200 mL/hr for next 3 days". This unstructured text **205** may be provided within a request, such as shown in the exemplary detect entities request **130**A, which may be an API call issued to an endpoint associated with the UTAS **112** that identifies one or more of the service ("UTAS"), the method ("DETECT-ENTITIES"), an endpoint, a region, and/or the text itself.

Turning back to FIG. **1**, the request **130** can be provided to an orchestrator **116** implementing a "front end" of the service. The orchestrator **116** in some embodiments is implemented by a fleet of multiple compute instances, where each compute instance may implement one or both of a TSE **126** and an output consolidator **128**. Thus, in some embodiments, the requests **130** may be load balanced between multiple such orchestrator **116** instances (or TSE **126** instances).

Upon receipt of each request by the orchestrator **116**, the request **130** (or elements thereof, such as the text) may be provided to a TSE **126** at circle (2). Each TSE **126** may split the text into one or more segments, which may be based on applying a set of rules that indicate where the text is to be split. For example, the segmentation may include splitting the text based on the existence of newline characters, periods, and/or other delimiters, to yield a set of one or more segments.

In some embodiments, the TSE **126** then tokenizes the segments to identify one or more "tokens" within each segment. A token may be a word or a grouping of characters, and the tokenization may be performed by applying another set of rules that indicate where the segment is to be split. For example, the tokenization may include identifying the existence of spaces, tabs, column delimiters (such as pipes or colons), etc., to thus identify the beginning and end of a token. Thus, the TSE **126** may generate token metadata indicating a beginning location and an ending location of a token (within a segment) or a character length. Thus, for an example segment "Infuse Sodium Chloride 0.9% solution", a token of "Infuse" may be identified via a beginning offset of "0" and an ending offset of "6," or via a beginning offset of "0" and a length of "6." Likewise, a token of "0.9%" (as one example way of tokenizing including the "%" character) may be identified via a beginning offset of "23" and an ending offset of "28," or via a beginning offset of "23" and a length of "5."

In some embodiments, each identified segment of text and metadata identifying the tokens therein is provided, by the orchestrator **116**, to multiple ML models **120**A-**120**E according to a "scatter" type technique as reflected by circle (3). Each of the ML models **120**A-**120**E may be trained to detect a particular entity type from within unstructured text, and in some cases, ones of the models **120** may be executed in parallel for a same segment or group of segments. In this example, the orchestrator **116** is shown as utilizing five models **120**A-**120**E, though in other embodiments more or fewer models (e.g., via more or fewer services **118**A-**118**E) may be used.

As illustrated, each ML model **120** may be implemented as part of a service (or "micro-service") that receives inference requests, optionally pre-processes the input data, provides the provided input (or pre-processed input) to an ML model trained to identify a particular type of entity, optionally post-processes the output inference result, and returns the (optionally post-processed) inference result to the client—here, the orchestrator **116**. In this example system, a first model **120**A may be part of a medication service **118**A that identifies medications and/or dosage information at (4A), a second model **120**B may be part of a medical condition service **118**B that identifies symptoms and diagnosis of medical conditions at (4B), a third model **120**C may be part of a PHI service **118**C that detects a patient's personal information (e.g., address, age, email address, personal identifier, name, phone number, profession, etc.) at (4C), a fourth model **120**D may be part of a Test and Treatment Procedure (TTP) service **118**D that detects procedures used to determine a medical condition at (4D), and a fifth model **120**E that may be part of an anatomy service **118**E that detects references to the parts of the body or body systems and the locations of those parts or systems at (4E).

In some embodiments, one or more of the ML models **120** are trained using annotated training data, e.g., doctors' notes that have been annotated by humans and/or automated processes (e.g., active learning techniques) and the like, to cause the ML models **120** to be able to detect particular entities types. The ML models **120** may be based on a variety of ML algorithms known to those of skill in the art, such as a neural network (e.g., a Long short-term memory (LSTM) neural network or other type of Recurrent Neural Network (RNN)). The training may be performed via use of an ML service and may include the use of hyperparameter tuning techniques to create a highly-accurate model. The resulting trained models, in some embodiments, are hosted by an ML service, which can deploy these models as services.

In some embodiments, the UTAS **112**—via use of these ML models—may detect information in multiples classes (or "object types"), such as entities, categories, types, attributes, traits, etc. An entity generally refers to a textual reference to the name of relevant objects, such as people, treatments, medications, or medical conditions—for example, "Ibuprofen" may be an entity. A category generally refers to a generalized grouping to which a detected entity belongs, for example, "Ibuprofen" may be part of a MEDICATION category, where a category may be associated with a particular model **120** and thus entities of that category may be detected by that model. A type generally refers to a type of the entity detected, scoped to a category. For example, "Ibuprofen" is in the GENERIC_NAME type in the MEDICATION category. An attribute generally refers to information related to a detected entity, such as a dosage of a medication—for example, "200 mg" is an attribute of an "Ibuprofen" entity. A trait generally refers to something that the UTAS **112** understands about an entity, based on context. For example, a medication may have a "NEGATION" trait if it determined that a patient is not taking it.

In some embodiments, the medical condition service **118**B may, via use of model **120**B, detect symptoms and diagnosis of medical conditions. The output of the medical condition service **118**B may contains up to two entity types and up to four traits, where one or more traits can be associated with a type. The entity types may be an "ACUITY" that provides a determination of disease instance, such as chronic, acute, sudden, persistent, or gradual, and/or a "DX_NAME" that provides all medical conditions listed. The DX_NAME type may thus include a present illness, reason for visit, medical history, review of systems, family history, or patient education. The traits may include a "DIAGNOSIS" that applies to the DX_NAME type and that provides a medical condition that is determined as a cause or result of the symptoms through physical findings, laboratory or radiological reports, or any other means that the patient may or may not have had. The traits may also include a NEGATION, which is an indication that a result or action is negative or not being performed, a SIGN, which applies to the DX_NAME type and indicates a medical condition that the physician reported, and/or a SYMPTOM, which applies to the DX_NAME type and indicates a medical condition reported by the patient.

For example, upon being provided a segment "Patient is suffering from chronic aching pain 4/10", the medical condition service **118**B may return "aching pain" as a DX_NAME type of entity that is of a SYMPTOM trait type, as well as another entity of "chronic" that is of the ACUITY trait type. The medical condition service **118**B may also provide associated confidence scores generated by the model **120**B when detecting each entity.

This information may be returned to the orchestrator **116** in a variety of formats, such as the following exemplary format. Notably, this example shows a portion which specifies, for each detected entity, one or more of: an identifier ("Id"), a beginning offset and ending offset indicating where in the segment the entity was found, a confidence score generated by the ML model **120**B, the text of the entity, a type of the entity, any found traits, etc.


```
{
  "Entities": [
    {
      "Id": 0,
      "BeginOffset": 26,
      "EndOffset": 33,
      "Score": 0.9961825013160706,
      "Text": "chronic",
      "Category": "MEDICAL_CONDITION",
      "Type": "ACUITY",
      "Traits": [ ]
    },
    {
      "Id": 1,
      "BeginOffset": 34,
      "EndOffset": 45,
      "Score": 0.8380221724510193,
      "Text": "aching pain",
      "Category": "MEDICAL_CONDITION",
      "Type": "DX_NAME",
      "Traits": [
        {
          "Name": "SYMPTOM",
          "Score": 0.6004688739776611
        }
      ]
    }
  ],
  "UnmappedAttributes": [ ]
}
```


Similarly, in some embodiments, the PHI service **118**C may, via use of model **120**C, detect PHI-related entities. This may occur as part of a "general" request such as a DetectEntities API request, or may occur responsive to a DetectPHI API request that only solicits the detection of PHI entities. The PHI service **118**C may detect a variety of different types of entities, including but not limited to an AGE type that represents components of age, spans of age, or other age mentioned in the unstructured text, a NAME type that represents names mentioned in the text, typically belonging to a patient, family, or provider, a PHONE_OR_FAX type that represents phone numbers or FAX numbers (and may eliminate certain named phone numbers, such as 1-800-QUIT-NOW or 911), an EMAIL type that represents email addresses, an ID type that represents a social security number, medical record number, facility identification number, clinical trial number, certificate or license number, vehicle or device number, or biometric number as it pertains to the patient, place of care, or provider, a URL type that represents a web URL, an ADDRESS type that represents geographical subdivisions of an address of any facility, named medical facilities, or wards within a facility, a PROFESSION type that represents a profession or employer mentioned in a note as it pertains to a patient or the patient's family.

By way of example, an unstructured text input may be "Patient is John Smith, a 48 year old teacher and resident of Seattle, Wash." and the PHI service **118**C may return that "John Smith" is an entity of type NAME, "48" is an entity of type AGE, "teacher" is an entity of type PROFESSION, "Seattle, Wash." is an ADDRESS entity.

In some embodiments, the anatomy service **118**E may, via use of model **120**E, detect references to the parts of the body or body systems and the locations of those parts or systems. The anatomy service **118**E may be able to detect multiple (e.g., two) entity types, such as a DIRECTION entity, which is a directional term such as left, right medial, lateral, upper, lower, posterior, anterior, distal, proximal, contralateral, bilateral, ipsilateral, dorsal, ventral, and so on, and/or a SYSTEM_ORGAN_SITE entity, which is a body system, anatomic location or region, and/or body site. As an example, with unstructured text input of "Patient's left lung", the anatomy service **118**E may identify "left" as an entity of DIRECTION type and "lung" as an entity of SYSTEM_ORGAN_SITE type.

In some embodiments, the medication service **118**A may, via use of model **120**A, detect medication and dosage information for a patient. The medication service **118**A, in response to a request, may return information that may include some or all of two entity types, seven attributes, and one trait. One or more attributes can apply to an entity type. The entity types may include a BRAND_NAME, which is a copyrighted brand name of the medication or therapeutic agent, or a GENERIC_NAME, which is a non-brand name, ingredient name, or formula mixture of the medication or therapeutic agent. The attributes may include one or more of a DOSAGE attribute representing an amount of medication ordered, a DURATION attribute representing how long the medication should be administered, a FORM attribute representing a form of the medication, a FREQUENCY attribute representing how often to administer the medication, a RATE attribute representing an administration rate of the medication (e.g., for medication infusions or IVs), a ROUTE_OR_MODE attribute representing the administration method of a medication, a STRENGTH attribute for medication infusions or IVs a medication strength, etc. One or more traits may also be detected, such as a NEGATION trait identifying whether there exists an indication that the patient is not taking a medication.

In some embodiments, upon receiving the detected information back from a service (e.g., the medication service **118**A), the orchestrator **116** may send this information (optionally along with other information received from other models/services) with the segment at circle (5) to one or more relationship services **122** that utilize one or more relationship models **124**A-**124**N to detect relationships between these entities (or other types of information) at circle (6). These relationship models may be, for example, neural networks such as Convolutional Neural Networks (CNNs) trained with labeled training data indicating relationships between entities and attributes, etc.

In some embodiments the orchestrator **116** sends results obtained from the medication service **118**A to a relationship service **122** to cause the relationship service **122** to identify relationships between the detected information—e.g., which attributes belong to (or, are associated with) which entities. This relationship information can be used to generate more detailed results back for the requesting client, allow for more sophisticated exploration or searching of the data, etc. For example, by detecting that an attribute of "80 mg" and an attribute of "daily" is associated with an entity of "Aspirin" in the unstructured text "The patient has been daily taking 80 mg of Aspirin", a client or user may then be able to identify this record when searching for all people who take 80 mg of Aspirin daily, but not identify the record when searching for similar but different things, such as people who take 80 mg of Furosemide daily.

For example, continuing the example provided earlier regarding unstructured text of (or including) "Infuse Sodium Chloride 0.9% solution 1000 mL intravenously daily Rate-200 mL/hr for next 3 days" received in/with a DetectEntities request **130**, this segment (along with token information) may be passed at circle (3) to multiple services **118** (e.g., services **118**A-**118**N), and in this case the intermediate results returned from the medication service **118**A may indicate that multiple entities (and/or attributes) were found with a threshold amount of confidence, and thus the orchestrator may send on those intermediate results with the segment to a relationship service **122** to identify which attributes correspond to which entities. As shown in the visual representation **210** shown in FIG. **2**, this may result in the orchestrator being able to determine that a number of attributes are all related to the "Sodium Chloride" entity—"Infuse" is a "route or mode" attribute, "0.9%" is a strength attribute, "solution" is a form attribute, "1000 mL" is a dosage attribute, "Intravenously" is a route or mode attribute, "daily" is a frequency attribute, and "3 days" is a duration attribute. This visual representation **210** may be provided to the client (or data enabling the client to generate such a visual representation), enabling the client to present this visualization **210** to a user.

For further detail, FIG. **3** is a diagram illustrating an abbreviated example result **300** including detected entities and relationships according to some embodiments. A result provided via an ultimate response **132** may be of a variety of formats. For example, in some embodiments the result includes an entry or node for each detected entity. Each Entity may include an array of Attributes extracted that relate to the entity, a BeginOffset integer that provides the 0-based character offset in the input text that shows where the entity begins, a string Category indicating what type the entity is (e.g., MEDICATION, MEDICAL_CONDITION, PROTECTED_HEALTH_INFORMATION, TEST_TREATMENT_PROCEDURE, ANATOMY, which correspond to models **118**/services **118**), an EndOffset integer that provides the 0-based character offset in the input text that shows where the entity ends, an Id integer that is a monotonically increasing identifier unique within this response rather than a global unique identifier, a Score float that indicates a level of confidence that the UTAS has in the accuracy of the detection (based on an accuracy/confidence score provided by the respective detecting model), a Text string indicating the segment of input text extracted as this entity, an array of Traits providing contextual information for the entity, a Type string describing the specific type of entity.

Each Attribute may similarly include a BeginOffset integer, an EndOffset integer, an Id, a RelationshipScore float indicating a level of confidence that the UTAS has that this attribute is correctly related to the particular entity, a Score float indicating the level of confidence that UTAS has that the segment of text is correctly recognized as an attribute, a Text string, an array of Traits, a Type string, etc. Each Trait may include, for example, a Name string providing a name or contextual description about the trait, a Score float indicating a level of confidence that UTAS has in the accuracy of this trait, etc.

This information can be beneficially used in a variety of ways. For example, for the unstructured text "Aspirin 100 mg Sodium Chloride 1000 ml", but Aspirin and Sodium Chloride may be recognized as being potentially associated with both 100 mg and 100 ml; however, it would likely be the case that 100 mg would be associated with Aspirin with a very high RelationshipScore and associated with 1000 ml with a very low RelationshipScore (the same, but in the inverse, would likely be true for Sodium Chloride). Thus, embodiments can beneficially provide for various confidences in the detected relationships, which could potentially be used by a client in different ways depending on the context of use.

In FIG. **3**, this example (abbreviated) result **300** is shown for the unstructured text "Infuse Sodium Chloride 0.9% solution 1000 mL intravenously daily Rate-200 mL/hr for next 3 days". In this case a top-level entity (of ID=1) exists for "Sodium Chloride" of the MEDICATION category. This entity has multiple attributes—two of which are represented here for the sake of illustration—one for the text "INFUSE" and one for the text "3 DAYS", each having an identified type of attribute, a score, etc. In this case, another set of unmapped attributes are also presented. Such unmapped attributes are those attributes that are unable to be "mapped" to a particular entity with a sufficient amount (e.g., threshold) of confidence, though the attribute itself was found with some threshold amount of confidence. In this example, a medication attribute of "1000 ML" was found as well as a medication attribute of "200 ML/HR".

Turning back to FIG. **1**, as another example of involving relationships, in some embodiments the orchestrator **116** sends results obtained from the TTP service **118**D to a relationship service **122** to cause the relationship service **122** to identify relationships between the detected information—e.g., which attributes belong to (or, are associated with) which entities.

In some embodiments, the TTP service **118**D may, via use of model **120**D, detect the procedures used to determine a medical condition. The TTP service **118**D may identify, for example, three entity types and two attribute types. One or more attributes can be related to an entity of the TEST_NAME type.

For example, in some embodiments the TTP service **118**D can detect PROCEDURE_NAME type entities, which are interventions as a one-time action performed on the patient to treat a medical condition or to provide patient care, and/or TEST_NAME type entities, which are procedures performed on a patient for diagnostic, measurement, screening, or rating that might have a resulting value, which may include a procedure, process, evaluation, or rating to determine a diagnosis, to rule out or find a condition, or to scale or score a patient. The TTP service **118**D may additionally or alternatively be able to detect TREATMENT_NAME type entities, which are interventions performed over a span of time for combating a disease or disorder, which can include groupings of medications, such as antivirals and vaccinations.

The TTP service **118**D, in some embodiments, can detect attributes such as a TEST_VALUE attribute representing a result of a test (which may apply to the TEST_NAME entity type) and/or TEST_UNIT attribute representing the unit of measure that might accompany the value of the test (which may apply to the TEST_NAME entity type).

As an example, the unstructured text of "Abdominal ultrasound noted acute appendicitis, recommend appendectomy followed by several series of broad spectrum antibiotics" may be analyzed by the TTP service **118**D to identify "Abdominal ultrasound" is a TEST_NAME type entity, "acute" is an ACUITY type entity, "appendicitis" is a DX_NAME type entity, that DIAGNOSIS is a trait of the "appendicitis" type entity, that "appendectomy" is a PROCEDURE_NAME type entity, and "broad spectrum antibiotics" is a TREATMENT_NAME type entity.

With the intermediate results obtained from each utilized service—e.g., results from services **118**A-**118**E and service(s) **122** for a DetectEntities request **130**, results from PHI service **118**C for a DetectPHI request **130**, etc. —an output consolidator **128** may operate upon these intermediate results at circle (7) to generate a single result (based on these intermediate results) that can be returned to the client **109** via a response **132** at circle (8).

For example, in some embodiments when the processing is successful, the response is sent back as a HTTP 200 response that carries JSON formatted data. This data may include a collection of the medical entities extracted from the input text and their associated information. For each entity, the response provides the entity text, the entity category, where the entity text begins and ends, and the level of confidence in the detection and analysis. Attributes and traits of the entity are also returned.

In some embodiments, the output consolidator **128** may include a versioning engine **129** that can be utilized to generate a model version token that may be included in the response **132**. In some cases, especially when the versions of the models **120**/**124** may be occasionally or continually updated or changed over time, a model version token may be provided in a response that can be used to identify which versions of which models were utilized to generate the result. The model version token may be generated based on model version identifiers corresponding to software release versions of the models—e.g., a concatenation of model version numbers is generated and then encrypted, etc. In such an example, the client/user may be unable to decrypt or de-obfuscate the model version token, though it could be provided back to the operator of the UTAS **112** who is in possession of the token generation logic and/or key used to encrypt the model version numeric data (e.g., when 2-way encryption is used). Such a scheme enables, for example, the operator of the UTAS **112** to analyze some problematic or unexpected output generated by the UTAS **112** by, among other things, determining which exact versions of the involved model(s) were utilized to generate that result.

The ultimate response can be presented to a user, utilized by an application, persisted for later use, etc. For example, FIG. **4** is a diagram including an illustration of detected entities and relationships from an unstructured medical text along with an exemplary graphical user interface for presenting the detected entities and relationships according to some embodiments.

In this example, a first result user interface **400** is illustrated showing different detected entities, attributes, etc. In this example, various aspects (e.g., entities, attributes, traits, etc.) are shown with underlines—which may be colorized to reflect which category (e.g., MEDICATION, MEDICAL_CONDITION, PROTECTED_HEALTH_INFORMATION, TEST_TREATMENT_PROCEDURE, ANATOMY) the information is. Relationships that are detected may also be shown with arrows linking an attribute to the entity, and in this example the arrows are labeled with the particular attribute identifier of the attribute (e.g., "0.2 mgs" is a strength attribute of the entity "Clonidine").

Another result user interface **410** may be presented—optionally together with the result user interface **400**—to present the result information in a different manner In this result user interface **410**, a number of "cards" (or entries) are shown that present more information. Each card shows the text and its entity type. Next to each of the entities, a score represents the confidence that the UTAS **112** has in the identification of the text as the type of entity shown. For example, a "Clonidine" medication entity was found with a greater than 99% confidence, while a medical condition of "Sleeping trouble" was found with an 82% confidence that is a symptom trait with a score of 67%.

FIG. **5** is a diagram illustrating an environment for synchronous specified entity detection from unstructured text according to some embodiments. As described herein, in some embodiments the orchestrator **116** of the UTAS **112** may utilize multiple ML models **120**/**124** to detect different types of entities in unstructured text. However, in some embodiments, the orchestrator **116** may also utilize just one service **118**C or ML model **120**C for this analysis. For example, in some embodiments a client **109**A may issue a request **130** (e.g., a Detect PHI request) at circle (1) to detect one particular type of entity (e.g., PHI entities). Again, the request can be segmented and tokenized at circle (2) as described herein, and at circle (3) the segments may be provided to one particular service—e.g., PHI service **118**C—to utilize an ML model **120**C trained to detect entities of only that type at circle (4), and this information is returned to the orchestrator **116**, which optionally could be directly returned within a response **132** at circle (6) or could be modified or consolidated in some manner at circle (5) before being sent in the response **132**. In some cases where attributes may be involved, the orchestrator **116** may further utilize one or more relationship services **122** as described above to identify which attributes (or other aspects) correspond to which entities, and then this information returned by the relationship service(s) **122** may also be used by the output consolidator **128** at circle (5) to generate a result to be sent back in the response **132** at circle (6). Although this example involves single entity detect for PHI (via a DetectPHI request, use of a PHI service **118**C, etc., it is to be understood that in other embodiments other services (or even combinations of services) and/or requests may be used to allow for different types or collections of types of entities to be detected.

In the embodiments illustrated with regard to FIG. **1** and FIG. **3**, the ultimate response **132** may be sent back synchronously (e.g., in a same combination session or connection) to a request **130**. However, in other embodiments the process may also be implemented in an asynchronous manner. For example, FIG. **6** is a diagram illustrating an environment for asynchronous entity and relationship detection from unstructured text according to some embodiments.

In this example, a client **109**A may provide unstructured text by optionally uploading it as unstructured data **606** to a storage location **604** of a storage service **602** at optional circle (1) and providing an identifier of this location to the UTAS **112** (e.g., within a request **130** sent at circle (2A)), providing the unstructured text directly within the request **130**, or providing an identifier of another storage location where the unstructured text is located (e.g., within a database, outside the provider network at a separate storage location, etc.) that allows the UTAS **112** to obtain the unstructured text. The request may be implemented alternatively to, or in addition to, the other types of requests described herein. For example, such an asynchronous request may be a "StartJob" request that identifies a storage location **604** of the unstructured data **606** to be used as input for the job and may further identify the same or a different storage location **604** to be used to store the output results of the job.

Optionally at circle (2B) the UTAS **112** may send a response **132** indicating that the request **130** was received, and/or that the processing is underway. The response **132** may include, for example, a unique identifier associated with the entity detection job that may be utilized to obtain further information regarding the job such as the job's status, the results of the job, etc. In other embodiments, this response **132** may alternatively be sent at a different stage, such as at some point after circle (3), etc., when the orchestrator **116** has verified that it will be able to run the job (e.g., based on it successfully obtaining the unstructured text).

At circle (3) the orchestrator **116** may obtain the unstructured text (as part of unstructured data **606**) by sending a request to the storage service **602** based on an identifier of the storage location(s) **604** provided by the request **130** or earlier-provided by the user **110** in another manner (e.g., during a point of configuration) to obtain some or all of the unstructured data **606**, and then receiving some or all of the unstructured data **606** from the storage service **602** in response. In some embodiments, the orchestrator **116** may keep this unstructured data **606** in volatile memory only to avoid persisting this data.

Thereafter, the orchestrator **116** may perform entity detection and optionally relationship detection according to one of the various techniques disclosed herein, such as via segmentation and tokenization using the TSE **126**, doing a "scatter" of each segment at circle (4) to potentially multiple models **120** at circles (5A)-(5E), optionally sending some of this returned information at circle (6) to one or more relationship services **122** at utilize one or more relationship detecting ML models **124** at circle (7), and consolidating the returned information at circle (8). In some embodiments, the orchestrator **116** may utilize a model hosting system **840** (described later herein with regard to FIG. **8**) of an ML service to host and execute the models **120/124** as services **118/122**.

Upon generating a result, the orchestrator **116** may delete any copies of the unstructured data **606** made for the processing (e.g., from memory) and/or cause the result **608** to be stored, at circle (9), at a storage location **604** (e.g., of a storage service **602**) that may have been specified in the request **130** or another location that may be indicated in the response **132**. This allows for the client (or another client, such as an application) to access the result **608** at some point in time—notably, in an non-synchronous manner with the original request **130**. For example, the client **109**A may send a request at circle (10) to download the result **608**, which may be returned to the client **109**A by the storage service **602**.

In some embodiments, the UTAS **112** may implement other types of API requests to allow users to manage and/or monitor the process of these jobs. For example, a variety of requests such as a StartEntitiesDetectionJob request that is used for starting a detection job (e.g., a "batch" job that performs the detection for many unstructured data elements), a ListEntitiesDetectionJob request that will cause the UTAS **112** to provide as a response details regarding the number of jobs and job statuses for that user/customer, a DescribeEntitiesDetectionJob request that that will cause the UTAS **112** to provide as a response details regarding a specific job identified in the DescribeEntitiesDetectionJob request, a StopEntitiesDetectionJob request that that will cause the UTAS **112** to stop processing a specific job identified in the DescribeEntitiesDetectionJob request, etc.

As described herein the models **120/124** may each be implemented in a different VM, container, or even physical host, which may allow for ease of scaling and excellent performance. However, in some embodiments multiples (or all) of the models **120/124** may implemented in a same VM, container, or physical host (potentially also with some or all of the orchestrator **116** logic), which may potentially eliminate some (or all) network traffic sent between these various components and thus may also result in improved performance. In such cases, a purposefully large VM may be chosen (or flexibly scaled up over time) to allow for high performance for all of these models. For example, a single "large" resource-rich VM (e.g., having a relatively large amount of processing capability, memory, specialized computational hardware available, etc.) may be selected to run a pre-processing container, one or more inference containers (for the one or more models), a post-processing container (e.g., to make the data compatible with analytic tools), etc.

FIG. **7** is a flow diagram illustrating operations of a method for entity detection from unstructured text according to some embodiments. Some or all of the operations **700** (or other processes described herein, or variations, and/or combinations thereof) are performed under the control of one or more computer systems configured with executable instructions and are implemented as code (e.g., executable instructions, one or more computer programs, or one or more applications) executing collectively on one or more processors, by hardware or combinations thereof. The code is stored on a computer-readable storage medium, for example, in the form of a computer program comprising instructions executable by one or more processors. The computer-readable storage medium is non-transitory. In some embodiments, one or more (or all) of the operations **700** are performed by the UTAS **112** depicted in the other figures.

The operations **700** include, at block **705**, receiving a request to identify entities in unstructured text. The request may be received at a web service endpoint of a provider network and may include an identifier of whether a particular type of entity (e.g., personal health information entities) or multiple entities are to be detected within the unstructured text. The request may include the unstructured text (e.g., alphanumeric data) itself or may include an identifier of a storage location where the unstructured text may be obtained from. The request may include an identifier of a storage location where a result is to be stored.

In some embodiments, the plurality of entities includes one or more, two or more, three or more, etc., or all of: a medication; a medical condition; personal health information; a test, treatment, or procedure; or an anatomical body part or system. However, in other embodiments, other types of entities may be detected.

The operations **700** further include, at block **710**, identifying a plurality of segments within the unstructured text. Block **710** may be performed based on applying one or more rules to the unstructured text to identify locations where the unstructured text is to be split. The one or more rules may specify one or more delimiters (e.g., a period character, a newline, etc.) that signify the end and/or beginning of a segment.

In some embodiments, the operations **700** further include identifying tokens within the plurality of segments, which may be performed based on applying another one or more rules to the unstructured text (e.g., each of the segments) to identify locations of each token. The another one or more rules may specify one or more delimiters (e.g., a space character, a semicolon, a tab, etc.) that signify the end and/or beginning of a token.

The operations **700** further include, at block **715**, executing, for each segment of the plurality of segments, a plurality of ML models trained to detect entities of a particular entity type to yield a corresponding plurality of outputs. In some embodiments, each of the plurality of ML models comprises a Recurrent Neural Network (RNN) model. Each of the plurality of ML models may be implemented by a separate service.

The operations **700** further include, at block **720**, generating a result based at least in part on the plurality of outputs, the result identifying one or more entities detected within the unstructured text. The result may include, for each of the entities, an identifier of the entity, a beginning and ending offset of the entity, a confidence score for the detection of the entity, the text of the entity, a category of the entity, any associated traits or attributes found within the unstructured text that are associated with the entity, etc.

In some embodiments, the operations **700** further include, prior to block **720**, executing, for each segment of the plurality of segments using at least the output from at least one of the plurality of ML models, another ML model trained to identify relationships between attributes and ones of the entities to yield another output, wherein the result is further based on the another output. For example, in some embodiments where one or more attributes are found that correspond to a detected entity, a block is included in the result for each of the one or more attributes that includes a type of the attribute, a confidence score in the detection of the attribute, a relationship score indicating a confidence in the association between the attribute and an associated entity, an identifier of the attribute, a beginning and ending offset of the attribute, the text of the attribute, any traits found to be associated with the attribute, etc. In some embodiments, the another ML model is a convolutional neural network (CNN) model.

In some embodiments, each of the plurality of ML models is executed by a separate one or more virtual machines or containers within a provider network. However, the plurality of ML models, in some embodiments, are implemented within a single container or a single virtual machine.

The operations **700** further include, at block **725**, transmitting the result (e.g., to a client that issued the request, to a storage location within or outside of a same provider network, etc.).

In some embodiments, the operations **700** further include identifying, for each of the plurality of segments, one or more locations of one or more tokens within the corresponding segment, wherein for each segment each of the plurality of requests further includes identifiers of the one or more locations, and wherein each of the plurality of ML models detects entities using, as input to the ML model, the segment and the identifiers of the one or more locations.

In some embodiments, the operations **700** further include obtaining a plurality of model version identifiers corresponding to software release versions of the plurality of ML models; and generating a model version token based on the plurality of model version identifiers, wherein the response further comprises the model version token.

The request, in some embodiments, was originated by a client and indicates that the result is to be generated and returned to the client synchronously via a same network connection; and the transmitting of the result occurs via the same network connection.

The request, in some embodiments, was originated by a client and identifies at least a storage location where the result is to be stored; and transmitting the result comprises sending the result to a storage service to be stored at the storage location.

FIG. **8** is a block diagram of an illustrative operating environment in which ML models are trained and hosted according to some embodiments. The operating environment includes end user devices **802** (e.g., a PC or mobile device, such as computing device(s) **108**), a model training system **820**, a model hosting system **840**, a training data store **860**, a training metrics data store **865**, a container data store **870**, a training model data store **875**, and a model prediction data store **880**. AN ML service described herein may include one or more of these entities, such as the model hosting system **840**, model training system **820**, etc.

In some embodiments, users, by way of user devices **802**, interact with the model training system **820** to provide data that causes the model training system **820** to train one or more ML models. AN ML model, generally, may be thought of as one or more equations that are "trained" using a set of data. In some embodiments, the model training system **820** provides ML functionalities as a Web service, and thus messaging between user devices **802** and the model training system **820** (or provider network **100**), and/or between components of the model training system **820** (or provider network **100**), may utilize HTTP messages to transfer data in a machine-readable file format, such as eXtensible Markup Language (XML) or JavaScript Object Notation (JSON).

The user devices **802** can interact with the model training system **820** via frontend **829** of the model training system **820**. For example, a user device **802** can provide a training request to the frontend **829** that includes a container image (or multiple container images, or an identifier of one or multiple locations where container images are stored), an indicator of input data (e.g., an address or location of input data), one or more hyperparameter values (e.g., values indicating how the algorithm will operate, how many algorithms to run in parallel, how many clusters into which to separate data, etc.), and/or information describing the computing machine on which to train an ML model (e.g., a graphical processing unit (GPU) instance type, a central processing unit (CPU) instance type, an amount of memory to allocate, a type of virtual machine instance to use for training, etc.).

In some embodiments, the container image can include one or more layers, where each layer represents an executable instruction. Some or all of the executable instructions together represent an algorithm that defines an ML model. The executable instructions (e.g., the algorithm) can be written in any programming language (e.g., Python, Ruby, C++, Java, etc.). In some embodiments, the algorithm is pre-generated and obtained by a user, via the user device **802**, from an algorithm repository (e.g., a network-accessible marketplace, a data store provided by an ML training service, etc.). In some embodiments, the algorithm is completely user-generated or partially user-generated (e.g., user-provided code modifies or configures existing algorithmic code).

In some embodiments, instead of providing a container image (or identifier thereof) in the training request, the user device **802** may provide, in the training request, an algorithm written in any programming language. The model training system **820** packages the algorithm into a container (optionally with other code, such as a "base" ML algorithm supplemented with user-provided code) that is eventually loaded into a virtual machine instance **822** for training an ML model, as described in greater detail below. For example, a user, via a user device **802**, may develop an algorithm/code using an application (e.g., an interactive web-based programming environment) and cause the algorithm/code to be provided—perhaps as part of a training request (or referenced in a training request)—to the model training system **820**, where this algorithm/code may be containerized on its own or used together with an existing container having an ML framework, for example.

In some embodiments, instead of providing a container image in the training request, the user device **802** provides, in the training request, an indicator of a container image (e.g., an indication of an address or a location at which a container image is stored). For example, the container image can be stored in a container data store **870**, and this container image may have been previously created/uploaded by the user. The model training system **820** can retrieve the container image from the indicated location and create a container using the retrieved container image. The container is then loaded into a virtual machine instance **822** for training an ML model, as described in greater detail below.

The model training system **820** can use the information provided by the user device **802** to train an ML model in one or more pre-established virtual machine instances **822** in some embodiments. In particular, the model training system **820** includes a single physical computing device or multiple physical computing devices that are interconnected using one or more computing networks (not shown), where the physical computing device(s) host one or more virtual machine instances **822**. The model training system **820** can handle the acquisition and configuration of compute capacity (e.g., containers, instances, etc., which are described in greater detail below) based on the information describing the computing machine on which to train an ML model provided by the user device **802**. The model training system **820** can then train ML models using the compute capacity, as is described in greater detail below. The model training system **820** can automatically scale up and down based on the volume of training requests received from user devices **802** via frontend **829**, thereby relieving the user from the burden of having to worry about over-utilization (e.g., acquiring too little computing resources and suffering performance issues) or under-utilization (e.g., acquiring more computing resources than necessary to train the ML models, and thus overpaying).

In some embodiments, the virtual machine instances **822** are utilized to execute tasks. For example, such tasks can include training an ML model. As shown in FIG. **8**, each virtual machine instance **822** includes an operating system (OS) **824**, a language runtime **826**, and one or more ML training containers **830**. Generally, the ML training containers **830** are logical units created within a virtual machine instance using the resources available on that instance and can be utilized to isolate execution of a task from other processes (e.g., task executions) occurring in the instance. In some embodiments, the ML training containers **830** are formed from one or more container images and a top container layer. Each container image may further include one or more image layers, where each image layer represents an executable instruction. As described above, some or all of the executable instructions together represent an algorithm that defines an ML model. Changes made to the ML training containers **830** (e.g., creation of new files, modification of existing files, deletion of files, etc.) are stored in the top container layer. If an ML training container **830** is deleted, the top container layer is also deleted. However, the container image(s) that form a portion of the deleted ML training container **830** can remain unchanged. The ML training containers **830** can be implemented, for example, as Linux containers (LXC), Docker containers, and the like.

The ML training containers **830** may include individual a runtime **834**, code **837**, and dependencies **832** needed by the code **837** in some embodiments. The runtime **834** can be defined by one or more executable instructions that form at least a portion of a container image that is used to form the ML training container **830** (e.g., the executable instruction(s) in the container image that define the operating system and/or runtime to run in the container formed from the container image). The code **837** includes one or more executable instructions that form at least a portion of a container image that is used to form the ML training container **830**. For example, the code **837** includes the executable instructions in the container image that represent an algorithm that defines an ML model, which may reference (or utilize) code or libraries from dependencies **832**. The runtime **834** is configured to execute the code **837** in response to an instruction to begin ML model training. Execution of the code **837** results in the generation of model data, as described in greater detail below.

In some embodiments, the code **837** includes executable instructions that represent algorithms that define different ML models. For example, the code **837** includes one set of executable instructions that represent a first algorithm that defines a first ML model and a second set of executable instructions that represent a second algorithm that defines a second ML model. In some embodiments, the virtual machine instance **822** executes the code **837** and trains all of the ML models. In some embodiments, the virtual machine instance **822** executes the code **837**, selecting one of the ML models to train. For example, the virtual machine instance **822** can identify a type of training data indicated by the training request and select an ML model to train (e.g., execute the executable instructions that represent an algorithm that defines the selected ML model) that corresponds with the identified type of training data.

In some embodiments, the runtime **834** is the same as the runtime **826** utilized by the virtual machine instance **822**. In some embodiments, the runtime **834** is different than the runtime **826** utilized by the virtual machine instance **822**.

In some embodiments, the model training system **820** uses one or more container images included in a training request (or a container image retrieved from the container data store **870** in response to a received training request) to create and initialize an ML training container **830** in a virtual machine instance **822**. For example, the model training system **820** creates an ML training container **830** that includes the container image(s) and/or a top container layer.

Prior to beginning the training process, in some embodiments, the model training system **820** retrieves training data from the location indicated in the training request. For example, the location indicated in the training request can be a location in the training data store **860**. Thus, the model training system **820** retrieves the training data from the indicated location in the training data store **860**. In some embodiments, the model training system **820** does not retrieve the training data prior to beginning the training process. Rather, the model training system **820** streams the training data from the indicated location during the training process. For example, the model training system **820** can initially retrieve a portion of the training data and provide the retrieved portion to the virtual machine instance **822** training the ML model. Once the virtual machine instance **822** has applied and used the retrieved portion or once the virtual machine instance **822** is about to use all of the retrieved portion (e.g., a buffer storing the retrieved portion is nearly empty), then the model training system **820** can retrieve a second portion of the training data and provide the second retrieved portion to the virtual machine instance **822**, and so on.

To perform the ML model training, the virtual machine instance **822** executes code **837** stored in the ML training container **830** in some embodiments. For example, the code **837** includes some or all of the executable instructions that form the container image of the ML training container **830** initialized therein. Thus, the virtual machine instance **822** executes some or all of the executable instructions that form the container image of the ML training container **830** initialized therein to train an ML model. The virtual machine instance **822** executes some or all of the executable instructions according to the hyperparameter values included in the training request. As an illustrative example, the virtual machine instance **822** trains an ML model by identifying values for certain parameters (e.g., coefficients, weights, centroids, etc.). The identified values depend on hyperparameters that define how the training is performed. Thus, the virtual machine instance **822** can execute the executable instructions to initiate an ML model training process, where the training process is run using the hyperparameter values included in the training request. Execution of the executable instructions can include the virtual machine instance **822** applying the training data retrieved by the model training system **820** as input parameters to some or all of the instructions being executed.

In some embodiments, executing the executable instructions causes the virtual machine instance **822** (e.g., the ML training container **830**) to generate model data. For example, the ML training container **830** generates model data and stores the model data in a file system of the ML training container **830**. The model data includes characteristics of the ML model being trained, such as a number of layers in the ML model, hyperparameters of the ML model, coefficients of the ML model, weights of the ML model, and/or the like. In particular, the generated model data includes values for the characteristics that define an ML model being trained. In some embodiments, executing the executable instructions causes a modification to the ML training container **830** such that the model data is written to the top container layer of the ML training container **830** and/or the container image(s) that forms a portion of the ML training container **830** is modified to include the model data.

The virtual machine instance **822** (or the model training system **820** itself) pulls the generated model data from the ML training container **830** and stores the generated model data in the training model data store **875** in an entry associated with the virtual machine instance **822** and/or the ML model being trained. In some embodiments, the virtual machine instance **822** generates a single file that includes model data and stores the single file in the training model data store **875**. In some embodiments, the virtual machine instance **822** generates multiple files during the course of training an ML model, where each file includes model data. In some embodiments, each model data file includes the same or different model data information (e.g., one file identifies the structure of an algorithm, another file includes a list of coefficients, etc.). The virtual machine instance **822** can package the multiple files into a single file once training is complete and store the single file in the training model data store **875**. Alternatively, the virtual machine instance **822** stores the multiple files in the training model data store **875**. The virtual machine instance **822** stores the file(s) in the training model data store **875** while the training process is ongoing and/or after the training process is complete.

In some embodiments, the virtual machine instance **822** regularly stores model data file(s) in the training model data store **875** as the training process is ongoing. Thus, model data file(s) can be stored in the training model data store **875** at different times during the training process. Each set of model data files corresponding to a particular time or each set of model data files present in the training model data store **875** as of a particular time could be checkpoints that represent different versions of a partially-trained ML model during different stages of the training process. Accordingly, before training is complete, a user, via the user device **802** can submit a deployment and/or execution request in a manner as described below to deploy and/or execute a version of a partially trained ML model (e.g., an ML model trained as of a certain stage in the training process). A version of a partially-trained ML model can be based on some or all of the model data files stored in the training model data store **875**.

In some embodiments, a virtual machine instance **822** executes code **837** stored in a plurality of ML training containers **830**. For example, the algorithm included in the container image can be in a format that allows for the parallelization of the training process. Thus, the model training system **820** can create multiple copies of the container image provided in a training request and cause the virtual machine instance **822** to load each container image copy in a separate ML training container **830**. The virtual machine instance **822** can then execute, in parallel, the code **837** stored in the ML training containers **830**. The virtual machine instance **822** can further provide configuration information to each ML training container **830** (e.g., information indicating that N ML training containers **830** are collectively training an ML model and that a particular ML training container **830** receiving the configuration information is ML training container **830** number X of N), which can be included in the resulting model data. By parallelizing the training process, the model training system **820** can significantly reduce the training time in some embodiments.

In some embodiments, a plurality of virtual machine instances **822** execute code **837** stored in a plurality of ML training containers **830**. For example, the resources used to train a particular ML model can exceed the limitations of a single virtual machine instance **822**. However, the algorithm included in the container image can be in a format that allows for the parallelization of the training process. Thus, the model training system **820** can create multiple copies of the container image provided in a training request, initialize multiple virtual machine instances **822**, and cause each virtual machine instance **822** to load a container image copy in one or more separate ML training containers **830**. The virtual machine instances **822** can then each execute the code **837** stored in the ML training containers **830** in parallel. The model training system **820** can further provide configuration information to each ML training container **830** via the virtual machine instances **822** (e.g., information indicating that N ML training containers **830** are collectively training an ML model and that a particular ML training container **830** receiving the configuration information is ML training container **830** number X of N, information indicating that M virtual machine instances **822** are collectively training an ML model and that a particular ML training container **830** receiving the configuration information is initialized in virtual machine instance **822** number Y of M, etc.), which can be included in the resulting model data. As described above, by parallelizing the training process, the model training system **820** can significantly reduce the training time in some embodiments.

In some embodiments, the model training system **820** includes a plurality of physical computing devices and two or more of the physical computing devices hosts one or more virtual machine instances **822** that execute the code **837**. Thus, the parallelization can occur over different physical computing devices in addition to over different virtual machine instances **822** and/or ML training containers **830**.

In some embodiments, the model training system **820** includes an ML model evaluator **828**. The ML model evaluator **828** can monitor virtual machine instances **822** as ML models are being trained, obtaining the generated model data and processing the obtained model data to generate model metrics. For example, the model metrics can include quality metrics, such as an error rate of the ML model being trained, a statistical distribution of the ML model being trained, a latency of the ML model being trained, a confidence level of the ML model being trained (e.g., a level of confidence that the accuracy of the ML model being trained is known, etc. The ML model evaluator **828** can obtain the model data for an ML model being trained and evaluation data from the training data store **860**. The evaluation data is separate from the data used to train an ML model and includes both input data and expected outputs (e.g., known results), and thus the ML model evaluator **828** can define an ML model using the model data and execute the ML model by providing the input data as inputs to the ML model. The ML model evaluator **828** can then compare the outputs of the ML model to the expected outputs and determine one or more quality metrics of the ML model being trained based on the comparison (e.g., the error rate can be a difference or distance between the ML model outputs and the expected outputs).

The ML model evaluator **828** periodically generates model metrics during the training process and stores the model metrics in the training metrics data store **865** in some embodiments. While the ML model is being trained, a user, via the user device **802**, can access and retrieve the model metrics from the training metrics data store **865**. The user can then use the model metrics to determine whether to adjust the training process and/or to stop the training process. For example, the model metrics can indicate that the ML model is performing poorly (e.g., has an error rate above a threshold value, has a statistical distribution that is not an expected or desired distribution (e.g., not a binomial distribution, a Poisson distribution, a geometric distribution, a normal distribution, Gaussian distribution, etc.), has an execution latency above a threshold value, has a confidence level below a threshold value)) and/or is performing progressively worse (e.g., the quality metric continues to worsen over time). In response, in some embodiments, the user, via the user device **802**, can transmit a request to the model training system **820** to modify the ML model being trained (e.g., transmit a modification request). The request can include a new or modified container image, a new or modified algorithm, new or modified hyperparameter(s), and/or new or modified information describing the computing machine on which to train an ML model. The model training system **820** can modify the ML model accordingly. For example, the model training system **820** can cause the virtual machine instance **822** to optionally delete an existing ML training container **830**, create and initialize a new ML training container **830** using some or all of the information included in the request, and execute the code **837** stored in the new ML training container **830** to restart the ML model training process. As another example, the model training system **820** can cause the virtual machine instance **822** to modify the execution of code stored in an existing ML training container **830** according to the data provided in the modification request. In some embodiments, the user, via the user device **802**, can transmit a request to the model training system **820** to stop the ML model training process. The model training system **820** can then instruct the virtual machine instance **822** to delete the ML training container **830** and/or to delete any model data stored in the training model data store **875**.

As described below, in some embodiments, the model data stored in the training model data store **875** is used by the model hosting system **840** to deploy ML models. Alternatively or additionally, a user device **802** or another computing device (not shown) can retrieve the model data from the training model data store **875** to implement a learning algorithm in an external device. As an illustrative example, a robotic device can include sensors to capture input data. A user device **802** can retrieve the model data from the training model data store **875** and store the model data in the robotic device. The model data defines an ML model. Thus, the robotic device can provide the captured input data as an input to the ML model, resulting in an output. The robotic device can then perform an action (e.g., move forward, raise an arm, generate a sound, etc.) based on the resulting output.

While the virtual machine instances **822** are shown in FIG. **8** as a single grouping of virtual machine instances **822**, some embodiments of the present application separate virtual machine instances **822** that are actively assigned to execute tasks from those virtual machine instances **822** that are not actively assigned to execute tasks. For example, those virtual machine instances **822** actively assigned to execute tasks are grouped into an "active pool," while those virtual machine instances **822** not actively assigned to execute tasks are placed within a "warming pool." In some embodiments, those virtual machine instances **822** within the warming pool can be pre-initialized with an operating system, language runtimes, and/or other software required to enable rapid execution of tasks (e.g., rapid initialization of ML model training in ML training container(s) **830**) in response to training requests.

In some embodiments, the model training system **820** includes a processing unit, a network interface, a computer-readable medium drive, and an input/output device interface, all of which can communicate with one another by way of a communication bus. The network interface can provide connectivity to one or more networks or computing systems. The processing unit can thus receive information and instructions from other computing systems or services (e.g., user devices **802**, the model hosting system **840**, etc.). The processing unit can also communicate to and from a memory of a virtual machine instance **822** and further provide output information for an optional display via the input/output device interface. The input/output device interface can also accept input from an optional input device. The memory can contain computer program instructions (grouped as modules in some embodiments) that the processing unit executes in order to implement one or more aspects of the present disclosure.

In some embodiments, the model hosting system **840** includes a single physical computing device or multiple physical computing devices that are interconnected using one or more computing networks (not shown), where the physical computing device(s) host one or more virtual machine instances **842**. The model hosting system **840** can handle the acquisition and configuration of compute capacity (e.g., containers, instances, etc.) based on demand for the execution of trained ML models. The model hosting system **840** can then execute ML models using the compute capacity, as is described in greater detail below. The model hosting system **840** can automatically scale up and down based on the volume of execution requests received from user devices **802** via frontend **849** of the model hosting system **840**, thereby relieving the user from the burden of having to worry about over-utilization (e.g., acquiring too little computing resources and suffering performance issues) or under-utilization (e.g., acquiring more computing resources than necessary to run the ML models, and thus overpaying).

In some embodiments, the virtual machine instances **842** are utilized to execute tasks. For example, such tasks can include executing an ML model. As shown in FIG. **8**, each virtual machine instance **842** includes an operating system (OS) **844**, a language runtime **846**, and one or more ML scoring containers **850**. The ML scoring containers **850** are similar to the ML training containers **830** in that the ML scoring containers **850** are logical units created within a virtual machine instance using the resources available on that instance and can be utilized to isolate execution of a task from other processes (e.g., task executions) occurring in the instance. In some embodiments, the ML scoring containers **850** are formed from one or more container images and a top container layer. Each container image further includes one or more image layers, where each image layer represents an executable instruction. As described above, some or all of the executable instructions together represent an algorithm that defines an ML model. Changes made to the ML scoring containers **850** (e.g., creation of new files, modification of existing files, deletion of files, etc.) are stored in the top container layer. If an ML scoring container **850** is deleted, the top container layer is also deleted. However, the container image(s) that form a portion of the deleted ML scoring container **850** can remain unchanged. The ML scoring containers **850** can be implemented, for example, as Linux containers.

The ML scoring containers **850** each include a runtime **854**, code **856**, and dependencies **852** (e.g., supporting software such as libraries) needed by the code **856** in some embodiments. The runtime **854** can be defined by one or more executable instructions that form at least a portion of a container image that is used to form the ML scoring container **850** (e.g., the executable instruction(s) in the container image that define the operating system and/or runtime to run in the container formed from the container image). The code **856** includes one or more executable instructions that form at least a portion of a container image that is used to form the ML scoring container **850**. For example, the code **856** includes the executable instructions in the container image that represent an algorithm that defines an ML model, which may reference dependencies **852**. The code **856** can also include model data that represent characteristics of the defined ML model, as described in greater detail below. The runtime **854** is configured to execute the code **856** in response to an instruction to begin execution of an ML model. Execution of the code **856** results in the generation of outputs (e.g., predicted or "inferred" results), as described in greater detail below.

In some embodiments, the runtime **854** is the same as the runtime **846** utilized by the virtual machine instance **842**. In some embodiments, runtime **854** is different than the runtime **846** utilized by the virtual machine instance **842**.

In some embodiments, the model hosting system **840** uses one or more container images included in a deployment request (or a container image retrieved from the container data store **870** in response to a received deployment request) to create and initialize an ML scoring container **850** in a virtual machine instance **842**. For example, the model hosting system **840** creates an ML scoring container **850** that includes the container image(s) and/or a top container layer.

As described above, a user device **802** can submit a deployment request and/or an execution request to the model hosting system **840** via the frontend **849** in some embodiments. A deployment request causes the model hosting system **840** to deploy a trained ML model into a virtual machine instance **842**. For example, the deployment request can include an identification of an endpoint (e.g., an endpoint name, such as an HTTP endpoint name) and an identification of one or more trained ML models (e.g., a location of one or more model data files stored in the training model data store **875**). Optionally, the deployment request also includes an identification of one or more container images stored in the container data store **870**.

Upon receiving the deployment request, the model hosting system **840** initializes ones or more ML scoring containers **850** in one or more hosted virtual machine instance **842**. In embodiments in which the deployment request includes an identification of one or more container images, the model hosting system **840** forms the ML scoring container(s) **850** from the identified container image(s). For example, a container image identified in a deployment request can be the same container image used to form an ML training container **830** used to train the ML model corresponding to the deployment request. Thus, the code **856** of the ML scoring container(s) **850** includes one or more executable instructions in the container image(s) that represent an algorithm that defines an ML model. In embodiments in which the deployment request does not include an identification of a container image, the model hosting system **840** forms the ML scoring container(s) **850** from one or more container images stored in the container data store **870** that are appropriate for executing the identified trained ML model(s). For example, an appropriate container image can be a container image that includes executable instructions that represent an algorithm that defines the identified trained ML model(s).

The model hosting system **840** further forms the ML scoring container(s) **850** by retrieving model data corresponding to the identified trained ML model(s) in some embodiments. For example, the deployment request can identify a location of model data file(s) stored in the training model data store **875**. In embodiments in which a single model data file is identified in the deployment request, the model hosting system **840** retrieves the identified model data file from the training model data store **875** and inserts the model data file into a single ML scoring container **850**, which forms a portion of code **856**. In some embodiments, the model data file is archived or compressed (e.g., formed from a package of individual files). Thus, the model hosting system **840** unarchives or decompresses the model data file to obtain multiple individual files and inserts the individual files into the ML scoring container **850**. In some embodiments, the model hosting system **840** stores the model data file in the same location as the location in which the model data file was stored in the ML training container **830** that generated the model data file. For example, the model data file initially was stored in the top container layer of the ML training container **830** at a certain offset, and the model hosting system **840** then stores the model data file in the top container layer of the ML scoring container **850** at the same offset.

In embodiments in which multiple model data files are identified in the deployment request, the model hosting system **840** retrieves the identified model data files from the training model data store **875**. The model hosting system **840** can insert the model data files into the same ML scoring container **850**, into different ML scoring containers **850** initialized in the same virtual machine instance **842**, or into different ML scoring containers **850** initialized in different virtual machine instances **842**. As an illustrative example, the deployment request can identify multiple model data files corresponding to different trained ML models because the trained ML models are related (e.g., the output of one trained ML model is used as an input to another trained ML model). Thus, the user may desire to deploy multiple ML models to eventually receive a single output that relies on the outputs of multiple ML models.

In some embodiments, the model hosting system **840** associates the initialized ML scoring container(s) **850** with the endpoint identified in the deployment request. For example, each of the initialized ML scoring container(s) **850** can be associated with a network address. The model hosting system **840** can map the network address(es) to the identified endpoint, and the model hosting system **840** or another system (e.g., a routing system, not shown) can store the mapping. Thus, a user device **802** can refer to trained ML model(s) stored in the ML scoring container(s) **850** using the endpoint. This allows for the network address of an ML scoring container **850** to change without causing the user operating the user device **802** to change the way in which the user refers to a trained ML model.

Once the ML scoring container(s) **850** are initialized, the ML scoring container(s) **850** are ready to execute trained ML model(s). In some embodiments, the user device **802** transmits an execution request to the model hosting system **840** via the frontend **849**, where the execution request identifies an endpoint and includes an input to an ML model (e.g., a set of input data). The model hosting system **840** or another system (e.g., a routing system, not shown) can obtain the execution request, identify the ML scoring container(s) **850** corresponding to the identified endpoint, and route the input to the identified ML scoring container(s) **850**.

In some embodiments, a virtual machine instance **842** executes the code **856** stored in an identified ML scoring container **850** in response to the model hosting system **840** receiving the execution request. In particular, execution of the code **856** causes the executable instructions in the code **856** corresponding to the algorithm to read the model data file stored in the ML scoring container **850**, use the input included in the execution request as an input parameter, and generate a corresponding output. As an illustrative example, the algorithm can include coefficients, weights, layers, cluster centroids, and/or the like. The executable instructions in the code **856** corresponding to the algorithm can read the model data file to determine values for the coefficients, weights, layers, cluster centroids, and/or the like. The executable instructions can include input parameters, and the input included in the execution request can be supplied by the virtual machine instance **842** as the input parameters. With the ML model characteristics and the input parameters provided, execution of the executable instructions by the virtual machine instance **842** can be completed, resulting in an output.

In some embodiments, the virtual machine instance **842** stores the output in the model prediction data store **880**. Alternatively or in addition, the virtual machine instance **842** transmits the output to the user device **802** that submitted the execution result via the frontend **849**.

In some embodiments, the execution request corresponds to a group of related trained ML models. Thus, the ML scoring container **850** can transmit the output to a second ML scoring container **850** initialized in the same virtual machine instance **842** or in a different virtual machine instance **842**. The virtual machine instance **842** that initialized the second ML scoring container **850** can then execute second code **856** stored in the second ML scoring container **850**, providing the received output as an input parameter to the executable instructions in the second code **856**. The second ML scoring container **850** further includes a model data file stored therein, which is read by the executable instructions in the second code **856** to determine values for the characteristics defining the ML model. Execution of the second code **856** results in a second output. The virtual machine instance **842** that initialized the second ML scoring container **850** can then transmit the second output to the model prediction data store **880** and/or the user device **802** via the frontend **849** (e.g., if no more trained ML models are needed to generate an output) or transmit the second output to a third ML scoring container **850** initialized in the same or different virtual machine instance **842** (e.g., if outputs from one or more additional trained ML models are needed), and the above-referenced process can be repeated with respect to the third ML scoring container **850**.

While the virtual machine instances **842** are shown in FIG. **8** as a single grouping of virtual machine instances **842**, some embodiments of the present application separate virtual machine instances **842** that are actively assigned to execute tasks from those virtual machine instances **842** that are not actively assigned to execute tasks. For example, those virtual machine instances **842** actively assigned to execute tasks are grouped into an "active pool," while those virtual machine instances **842** not actively assigned to execute tasks are placed within a "warming pool." In some embodiments, those virtual machine instances **842** within the warming pool can be pre-initialized with an operating system, language runtimes, and/or other software required to enable rapid execution of tasks (e.g., rapid initialization of ML scoring container(s) **850**, rapid execution of code **856** in ML scoring container(s), etc.) in response to deployment and/or execution requests.

In some embodiments, the model hosting system **840** includes a processing unit, a network interface, a computer-readable medium drive, and an input/output device interface, all of which can communicate with one another by way of a communication bus. The network interface can provide connectivity to one or more networks or computing systems. The processing unit can thus receive information and instructions from other computing systems or services (e.g., user devices **802**, the model training system **820**, etc.). The processing unit can also communicate to and from a memory of a virtual machine instance **842** and further provide output information for an optional display via the input/output device interface. The input/output device interface can also accept input from an optional input device. The memory can contain computer program instructions (grouped as modules in some embodiments) that the processing unit executes in order to implement one or more aspects of the present disclosure.

In some embodiments, the operating environment supports many different types of ML models, such as multi-arm bandit models, reinforcement learning models, ensemble ML models, deep learning models, or the like.

The model training system **820** and the model hosting system **840** depicted in FIG. **8** are not meant to be limiting. For example, the model training system **820** and/or the model hosting system **840** could also operate within a computing environment having a fewer or greater number of devices than are illustrated in FIG. **8**. Thus, the depiction of the model training system **820** and/or the model hosting system **840** in FIG. **8** may be taken as illustrative and not limiting to the present disclosure. For example, the model training system **820** and/or the model hosting system **840** or various constituents thereof could implement various Web services components, hosted or "cloud" computing environments, and/or peer-to-peer network configurations to implement at least a portion of the processes described herein. In some embodiments, the model training system **820** and/or the model hosting system **840** are implemented directly in hardware or software executed by hardware devices and may, for instance, include one or more physical or virtual servers implemented on physical computer hardware configured to execute computer-executable instructions for performing the various features that are described herein. The one or more servers can be geographically dispersed or geographically co-located, for instance, in one or more points of presence (POPs) or regional data centers.

The frontend **829** processes all training requests received from user devices **802** and provisions virtual machine instances **822**. In some embodiments, the frontend **829** serves as a front door to all the other services provided by the model training system **820**. The frontend **829** processes the requests and makes sure that the requests are properly authorized. For example, the frontend **829** may determine whether the user associated with the training request is authorized to initiate the training process.

Similarly, frontend **849** processes all deployment and execution requests received from user devices **802** and provisions virtual machine instances **842**. In some embodiments, the frontend **849** serves as a front door to all the other services provided by the model hosting system **840**. The frontend **849** processes the requests and makes sure that the requests are properly authorized. For example, the frontend **849** may determine whether the user associated with a deployment request or an execution request is authorized to access the indicated model data and/or to execute the indicated ML model.

The training data store **860** stores training data and/or evaluation data. The training data can be data used to train ML models and evaluation data can be data used to evaluate the performance of ML models. In some embodiments, the training data and the evaluation data have common data. In some embodiments, the training data and the evaluation data do not have common data. In some embodiments, the training data includes input data and expected outputs. While the training data store **860** is depicted as being located external to the model training system **820** and the model hosting system **840**, this is not meant to be limiting. For example, in some embodiments not shown, the training data store **860** is located internal to at least one of the model training system **820** or the model hosting system **840**.

In some embodiments, the training metrics data store **865** stores model metrics. While the training metrics data store **865** is depicted as being located external to the model training system **820** and the model hosting system **840**, this is not meant to be limiting. For example, in some embodiments not shown, the training metrics data store **865** is located internal to at least one of the model training system **820** or the model hosting system **840**.

The container data store **870** stores container images, such as container images used to form ML training containers **830** and/or ML scoring containers **850**, that can be retrieved by various virtual machine instances **822** and/or **842**. While the container data store **870** is depicted as being located external to the model training system **820** and the model hosting system **840**, this is not meant to be limiting. For example, in some embodiments not shown, the container data store **870** is located internal to at least one of the model training system **820** and the model hosting system **840**.

The training model data store **875** stores model data files. In some embodiments, some of the model data files are comprised of a single file, while other model data files are packages of multiple individual files. While the training model data store **875** is depicted as being located external to the model training system **820** and the model hosting system **840**, this is not meant to be limiting. For example, in some embodiments not shown, the training model data store **875** is located internal to at least one of the model training system **820** or the model hosting system **840**.

The model prediction data store **880** stores outputs (e.g., execution results) generated by the ML scoring containers **850** in some embodiments. While the model prediction data store **880** is depicted as being located external to the model training system **820** and the model hosting system **840**, this is not meant to be limiting. For example, in some embodiments not shown, the model prediction data store **880** is located internal to at least one of the model training system **820** and the model hosting system **840**.

While the model training system **820**, the model hosting system **840**, the training data store **860**, the training metrics data store **865**, the container data store **870**, the training model data store **875**, and the model prediction data store **880** are illustrated as separate components, this is not meant to be limiting. In some embodiments, any one or all of these components can be combined to perform the functionality described herein. For example, any one or all of these components can be implemented by a single computing device, or by multiple distinct computing devices, such as computer servers, logically or physically grouped together to collectively operate as a server system. Any one or all of these components can communicate via a shared internal network, and the collective system (e.g., also referred to herein as an ML service) can communicate with one or more of the user devices **802** via the one or more network(s) **106**.

Various example user devices **802** are shown in FIG. **8**, including a desktop computer, laptop, and a mobile phone, each provided by way of illustration. In general, the user devices **802** can be any computing device such as a desktop, laptop or tablet computer, personal computer, wearable computer, server, personal digital assistant (PDA), hybrid PDA/mobile phone, mobile phone, electronic book reader, set-top box, voice command device, camera, digital media player, and the like. In some embodiments, the model training system **820** and/or the model hosting system **840** provides the user devices **802** with one or more user interfaces, command-line interfaces (CLI), application programing interfaces (API), and/or other programmatic interfaces for submitting training requests, deployment requests, and/or execution requests. In some embodiments, the user devices **802** can execute a stand-alone application that interacts with the model training system **820** and/or the model hosting system **840** for submitting training requests, deployment requests, and/or execution requests.

In some embodiments, the network **106** includes any wired network, wireless network, or combination thereof. For example, the network **106** may be a personal area network, local area network, wide area network, over-the-air broadcast network (e.g., for radio or television), cable network, satellite network, cellular telephone network, or combination thereof. As a further example, the network **106** may be a publicly accessible network of linked networks, possibly operated by various distinct parties, such as the Internet. In some embodiments, the network **106** may be a private or semi-private network, such as a corporate or university intranet. The network **106** may include one or more wireless networks, such as a Global System for Mobile Communications (GSM) network, a Code Division Multiple Access (CDMA) network, a Long Term Evolution (LTE) network, or any other type of wireless network. The network **106** can use protocols and components for communicating via the Internet or any of the other aforementioned types of networks. For example, the protocols used by the network **106** may include HTTP, HTTP Secure (HTTPS), Message Queue Telemetry Transport (MQTT), Constrained Application Protocol (CoAP), and the like. Protocols and components for communicating via the Internet or any of the other aforementioned types of communication networks are well known to those skilled in the art and, thus, are not described in more detail herein.

FIG. **9** illustrates an example provider network (or "service provider system") environment according to some embodiments. A provider network **900** may provide resource virtualization to customers via one or more virtualization services **910** that allow customers to purchase, rent, or otherwise obtain instances **912** of virtualized resources, including but not limited to computation and storage resources, implemented on devices within the provider network or networks in one or more data centers. Local Internet Protocol (IP) addresses **916** may be associated with the resource instances **912**; the local IP addresses are the internal network addresses of the resource instances **912** on the provider network **900**. In some embodiments, the provider network **900** may also provide public IP addresses **914** and/or public IP address ranges (e.g., Internet Protocol version 4 (IPv4) or Internet Protocol version 6 (IPv6) addresses) that customers may obtain from the provider **900**.

Conventionally, the provider network **900**, via the virtualization services **910**, may allow a customer of the service provider (e.g., a customer that operates one or more client networks **950**A-**950**C including one or more customer device(s) **952**) to dynamically associate at least some public IP addresses **914** assigned or allocated to the customer with particular resource instances **912** assigned to the customer. The provider network **900** may also allow the customer to remap a public IP address **914**, previously mapped to one virtualized computing resource instance **912** allocated to the customer, to another virtualized computing resource instance **912** that is also allocated to the customer. Using the virtualized computing resource instances **912** and public IP addresses **914** provided by the service provider, a customer of the service provider such as the operator of customer network(s) **950**A-**950**C may, for example, implement customer-specific applications and present the customer's applications on an intermediate network **940**, such as the Internet. Other network entities **920** on the intermediate network **940** may then generate traffic to a destination public IP address **914** published by the customer network(s) **950**A-**950**C; the traffic is routed to the service provider data center, and at the data center is routed, via a network substrate, to the local IP address **916** of the virtualized computing resource instance **912** currently mapped to the destination public IP address **914**. Similarly, response traffic from the virtualized computing resource instance **912** may be routed via the network substrate back onto the intermediate network **940** to the source entity **920**.

Local IP addresses, as used herein, refer to the internal or "private" network addresses, for example, of resource instances in a provider network. Local IP addresses can be within address blocks reserved by Internet Engineering Task Force (IETF) Request for Comments (RFC) 1918 and/or of an address format specified by IETF RFC 4193, and may be mutable within the provider network. Network traffic originating outside the provider network is not directly routed to local IP addresses; instead, the traffic uses public IP addresses that are mapped to the local IP addresses of the resource instances. The provider network may include networking devices or appliances that provide network address translation (NAT) or similar functionality to perform the mapping from public IP addresses to local IP addresses and vice versa.

Public IP addresses are Internet mutable network addresses that are assigned to resource instances, either by the service provider or by the customer. Traffic routed to a public IP address is translated, for example via 1:1 NAT, and forwarded to the respective local IP address of a resource instance.

Some public IP addresses may be assigned by the provider network infrastructure to particular resource instances; these public IP addresses may be referred to as standard public IP addresses, or simply standard IP addresses. In some embodiments, the mapping of a standard IP address to a local IP address of a resource instance is the default launch configuration for all resource instance types.

At least some public IP addresses may be allocated to or obtained by customers of the provider network **900**; a customer may then assign their allocated public IP addresses to particular resource instances allocated to the customer. These public IP addresses may be referred to as customer public IP addresses, or simply customer IP addresses. Instead of being assigned by the provider network **900** to resource instances as in the case of standard IP addresses, customer IP addresses may be assigned to resource instances by the customers, for example via an API provided by the service provider. Unlike standard IP addresses, customer IP addresses are allocated to customer accounts and can be remapped to other resource instances by the respective customers as necessary or desired. A customer IP address is associated with a customer's account, not a particular resource instance, and the customer controls that IP address until the customer chooses to release it. Unlike conventional static IP addresses, customer IP addresses allow the customer to mask resource instance or availability zone failures by remapping the customer's public IP addresses to any resource instance associated with the customer's account. The customer IP addresses, for example, enable a customer to engineer around problems with the customer's resource instances or software by remapping customer IP addresses to replacement resource instances.

FIG. **10** is a block diagram of an example provider network that provides a storage service and a hardware virtualization service to customers, according to some embodiments. Hardware virtualization service **1020** provides multiple computation resources **1024** (e.g., VMs) to customers. The computation resources **1024** may, for example, be rented or leased to customers of the provider network **1000** (e.g., to a customer that implements customer network **1050**). Each computation resource **1024** may be provided with one or more local IP addresses. Provider network **1000** may be configured to route packets from the local IP addresses of the computation resources **1024** to public Internet destinations, and from public Internet sources to the local IP addresses of computation resources **1024**.

Provider network **1000** may provide a customer network **1050**, for example coupled to intermediate network **1040** via local network **1056**, the ability to implement virtual computing systems **1092** via hardware virtualization service **1020** coupled to intermediate network **1040** and to provider network **1000**. In some embodiments, hardware virtualization service **1020** may provide one or more APIs **1002**, for example a web services interface, via which a customer network **1050** may access functionality provided by the hardware virtualization service **1020**, for example via a console **1094** (e.g., a web-based application, standalone application, mobile application, etc.). In some embodiments, at the provider network **1000**, each virtual computing system **1092** at customer network **1050** may correspond to a computation resource **1024** that is leased, rented, or otherwise provided to customer network **1050**.

From an instance of a virtual computing system **1092** and/or another customer device **1090** (e.g., via console **1094**), the customer may access the functionality of storage service **1010**, for example via one or more APIs **1002**, to access data from and store data to storage resources **1018**A-**1018**N of a virtual data store **1016** (e.g., a folder or "bucket", a virtualized volume, a database, etc.) provided by the provider network **1000**. In some embodiments, a virtualized data store gateway (not shown) may be provided at the customer network **1050** that may locally cache at least some data, for example frequently-accessed or critical data, and that may communicate with storage service **1010** via one or more communications channels to upload new or modified data from a local cache so that the primary store of data (virtualized data store **1016**) is maintained. In some embodiments, a user, via a virtual computing system **1092** and/or on another customer device **1090**, may mount and access virtual data store **1016** volumes via storage service **1010** acting as a storage virtualization service, and these volumes may appear to the user as local (virtualized) storage **1098**.

While not shown in FIG. **10**, the virtualization service(s) may also be accessed from resource instances within the provider network **1000** via API(s) **1002**. For example, a customer, appliance service provider, or other entity may access a virtualization service from within a respective virtual network on the provider network **1000** via an API **1002** to request allocation of one or more resource instances within the virtual network or within another virtual network.

Illustrative System

In some embodiments, a system that implements a portion or all of the techniques for entity and relationship detection from unstructured text as described herein may include a general-purpose computer system that includes or is configured to access one or more computer-accessible media, such as computer system **1100** illustrated in FIG. **11**. In the illustrated embodiment, computer system **1100** includes one or more processors **1110** coupled to a system memory **1120** via an input/output (I/O) interface **1130**. Computer system **1100** further includes a network interface **1140** coupled to I/O interface **1130**. While FIG. **11** shows computer system **1100** as a single computing device, in various embodiments a computer system **1100** may include one computing device or any number of computing devices configured to work together as a single computer system **1100**.

In various embodiments, computer system **1100** may be a uniprocessor system including one processor **1110**, or a multiprocessor system including several processors **1110** (e.g., two, four, eight, or another suitable number). Processors **1110** may be any suitable processors capable of executing instructions. For example, in various embodiments, processors **1110** may be general-purpose or embedded processors implementing any of a variety of instruction set architectures (ISAs), such as the x86, ARM, PowerPC, SPARC, or MIPS ISAs, or any other suitable ISA. In multiprocessor systems, each of processors **1110** may commonly, but not necessarily, implement the same ISA.

System memory **1120** may store instructions and data accessible by processor(s) **1110**. In various embodiments, system memory **1120** may be implemented using any suitable memory technology, such as random-access memory (RAM), static RAM (SRAM), synchronous dynamic RAM (SDRAM), nonvolatile/Flash-type memory, or any other type of memory. In the illustrated embodiment, program instructions and data implementing one or more desired functions, such as those methods, techniques, and data described above are shown stored within system memory **1120** as code **1125** and data **1126**.

In one embodiment, I/O interface **1130** may be configured to coordinate I/O traffic between processor **1110**, system memory **1120**, and any peripheral devices in the device, including network interface **1140** or other peripheral interfaces. In some embodiments, I/O interface **1130** may perform any necessary protocol, timing or other data transformations to convert data signals from one component (e.g., system memory **1120**) into a format suitable for use by another component (e.g., processor **1110**). In some embodiments, I/O interface **1130** may include support for devices attached through various types of peripheral buses, such as a variant of the Peripheral Component Interconnect (PCI) bus standard or the Universal Serial Bus (USB) standard, for example. In some embodiments, the function of I/O interface **1130** may be split into two or more separate components, such as a north bridge and a south bridge, for example. Also, in some embodiments some or all of the functionality of I/O interface **1130**, such as an interface to system memory **1120**, may be incorporated directly into processor **1110**.

Network interface **1140** may be configured to allow data to be exchanged between computer system **1100** and other devices **1160** attached to a network or networks **1150**, such as other computer systems or devices as illustrated in FIG. **1**, for example. In various embodiments, network interface **1140** may support communication via any suitable wired or wireless general data networks, such as types of Ethernet network, for example. Additionally, network interface **1140** may support communication via telecommunications/telephony networks such as analog voice networks or digital fiber communications networks, via storage area networks (SANs) such as Fibre Channel SANs, or via I/O any other suitable type of network and/or protocol.

In some embodiments, a computer system **1100** includes one or more offload cards **1170** (including one or more processors **1175**, and possibly including the one or more network interfaces **1140**) that are connected using an I/O interface **1130** (e.g., a bus implementing a version of the Peripheral Component Interconnect—Express (PCI-E) standard, or another interconnect such as a QuickPath interconnect (QPI) or UltraPath interconnect (UPI)). For example, in some embodiments the computer system **1100** may act as a host electronic device (e.g., operating as part of a hardware virtualization service) that hosts compute instances, and the one or more offload cards **1170** execute a virtualization manager that can manage compute instances that execute on the host electronic device. As an example, in some embodiments the offload card(s) **1170** can perform compute instance management operations such as pausing and/or un-pausing compute instances, launching and/or terminating compute instances, performing memory transfer/copying operations, etc. These management operations may, in some embodiments, be performed by the offload card(s) **1170** in coordination with a hypervisor (e.g., upon a request from a hypervisor) that is executed by the other processors **1110**A-**1110**N of the computer system **1100**. However, in some embodiments the virtualization manager implemented by the offload card(s) **1170** can accommodate requests from other entities (e.g., from compute instances themselves), and may not coordinate with (or service) any separate hypervisor.

In some embodiments, system memory **1120** may be one embodiment of a computer-accessible medium configured to store program instructions and data as described above. However, in other embodiments, program instructions and/or data may be received, sent or stored upon different types of computer-accessible media. Generally speaking, a computer-accessible medium may include non-transitory storage media or memory media such as magnetic or optical media, e.g., disk or DVD/CD coupled to computer system **1100** via I/O interface **1130**. A non-transitory computer-accessible storage medium may also include any volatile or non-volatile media such as RAM (e.g., SDRAM, double data rate (DDR) SDRAM, SRAM, etc.), read only memory (ROM), etc., that may be included in some embodiments of computer system **1100** as system memory **1120** or another type of memory. Further, a computer-accessible medium may include transmission media or signals such as electrical, electromagnetic, or digital signals, conveyed via a communication medium such as a network and/or a wireless link, such as may be implemented via network interface **1140**.

In the preceding description, various embodiments are described. For purposes of explanation, specific configurations and details are set forth in order to provide a thorough understanding of the embodiments. However, it will also be apparent to one skilled in the art that the embodiments may be practiced without the specific details. Furthermore, well-known features may be omitted or simplified in order not to obscure the embodiment being described.

Bracketed text and blocks with dashed borders (e.g., large dashes, small dashes, dot-dash, and dots) are used herein to illustrate optional operations that add additional features to some embodiments. However, such notation should not be taken to mean that these are the only options or optional operations, and/or that blocks with solid borders are not optional in certain embodiments.

Reference numerals with suffix letters (e.g., **1018**A-**1018**N) may be used to indicate that there can be one or multiple instances of the referenced entity in various embodiments, and when there are multiple instances, each does not need to be identical but may instead share some general traits or act in common ways. Further, the particular suffixes used are not meant to imply that a particular amount of the entity exists unless specifically indicated to the contrary. Thus, two entities using the same or different suffix letters may or may not have the same number of instances in various embodiments.

References to "one embodiment," "an embodiment," "an example embodiment," etc., indicate that the embodiment described may include a particular feature, structure, or characteristic, but every embodiment may not necessarily include the particular feature, structure, or characteristic. Moreover, such phrases are not necessarily referring to the same embodiment. Further, when a particular feature, structure, or characteristic is described in connection with an embodiment, it is submitted that it is within the knowledge of one skilled in the art to affect such feature, structure, or characteristic in connection with other embodiments whether or not explicitly described.

Moreover, in the various embodiments described above, unless specifically noted otherwise, disjunctive language such as the phrase "at least one of A, B, or C" is intended to be understood to mean either A, B, or C, or any combination thereof (e.g., A, B, and/or C). As such, disjunctive language is not intended to, nor should it be understood to, imply that a given embodiment requires at least one of A, at least one of B, or at least one of C to each be present.

The specification and drawings are, accordingly, to be regarded in an illustrative rather than a restrictive sense. It will, however, be evident that various modifications and changes may be made thereunto without departing from the broader spirit and scope of the disclosure as set forth in the claims.

What is claimed is:

1. A computer-implemented method comprising:

receiving, at a web service endpoint of a provider network, a request to identify entities in unstructured text, the request being originated by a client and including the unstructured text;

identifying a plurality of segments within the unstructured text;

identifying, for each of the plurality of segments, one or more locations of one or more tokens within the corresponding segment;

sending, for each segment of the plurality of segments, a request to each of a plurality of services within the provider network, wherein each request includes the segment and one or more identifiers of the one or more locations of the one or more tokens, and wherein each of the plurality of services utilizes the segment and the one or more identifiers with a machine learning (ML) model trained to detect entities of a particular entity type;

receiving a plurality of responses from the plurality of services;

sending, for one or more segments of the plurality of segments, a request to a relationship service of the provider network to identify relationships between entities and attributes in the one or more segments, wherein the request includes or is based on data returned in at least one of the plurality of responses;

generating a result based at least in part on the plurality of responses from the plurality of services and a response from the relationship service, the result identifying one or more entities detected within the unstructured text and wherein, for at least one entity of the one or more entities detected within the unstructured text, the result further comprises an attribute determined to be related to the entity and a trait representing an understanding about the entity; and

sending a response to the client, the response including the result, wherein sending the response causes a computer graphical user interface to be displayed, the computer graphical user interface comprising, for at least the at least one entity of the one or more entities detected within the unstructured text, an indication of all of:

the entity,

an attribute determined to be related to the entity,

a trait representing an understanding about the entity,

a numerical score indicating a confidence that the attribute is related to the entity, and

a numerical score indicating a confidence that the trait represents a correct understanding about the entity.

2. The computer-implemented method of claim **1**, wherein the one or more entities detected within the unstructured text is a plurality of entities detected within the unstructured text; and wherein the plurality of entities includes two or more of:

a medication;

a medical condition;

personal health information;

a test, treatment, or procedure; or

an anatomical body part or system.

3. A computer-implemented method comprising:

receiving a request to identify entities in unstructured text;

identifying a plurality of segments within the unstructured text;

executing, for each segment of the plurality of segments, a plurality of machine learning (ML) models trained to detect entities of a particular entity type to yield a plurality of outputs;

executing, for one or more segments of the plurality of segments, a machine learning model to identify relationships between entities and attributes in the one or more segments to yield an output, wherein an input to the machine learning model includes or is based on data of at least one of the plurality of outputs;

generating a result based at least in part on the plurality of outputs and the output of the machine learning model for identifying relationships between entities and attributes, the result identifying one or more entities detected within the unstructured text and wherein, for at least one entity of the one or more entities detected within the unstructured text, the result further comprises an attribute determined to be related to the entity and a trait representing an understanding about the entity; and

transmitting the result thereby causing a computer graphical user interface to be displayed, the computer graphical user interface comprising, for at least the at least one entity of the one or more entities detected within the unstructured text,

an indication of all of:

the entity,

an attribute determined to be related to the entity,

a trait representing an understanding about the entity,

a numerical score indicating a confidence that the attribute is related to the entity, and

a numerical score indicating a confidence that the trait represents a correct understanding about the entity.

4. The computer-implemented method of claim **3**, further comprising:

identifying, for each of the plurality of segments, one or more locations of one or more tokens within the corresponding segment,

wherein each of the plurality of ML models, for each segment of the plurality of segments, utilizes the segment and the one or more locations of tokens detected within the segment.

5. The computer-implemented method of claim **3**, wherein the machine learning model for identifying relationships between entities and attributes comprises a convolutional neural network (CNN) model.

6. The computer-implemented method of claim **3**, wherein each of the plurality of ML models comprises a Recurrent Neural Network (RNN) model.

7. The computer-implemented method of claim **3**, wherein each of the plurality of ML models is executed by a separate one or more virtual machines or containers within a provider network.

8. The computer-implemented method of claim **3**, further comprising:

obtaining a plurality of model version identifiers corresponding to software release versions of the plurality of ML models; and

generating a model version token based at least in part on the plurality of model version identifiers,

wherein the result further comprises the model version token.

9. The computer-implemented method of claim **3**, wherein the plurality of ML models are implemented within a single container or a single virtual machine.

10. The computer-implemented method of claim **3**, wherein:

the request was originated by a client and indicates that the result is to be generated and returned to the client synchronously via a same network connection; and

transmitting the result occurs via the same network connection.

11. The computer-implemented method of claim **3**, wherein:

the request was originated by a client and identifies at least one of a first storage location where the unstructured text is stored or a second storage location where the result is to be stored; and

the unstructured text comprises a plurality of unstructured text elements to be analyzed in a batch.

12. The computer-implemented method of claim **3**, wherein the one or more entities detected within the unstructured text is a plurality of entities detected within the unstructured text; and wherein the plurality of entities includes two or more of:

a medication;

a medical condition;

personal health information;

a test, treatment, or procedure; or

an anatomical body part or system.

13. A system comprising:

a plurality of analysis services implemented by a first one or more electronic devices, the plurality of analysis services comprising a plurality of machine learning models and a relationship service, each of the plurality of analysis services comprising at least one machine learning (ML) model of the plurality of machine learning models trained to identify medical entities, the relationship service comprising a machine learning model trained to identify relationships between entities and attributes; and

an orchestrator implemented by a second one or more electronic devices, the orchestrator including instructions that upon execution cause the orchestrator to:

obtain an unstructured text;

identify a plurality of segments within the unstructured text;

send, for each of the plurality of segments, a plurality of requests to the plurality of analysis services to detect medical entities to yield a corresponding plurality of outputs;

send, for one or more segments of the plurality of segments, a request to the relationship service of to identify relationships between entities and attributes in the one or more segments to yield an output, wherein the request includes or is based on data in in at least one of the plurality of outputs;

generate a result based at least in part on the plurality of outputs and the output of the relationship service, the result identifying one or more entities detected within the unstructured text and wherein, for at least one entity of the one or more entities detected within the unstructured text, the result further comprises an attribute determined to be related to the entity and a trait representing an understanding about the entity; and

transmitting the result to cause a computer graphical user interface to be displayed, the computer graphical user interface comprising, for at least the at least one entity of the one or more entities detected within the unstructured text, an indication of all of:

the entity,

an attribute determined to be related to the entity,

a trait representing an understanding about the entity, a numerical score indicating a confidence that the attribute is related to the entity, and

a numerical score indicating a confidence that the trait represents a correct understanding about the entity.

14. The system of claim **13**, wherein the instructions upon execution further cause the orchestrator to:

identify, for each of the plurality of segments, one or more locations of one or more tokens within the corresponding segment,

wherein for each segment each of the plurality of requests further includes identifiers of the one or more locations, and

wherein each of the plurality of machine learning models is to detect entities using, as input to the ML model, the segment and the identifiers of the one or more locations.

15. The system of claim **13**, wherein the machine learning model of the relationship service comprises a convolutional neural network (CNN) model.

16. The system of claim **13**, wherein each of the plurality of machine learning models comprises a Recurrent Neural Network (RNN) model.

17. The system of claim **13**, wherein each of the plurality of machine learning models is executed by a separate one or more virtual machines or containers.

18. The system of claim **13**, wherein the plurality of machine learning models is implemented within a single container or a single virtual machine.

19. The system of claim **13**, wherein the orchestrator further comprises instructions that upon execution cause the orchestrator to:

receive a request originated by a client via a network connection, the request to identify entities in the unstructured text, the request indicating that the result is to be generated and returned to the client synchronously via a same network connection; and

transmit the result via the network connection via which the request originated by the client is received.

20. The system of claim **13**, wherein the orchestrator further comprises instructions that upon execution cause the orchestrator to:

receive a request originated by a client, the request to identify entities in the unstructured text, the request identifying at least one of or both of:

a first storage location where the unstructured text is stored, or

a second storage location where the result is to be stored; and

wherein the unstructured text comprises a plurality of unstructured text elements to be analyzed in a batch.

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