US011321364B2

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Lee et al.

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(45) **Date of Patent: May 3, 2022**

(54) SYSTEM AND METHOD FOR ANALYSIS AND DETERMINATION OF RELATIONSHIPS FROM A VARIETY OF DATA SOURCES

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(73) Assignee: **KPMG LLP**, New York, NY (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 162 days.

(21) Appl. No.: **16/730,131**

(22) Filed: **Dec. 30, 2019**

(65) **Prior Publication Data**

US 2020/0133964 A1 Apr. 30, 2020

Related U.S. Application Data

(63) Continuation-in-part of application No. 16/159,088, filed on Oct. 12, 2018, now Pat. No. 10,846,341.
(Continued)

(51) **Int. Cl.**
G06F 16/28 (2019.01)
G06N 20/00 (2019.01)
(Continued)

(52) **U.S. Cl.**
CPC ***G06F 16/288*** (2019.01); ***G06F 16/258*** (2019.01); ***G06F 16/93*** (2019.01); ***G06N 20/00*** (2019.01)

(58) **Field of Classification Search**
CPC G06F 40/30; G06F 16/1794; G06F 16/90332; G06F 40/169; G06F 40/56
(Continued)

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(Continued)

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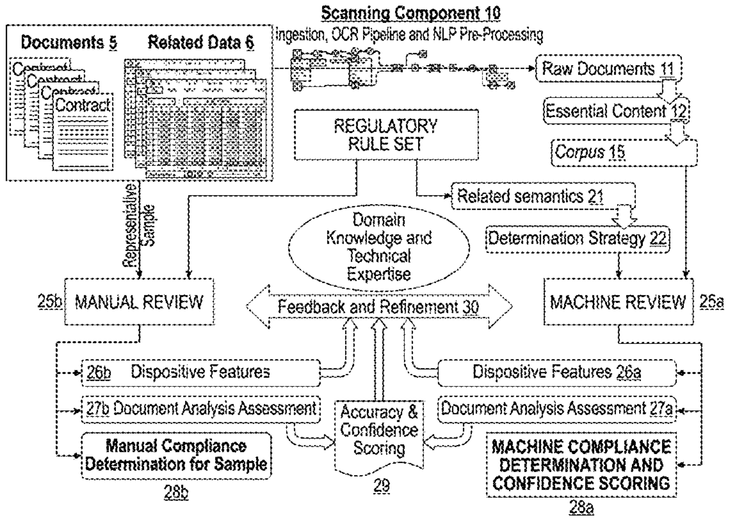
(Continued)

Primary Examiner — Hung T Vy
(74) *Attorney, Agent, or Firm* — Hunton Andrews Kurth LLP

(57) ABSTRACT

The invention relates to computer-implemented systems and methods for analyzing data from a variety of data sources. Embodiments of the systems and the methods further provide for generating responses to specific questions based on the analyzed data, wherein the generating includes: retrieving related documents associated with the analyzed data; determining which information should be reported from which of the retrieved related documents; and providing a response based on the determination and a graph schema associated with the related documents.

19 Claims, 20 Drawing Sheets


Scanning Component 10
Ingestion, OCR Pipeline and NLP Pre-Processing
Documents 5
Related Data 6
Contract
Raw Documents 11
Essential Content 12
Corpus 15
REGULATORY RULE SET
Related semantics 21
Determination Strategy 22
Representative Sample
Domain Knowledge and Technical Expertise
25b MANUAL REVIEW
Feedback and Refinement 30
MACHINE REVIEW 25a
26b Dispositive Features
Dispositive Features 26a
27b Document Analysis Assessment
Document Analysis Assessment 27a
Accuracy & Confidence Scoring
29
Manual Compliance Determination for Sample
28b
MACHINE COMPLIANCE DETERMINATION AND CONFIDENCE SCORING
28a

Related U.S. Application Data

(60) Provisional application No. 62/572,266, filed on Oct. 13, 2017.

(51) **Int. Cl.**

G06F 16/93	(2019.01)
G06F 16/25	(2019.01)

(58) **Field of Classification Search**
USPC 707/736
See application file for complete search history.

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International Searching Authority, PCT International Search Report and Written Opinion, International Application No. PCT/US20/66700, dated Mar. 16, 2021, pp. 1-20.

* cited by examiner

FIG. 1

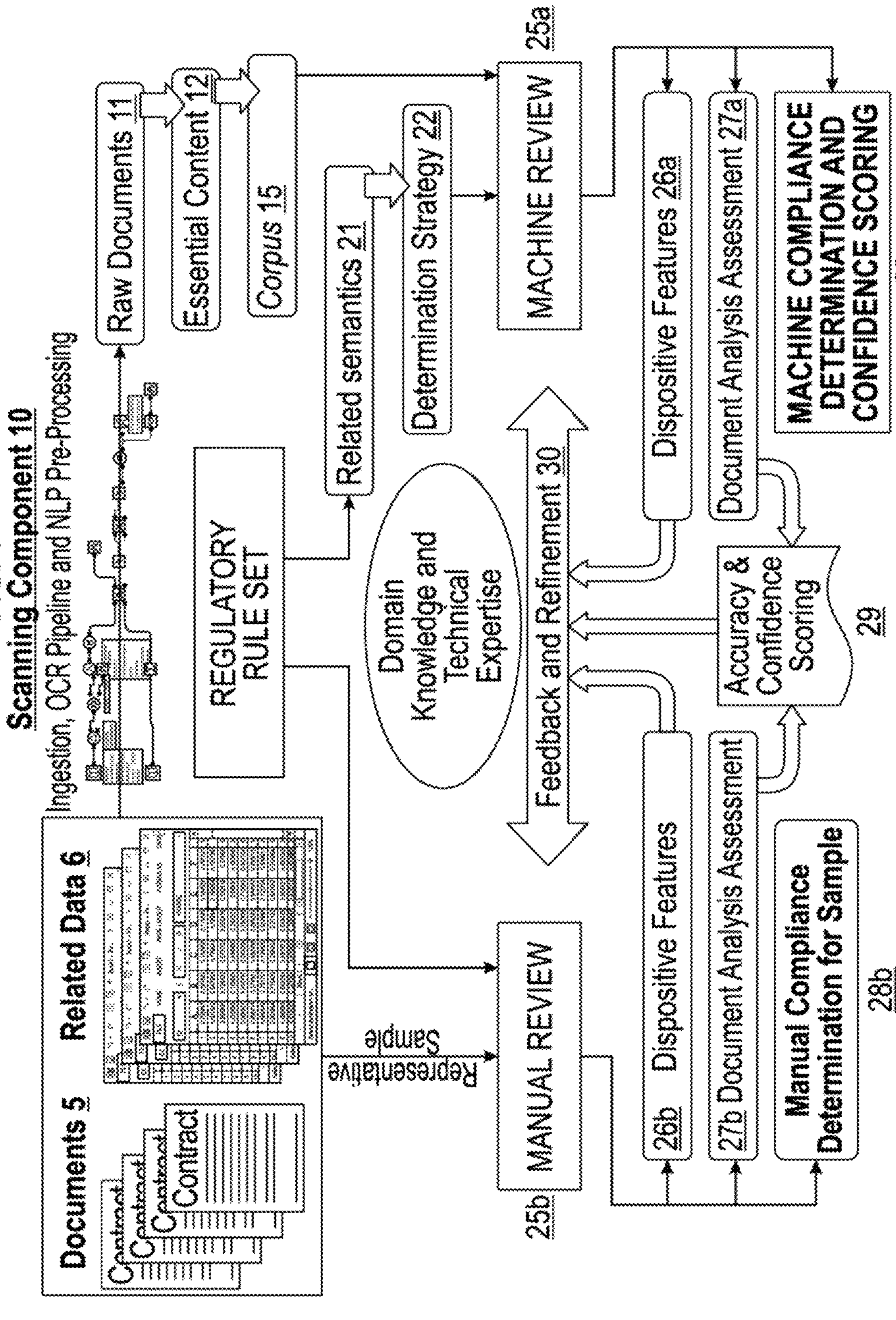

Scanning Component 10
Ingestion, OCR Pipeline and NLP Pre-Processing
Documents 5
Contract
Contract
Contract
Contract
Related Data 6
Raw Documents 11
Essential Content 12
Corpus 15
REGULATORY RULE SET
Related semantics 21
Determination Strategy 22
MACHINE REVIEW
25a
Representative Sample
MANUAL REVIEW
25b
Domain Knowledge and Technical Expertise
Feedback and Refinement 30
Dispositive Features 26a
Document Analysis Assessment 27a
MACHINE COMPLIANCE DETERMINATION AND CONFIDENCE SCORING
28a
Accuracy & Confidence Scoring
29
26b Dispositive Features
27b Document Analysis Assessment
Manual Compliance Determination for Sample
28b

FIG. 2

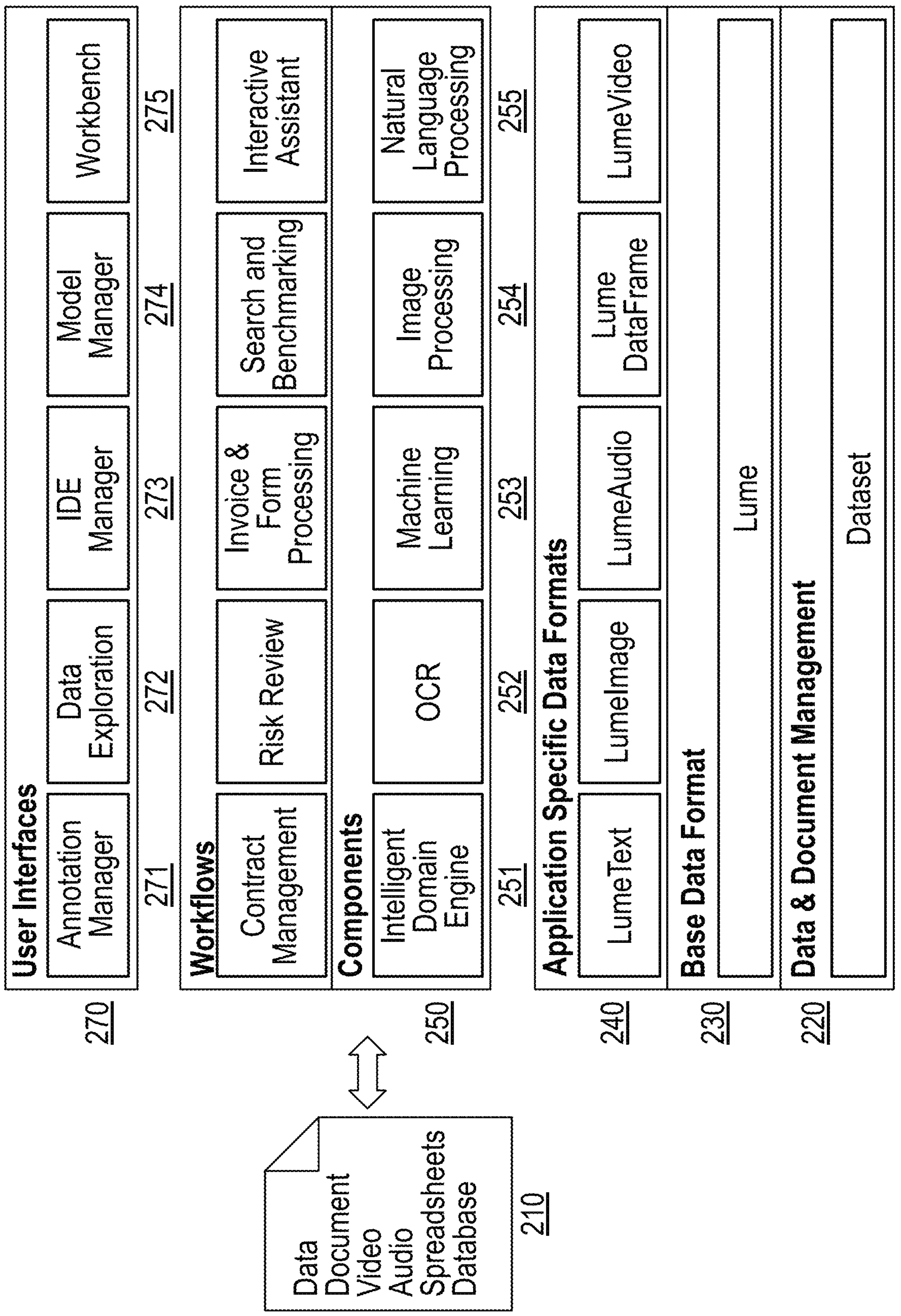
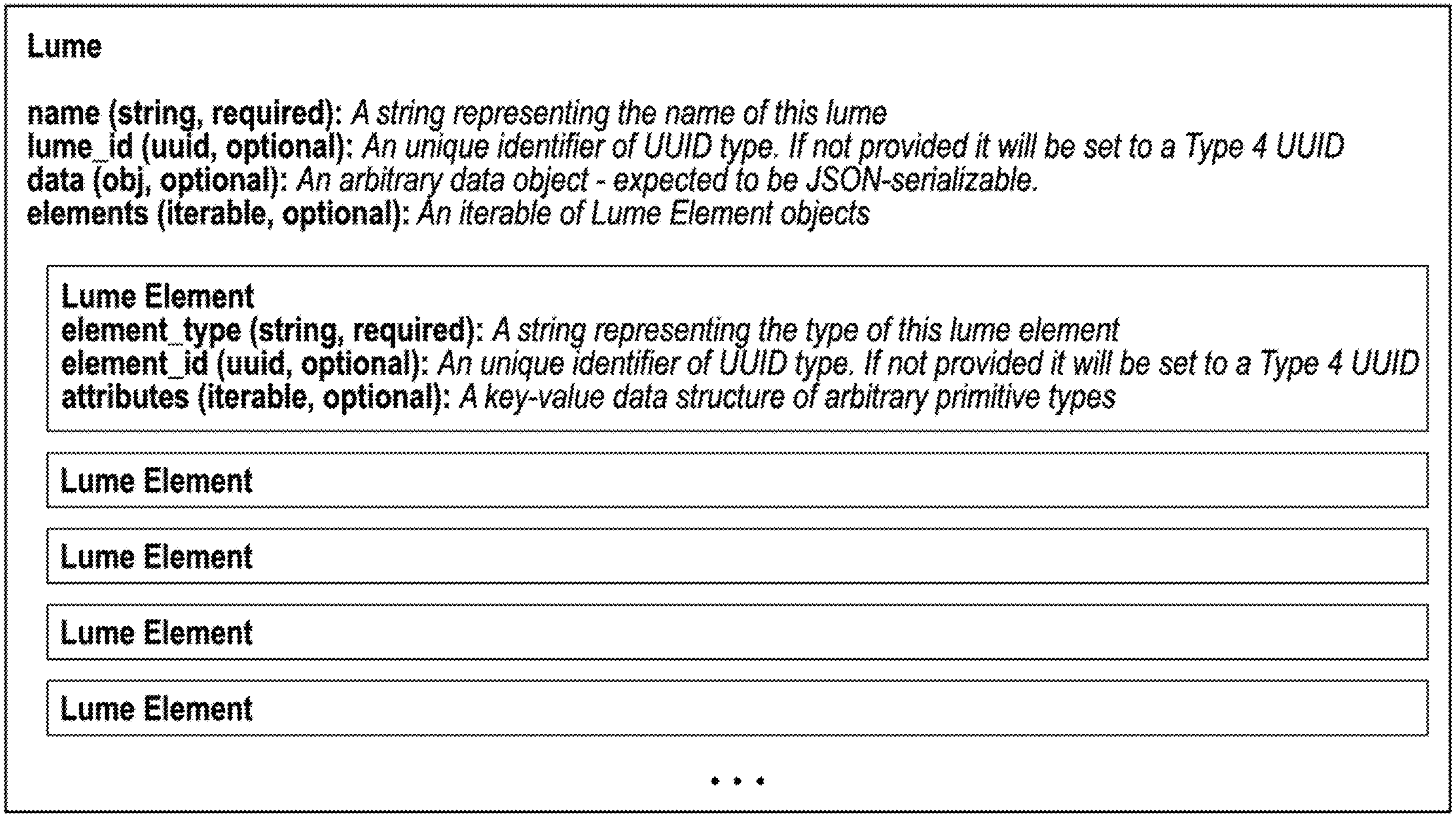

User Interfaces
270
Annotation Manager
271
Data Exploration
272
IDE Manager
273
Model Manager
274
Workbench
275
Workflows
Contract Management
Risk Review
Invoice & Form Processing
Search and Benchmarking
Interactive Assistant
Components
250
Intelligent Domain Engine
251
OCR
252
Machine Learning
253
Image Processing
254
Natural Language Processing
255
Application Specific Data Formats
240
LumeText
LumeImage
LumeAudio
Lume DataFrame
LumeVideo
Base Data Format
230
Lume
Data & Document Management
220
Dataset
Data
Document
Video
Audio
Spreadsheets
Database
210

FIG. 3



Lume

name (string, required): *A string representing the name of this lume*
lume_id (uuid, optional): *An unique identifier of UUID type. If not provided it will be set to a Type 4 UUID*
data (obj, optional): *An arbitrary data object - expected to be JSON-serializable.*
elements (iterable, optional): *An iterable of Lume Element objects*

Lume Element
element_type (string, required): *A string representing the type of this lume element*
element_id (uuid, optional): *An unique identifier of UUID type. If not provided it will be set to a Type 4 UUID*
attributes (iterable, optional): *A key-value data structure of arbitrary primitive types*

Lume Element

Lume Element

Lume Element

Lume Element

• • •

FIG. 4A

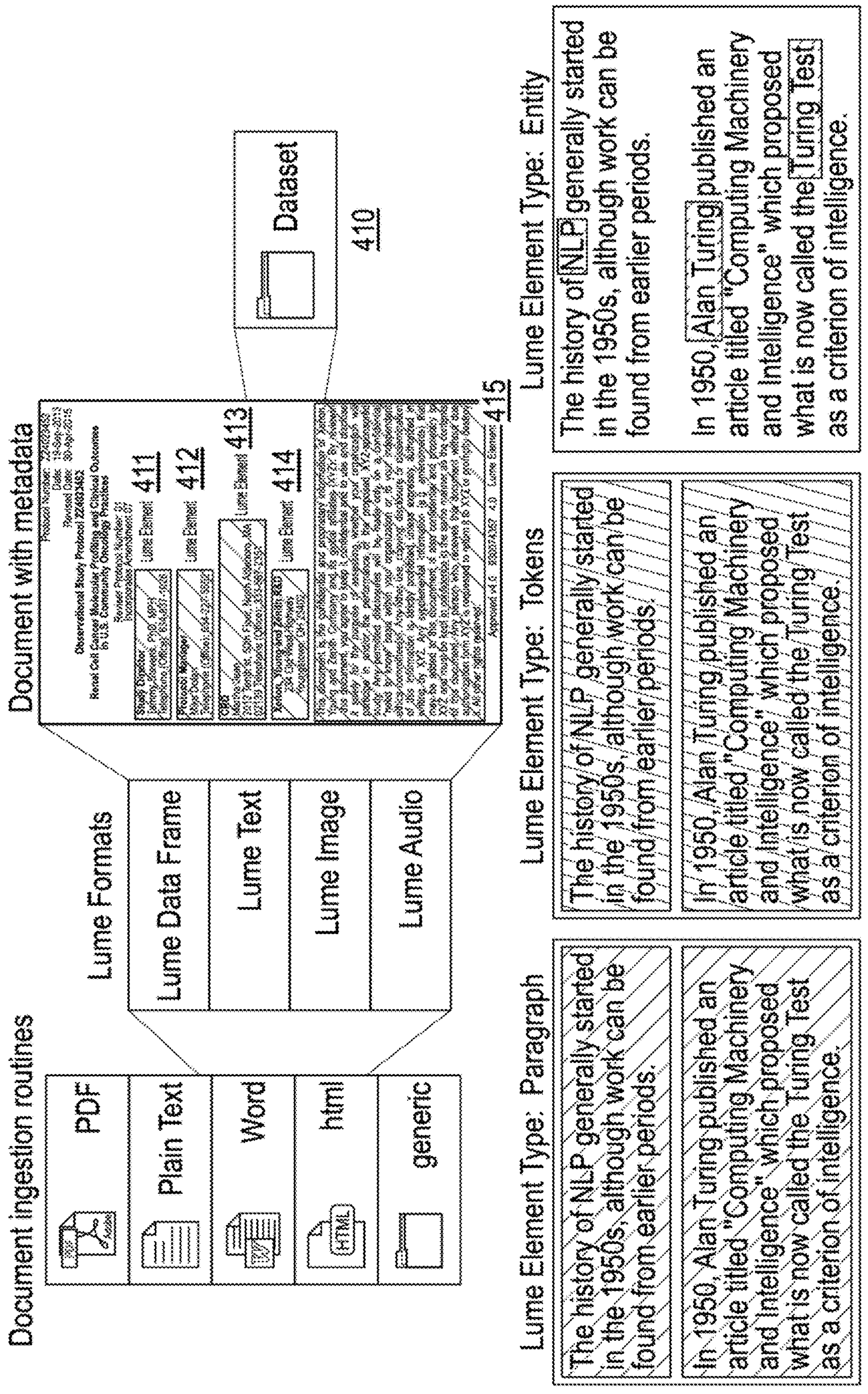
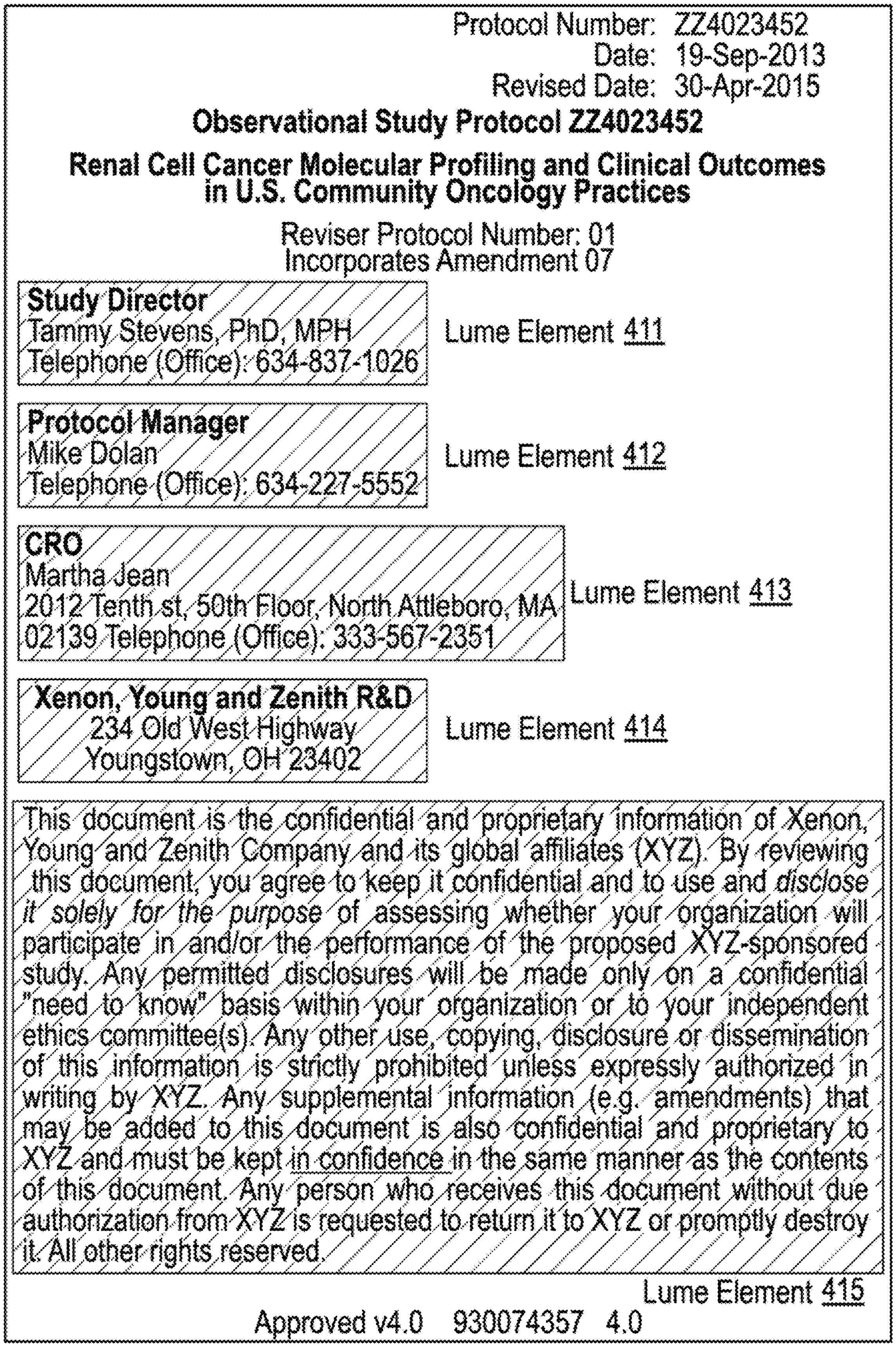

Document ingestion routines
PDF
Plain Text
Word
html
generic
Lume Formats
Lume Data Frame
Lume Text
Lume Image
Lume Audio
Document with metadata
Lume Element 411
Lume Element 412
Lume Element 413
Lume Element 414
Lume Element 415
Dataset
410
Lume Element Type: Paragraph
Lume Element Type: Tokens
Lume Element Type: Entity
The history of NLP generally started in the 1950s, although work can be found from earlier periods.
In 1950, Alan Turing published an article titled "Computing Machinery and Intelligence" which proposed what is now called the Turing Test as a criterion of intelligence.

FIG. 4B



Protocol Number: ZZ4023452
Date: 19-Sep-2013
Revised Date: 30-Apr-2015

Observational Study Protocol ZZ4023452

Renal Cell Cancer Molecular Profiling and Clinical Outcomes in U.S. Community Oncology Practices

Reviser Protocol Number: 01
Incorporates Amendment 07

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Tammy Stevens, PhD, MPH
Telephone (Office): 634-837-1026

Lume Element 411

Protocol Manager
Mike Dolan
Telephone (Office): 634-227-5552

Lume Element 412

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234 Old West Highway
Youngstown, OH 23402

Lume Element 414

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Lume Element 415

Approved v4.0 930074357 4.0

FIG. 5

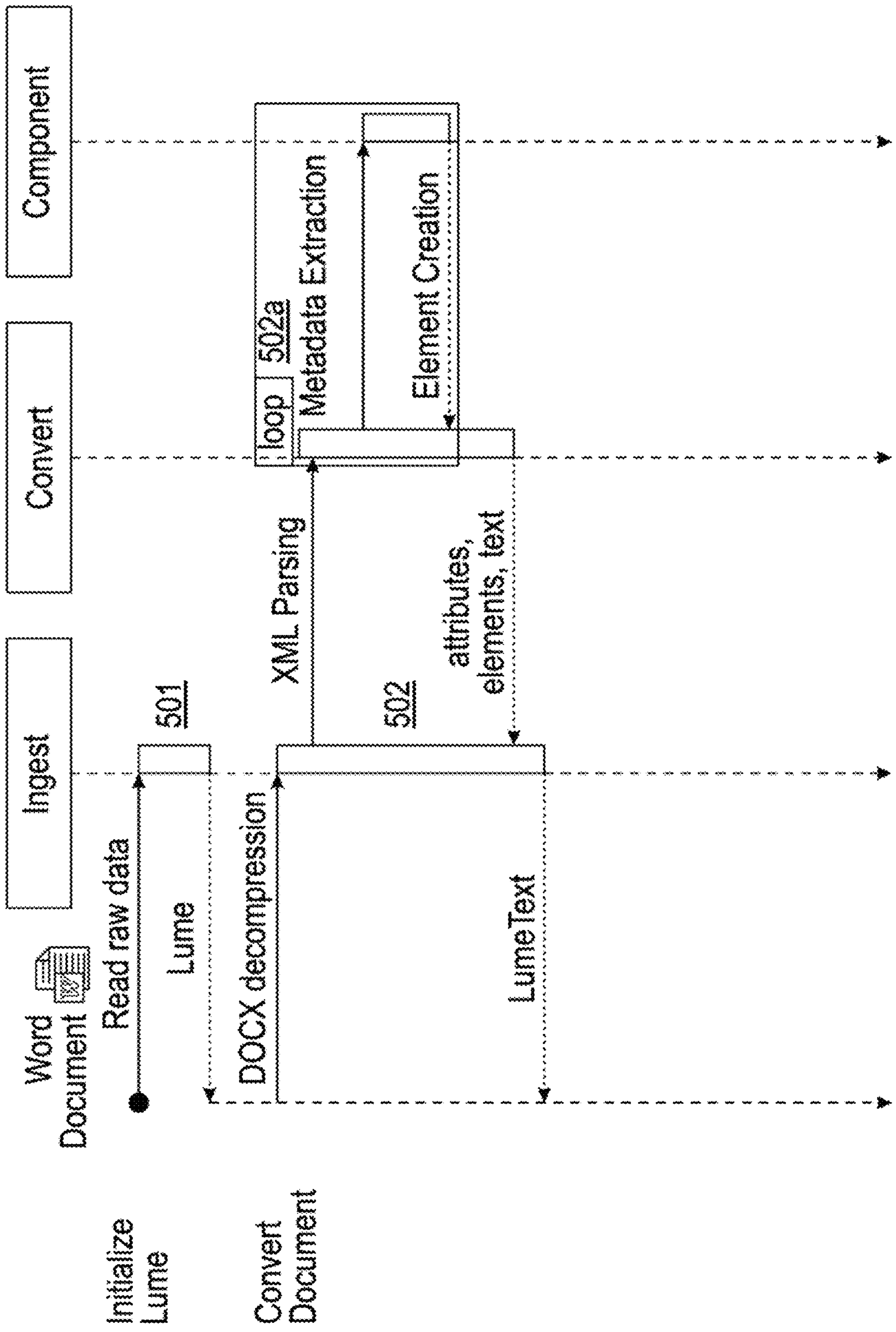

Component
Convert
Ingest
Word Document
Initialize Lume
Convert Document
Read raw data
Lume
501
DOCX decompression
502
XML Parsing
attributes, elements, text
LumeText
loop
502a
Metadata Extraction
Element Creation

FIG. 6

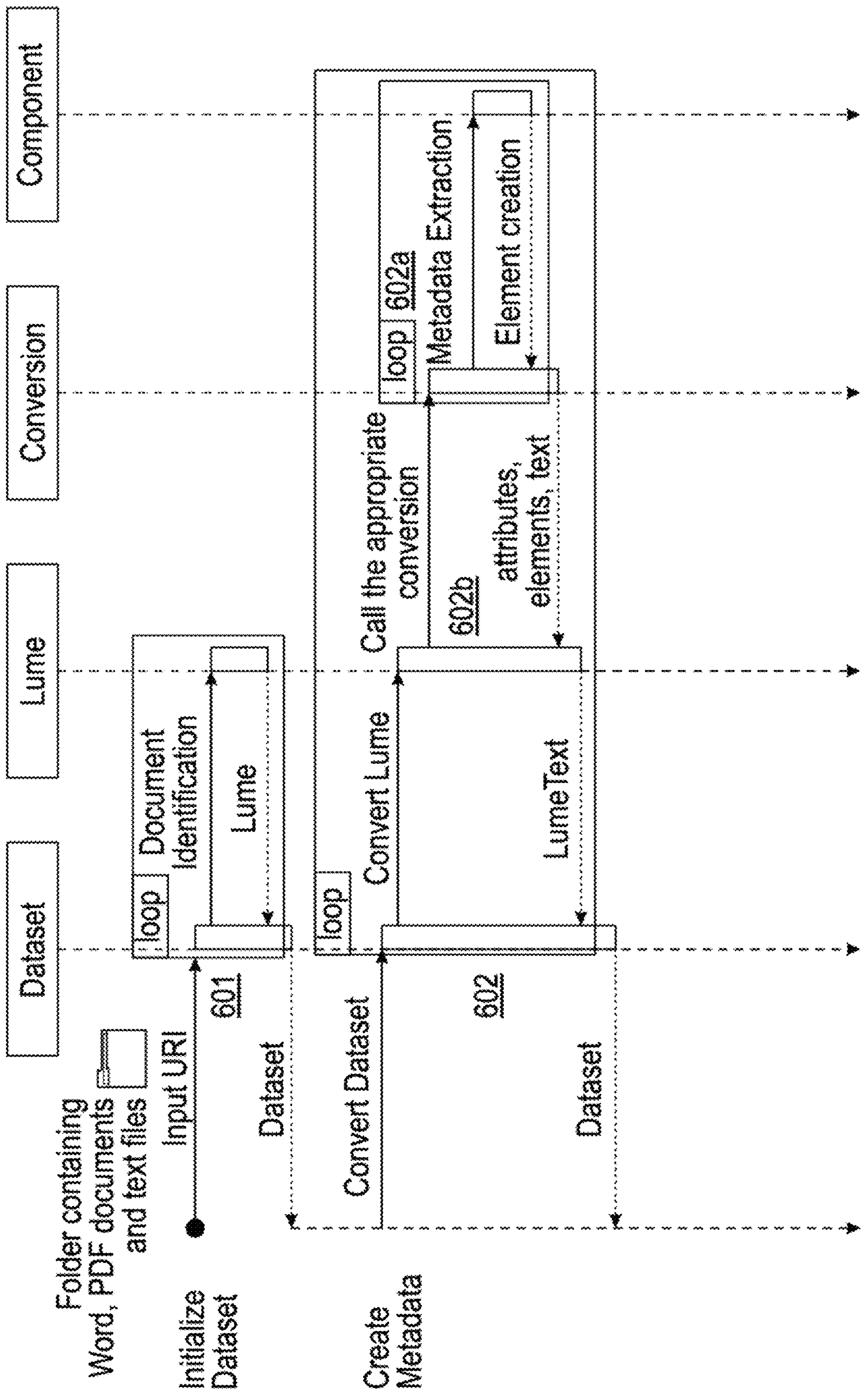

Dataset
Lume
Conversion
Component
Folder containing Word, PDF documents and text files
Initialize Dataset
Input URI
601
loop
Document Identification
Lume
Dataset
Create Metadata
Convert Dataset
602
loop
Convert Lume
Call the appropriate conversion
602b
loop
602a
Metadata Extraction
Element creation
attributes, elements, text
LumeText
Dataset

FIG. 7

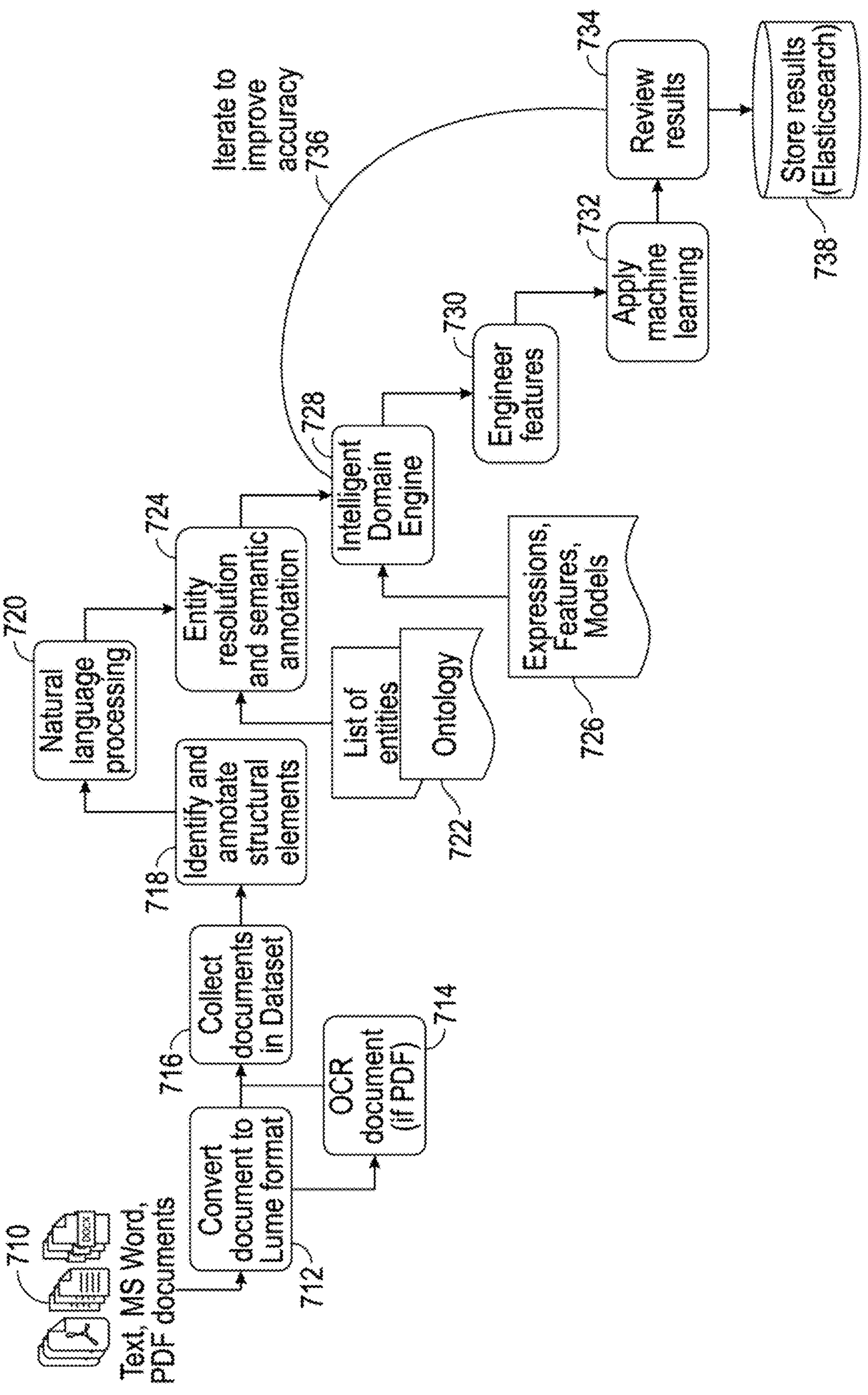
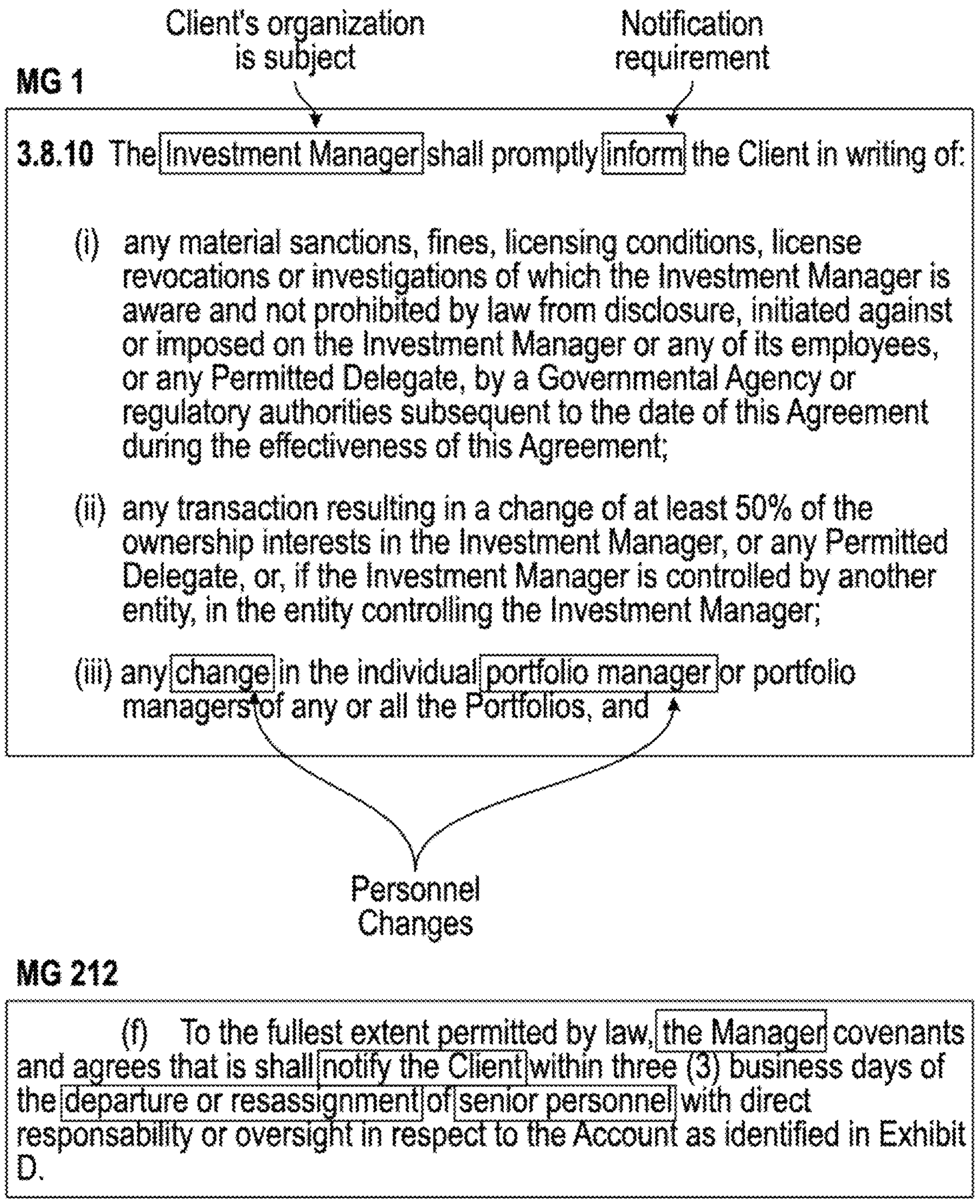

Text, MS Word, PDF documents
710
Convert document to Lume format
712
OCR document (if PDF)
714
Collect documents in Dataset
716
Identify and annotate structural elements
718
Natural language processing
720
List of entities
Ontology
722
Entity resolution and semantic annotation
724
Expressions, Features, Models
726
Intelligent Domain Engine
728
Engineer features
730
Apply machine learning
732
Review results
734
Iterate to improve accuracy
736
Store results (Elasticsearch)
738

FIG. 8


Client's organization is subject
Notification requirement
Personnel Changes

MG 1

3.8.10 The Investment Manager shall promptly inform the Client in writing of:

(i) any material sanctions, fines, licensing conditions, license revocations or investigations of which the Investment Manager is aware and not prohibited by law from disclosure, initiated against or imposed on the Investment Manager or any of its employees, or any Permitted Delegate, by a Governmental Agency or regulatory authorities subsequent to the date of this Agreement during the effectiveness of this Agreement;

(ii) any transaction resulting in a change of at least 50% of the ownership interests in the Investment Manager, or any Permitted Delegate, or, if the Investment Manager is controlled by another entity, in the entity controlling the Investment Manager;

(iii) any change in the individual portfolio manager or portfolio managers of any or all the Portfolios, and

MG 212

(f) To the fullest extent permitted by law, the Manager covenants and agrees that is shall notify the Client within three (3) business days of the departure or resassignment of senior personnel with direct responsability or oversight in respect to the Account as identified in Exhibit D.

FIG. 9

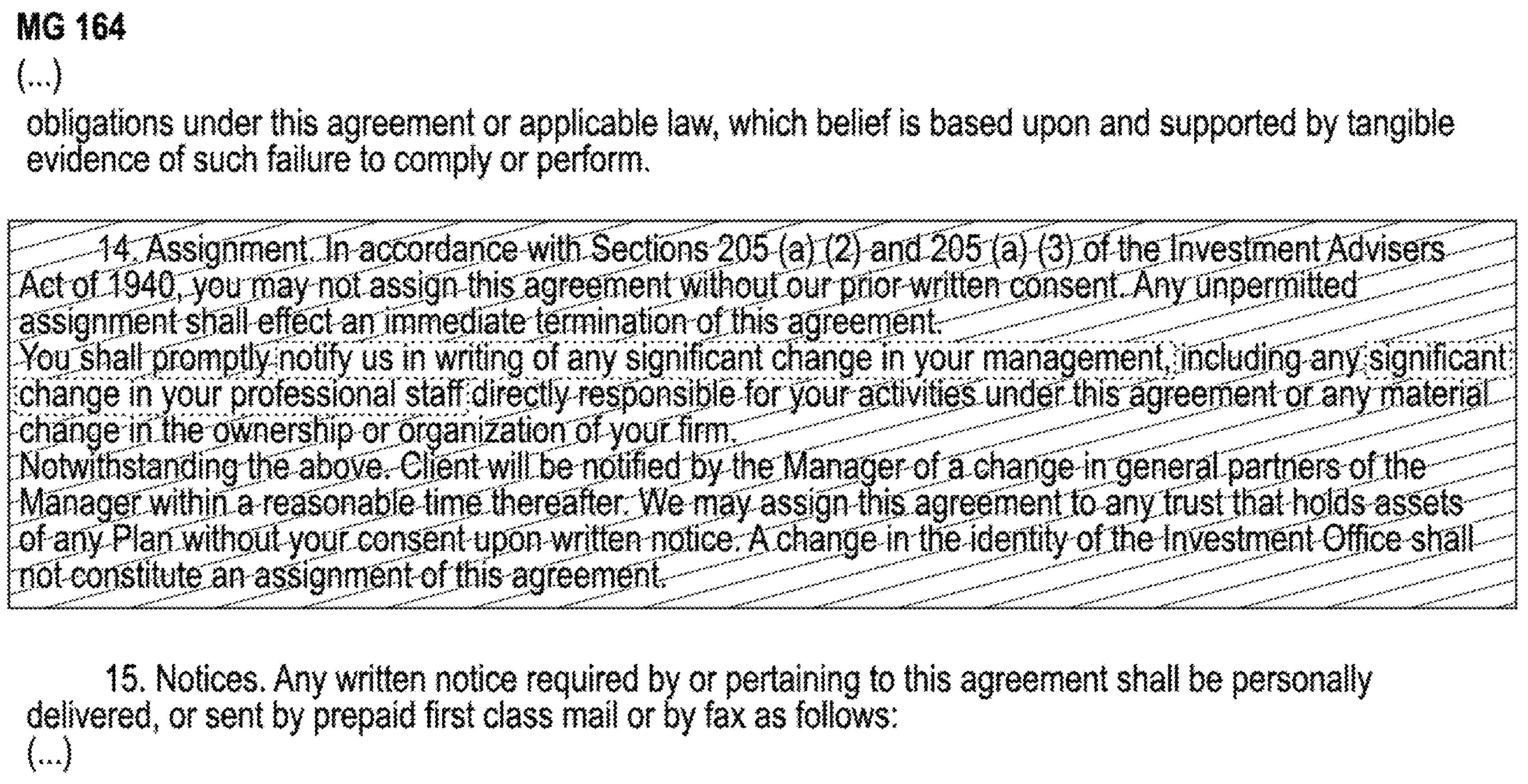
Name	Condition	Expression	Scope
Termination_Term_Date		**%ANNOTATE[<termination_date>] %FILTER[<DATE>] ((%TERMINATION_LANGUAGE %AND %CONTRACT_DATE_LANGUAGE) %IN <SENTENCE>)**	**%TERMINATION_CLAUSE**
Finds sentences that have both the termination language, and the contract date. In those sentences, the dates are extracted, and those dates are written back into the Lume as Lume Elements of type termination_date.			
Notification_Language		**"notify" %OR "notice" %OR "notified" %OR "inform" %OR "informing" %OR "informed"**	
This expression is used to capture language related to notification and the result is returned into the value of the variable $Notification_Language			
Key_Personnel		**"key person" "investment team" "professional staff" "senior staff" "senior officers" "portfolio manager" "portfolio managers" "investment managers" "key decision makers" "key employees"**	
This expression is used to capture language related to key personnel and the result is returned into the value of the variable $Key_Personnel			
Key_Personnel_ Notification_Sentence		**<SENTENCE> %CONTAINING ($Key_Personnel %AND $Notification_Language)**	**%NOTIFICATION_CLAUSE**
This expression searches for notification clauses section in the document that contain both the key personnel, and the notification language. The sentence that contains this clause is returned into the variable $Key_Personnel_Notification_Sentence			
Key_Personnel_ Notification_ Determination		**%ANNOTATE[<key_person_notification>] %ML_KEYPERSON_MODEL ($Key_Personnel_Notification_Sentence)**	
This model will run a Machine Learning classifier on the sentences identified in the $Key_Personnel_Notification_Sentence. The resulting determination and score are stored as annotations as Lume Elements of type key_person_notification.			
Key_Person_Identified	**$Key_Personnel_Noti fication_Determination**	**%WRITE[<key_person_identified value=True>]**	
If the $Key_Personnel_Notification_Determination is true, then the Lume Element with type key_person_identified, and attributes "value", True will be written into the Lume			

Syntax: %[OPERATOR] $[VARIABLE] <LUME ELEMENT> "STRING"

FIG. 10

Filename	Termination_ Term_Date	Key_Person_ Notification_ Determination (value)	Key_Person_ Notification_ Determination (Confidence Score)	Key_Person_ Identified
Contract1_AcmeCo.pdf	12/31/2020	30 days	.95	True
Contract2_AcmeCo.pdf	3/31/2018	60 days	.81	True
Contract1_AcmeIntl.pdf	9/30/2022	90 days	.40	False
Contract1_CA.pdf	7/31/2021	60 days	.92	True
Contract1_Util.pdf	4/15/2019	2 weeks	.88	True
Contract1_Anytown.pdf	4/1/2020	30 days	.92	True

FIG. 11



MG 164

(...)

obligations under this agreement or applicable law, which belief is based upon and supported by tangible evidence of such failure to comply or perform.

14. Assignment. In accordance with Sections 205 (a) (2) and 205 (a) (3) of the Investment Advisers Act of 1940, you may not assign this agreement without our prior written consent. Any unpermitted assignment shall effect an immediate termination of this agreement.
You shall promptly notify us in writing of any significant change in your management, including any significant change in your professional staff directly responsible for your activities under this agreement or any material change in the ownership or organization of your firm.
Notwithstanding the above. Client will be notified by the Manager of a change in general partners of the Manager within a reasonable time thereafter. We may assign this agreement to any trust that holds assets of any Plan without your consent upon written notice. A change in the identity of the Investment Office shall not constitute an assignment of this agreement.

15. Notices. Any written notice required by or pertaining to this agreement shall be personally delivered, or sent by prepaid first class mail or by fax as follows:
(...)

FIG. 12

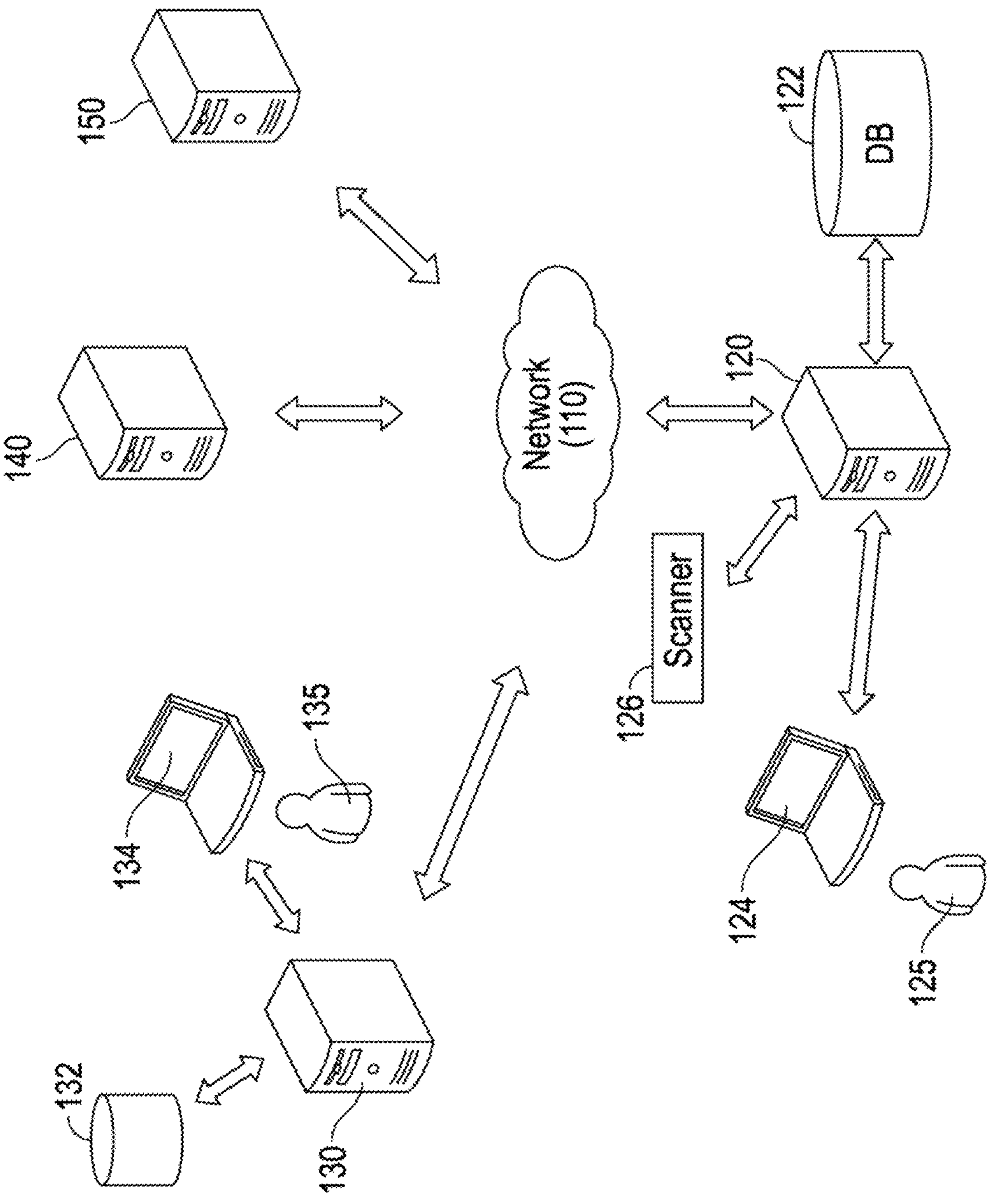
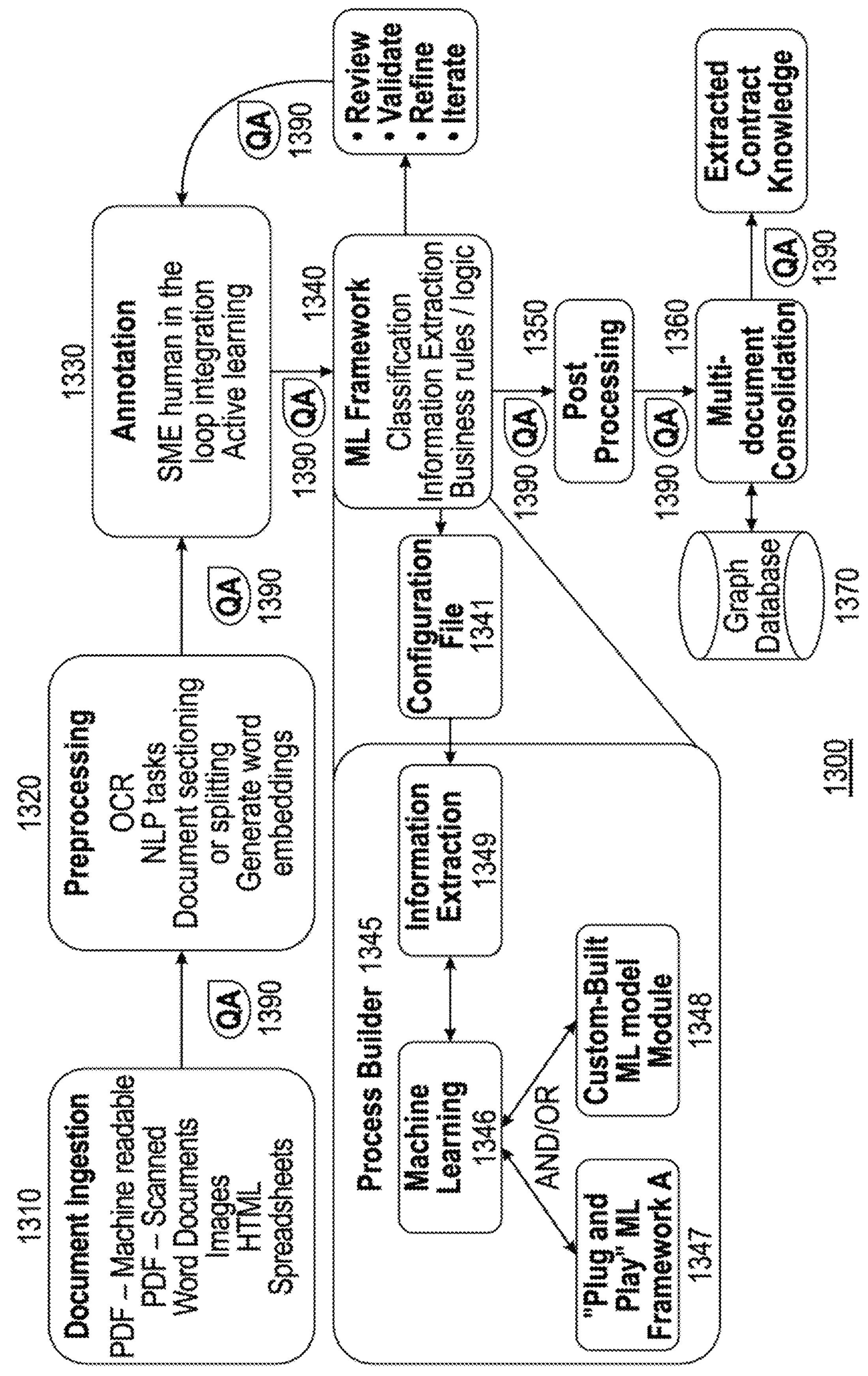

150
140
Network (110)
120
122
DB
126
Scanner
134
135
130
132
124
125

FIG. 13



1310
Document Ingestion
PDF – Machine readable
PDF – Scanned
Word Documents
Images
HTML
Spreadsheets
1320
Preprocessing
OCR
NLP tasks
Document sectioning or splitting
Generate word embeddings
1330
Annotation
SME human in the loop integration
Active learning
QA
1390
1340
ML Framework
Classification
Information Extraction
Business rules / logic
Review
Validate
Refine
Iterate
Configuration File
1341
Process Builder 1345
Information Extraction
1349
Machine Learning
1346
AND/OR
"Plug and Play" ML Framework A
1347
Custom-Built ML model Module
1348
1350
Post Processing
1360
Multi-document Consolidation
Graph Database
1370
Extracted Contract Knowledge
1300

FIG. 14

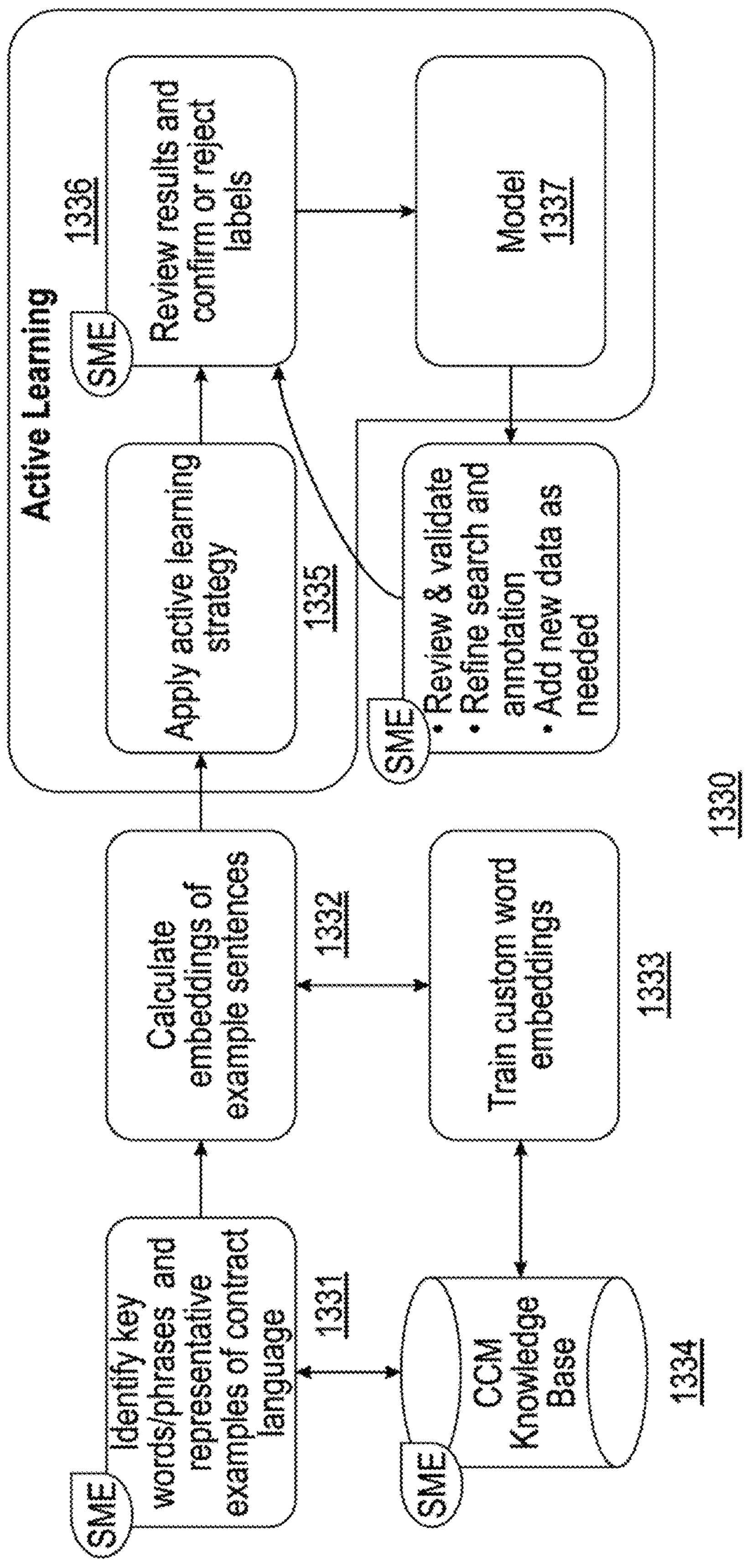

SME
Identify key words/phrases and representative examples of contract language
1331
SME
CCM Knowledge Base
1334
Calculate embeddings of example sentences
1332
Train custom word embeddings
1333
Active Learning
Apply active learning strategy
1335
SME
Review results and confirm or reject labels
1336
Model
1337
SME
• Review & validate
• Refine search and annotation
• Add new data as needed
1330

FIG. 15A

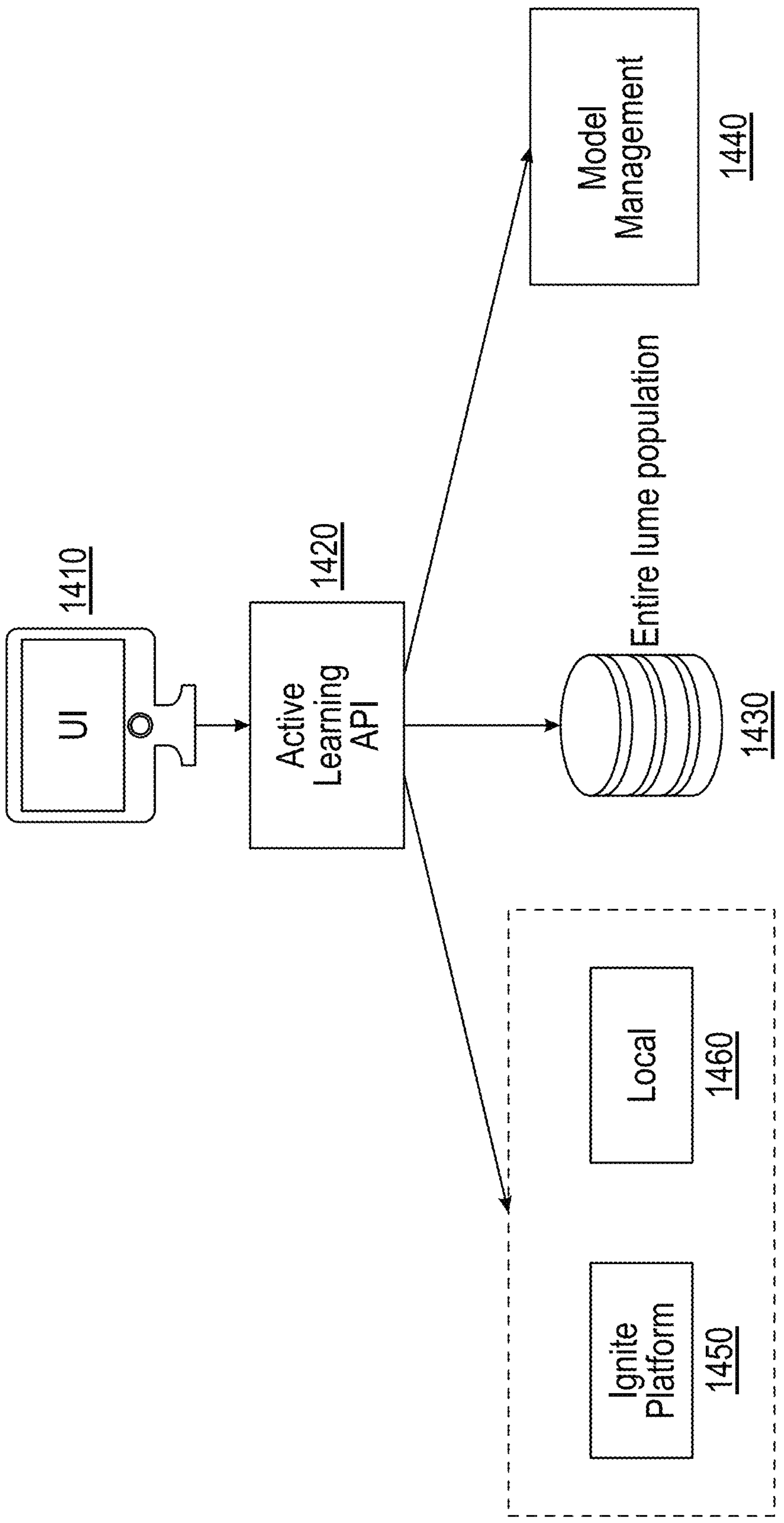

UI
1410
Active Learning API
1420
Entire lume population
1430
Model Management
1440
Ignite Platform
1450
Local
1460

FIG. 15B

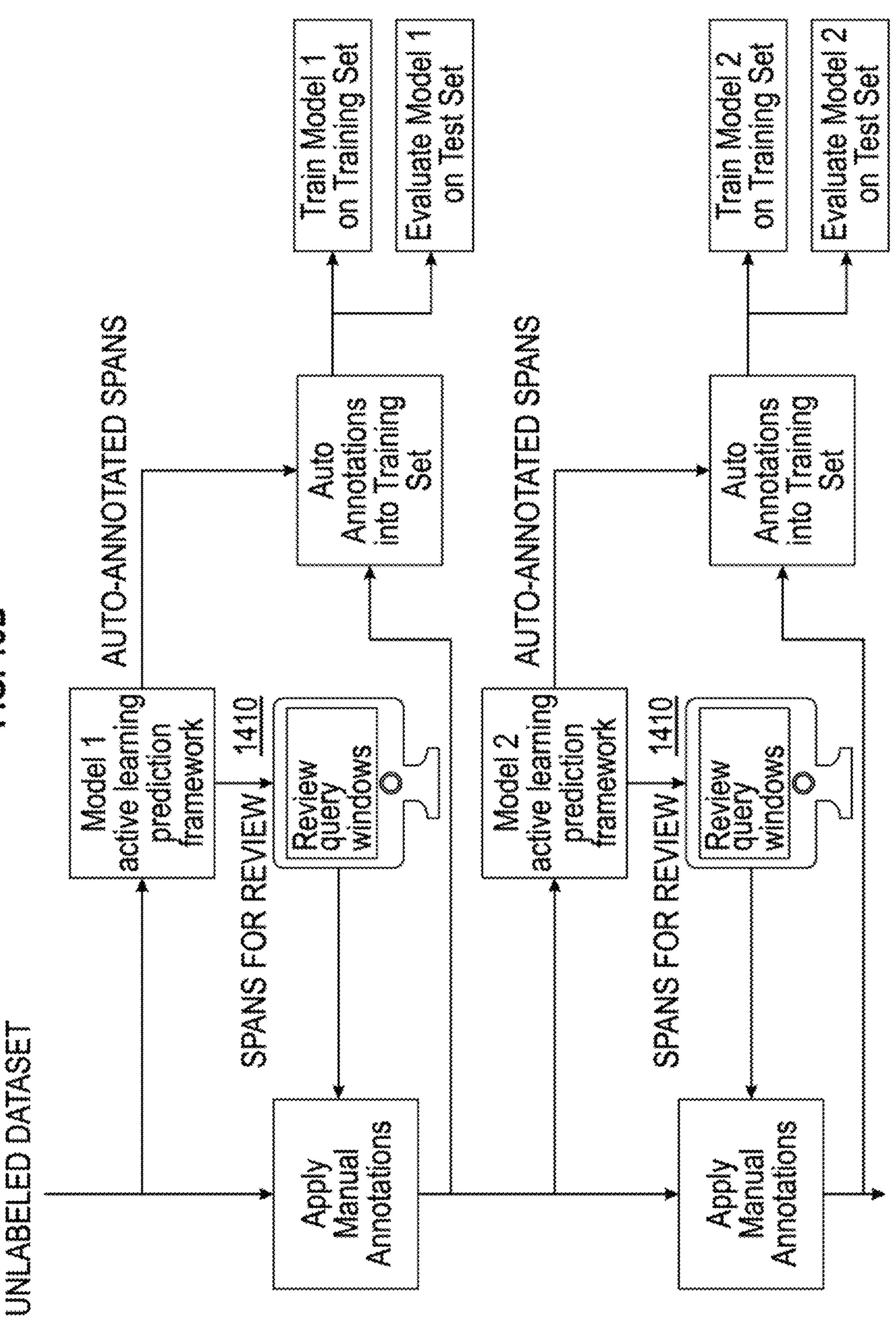

UNLABELED DATASET
Apply Manual Annotations
Model 1 active learning prediction framework
SPANS FOR REVIEW
1410
Review query windows
AUTO-ANNOTATED SPANS
Auto Annotations into Training Set
Train Model 1 on Training Set
Evaluate Model 1 on Test Set
Apply Manual Annotations
Model 2 active learning prediction framework
SPANS FOR REVIEW
1410
Review query windows
AUTO-ANNOTATED SPANS
Auto Annotations into Training Set
Train Model 2 on Training Set
Evaluate Model 2 on Test Set

FIG. 16

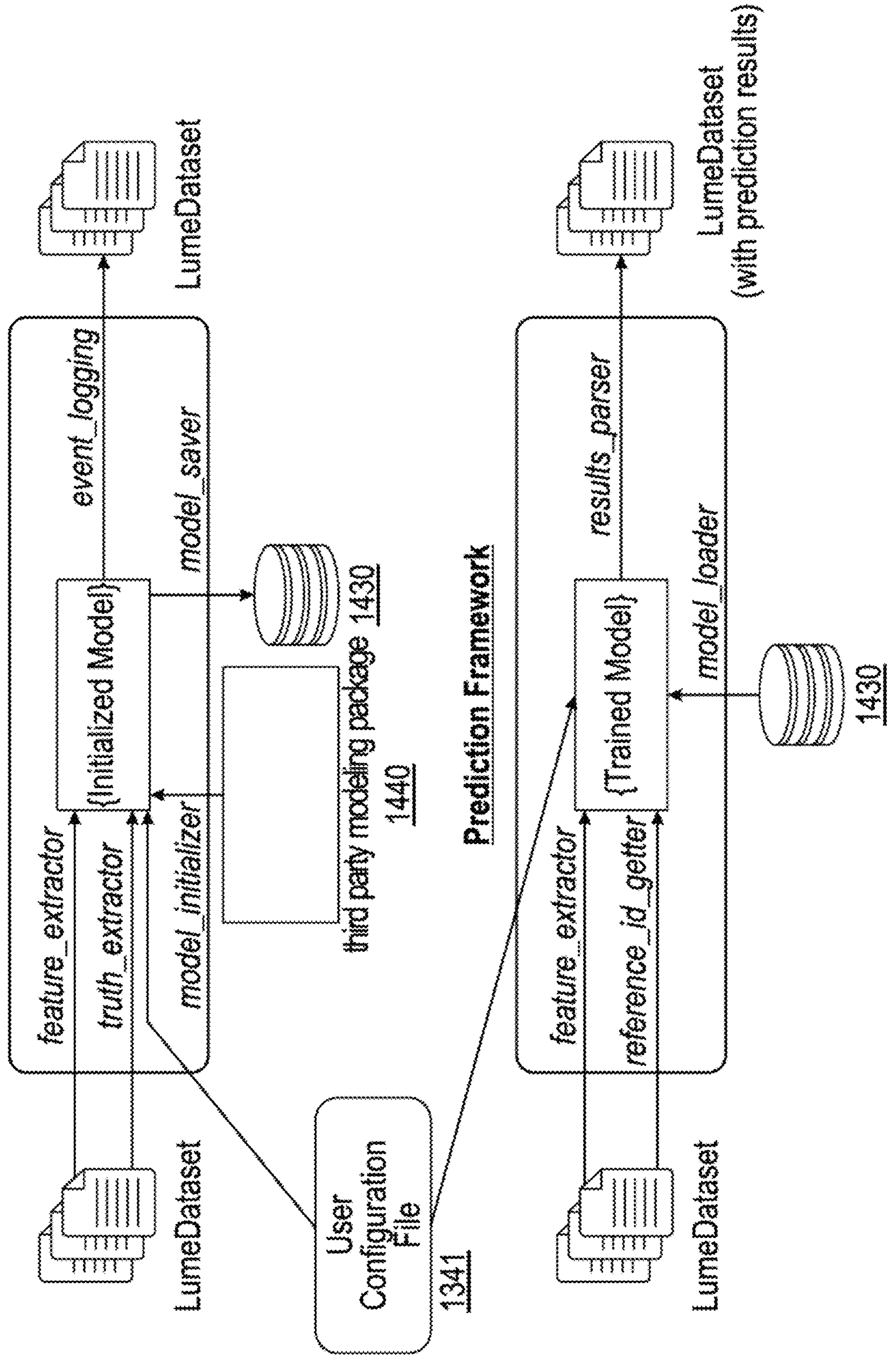

Training Framework
LumeDataset
feature_extractor
truth_extractor
model_initializer
{Initialized Model}
event_logging
model_saver
LumeDataset
1430
third party modeling package
1440
User Configuration File
1341
Prediction Framework
LumeDataset
feature_extractor
reference_id_getter
{Trained Model}
model_loader
1430
results_parser
LumeDataset (with prediction results)

FIG. 17

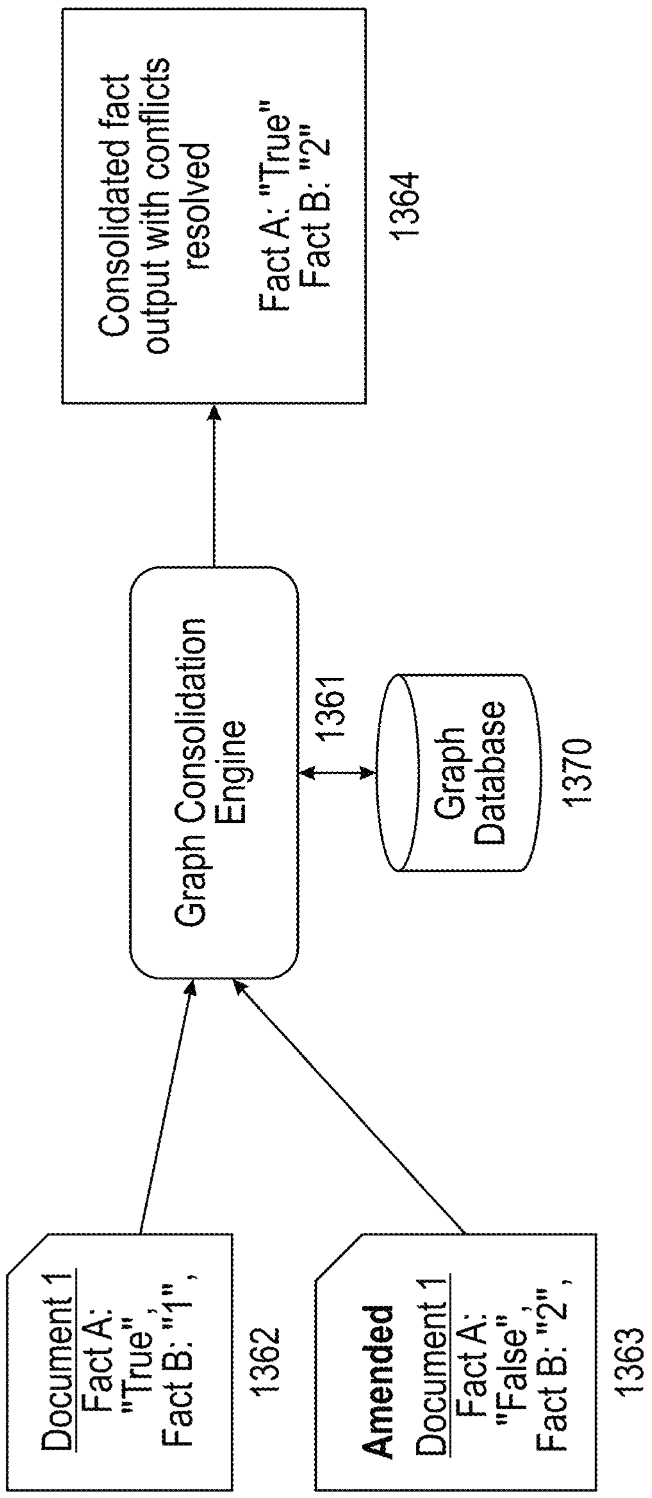
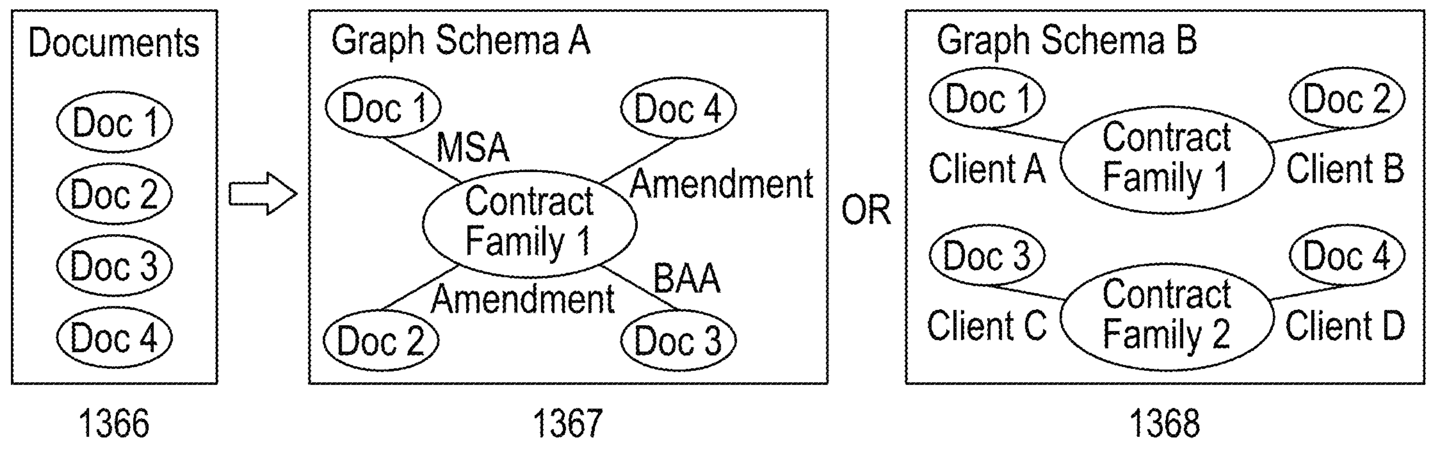

Document 1
Fact A: "True", Fact B: "1",
1362
Amended Document 1
Fact A: "False", Fact B: "2",
1363
Graph Consolidation Engine
1361
Graph Database
1370
Consolidated fact output with conflicts resolved
Fact A: "True"
Fact B: "2"
1364

FIG. 18


Documents
Doc 1
Doc 2
Doc 3
Doc 4
1366
Graph Schema A
Doc 1
MSA
Doc 4
Amendment
Contract Family 1
Amendment
BAA
Doc 2
Doc 3
1367
OR
Graph Schema B
Doc 1
Client A
Contract Family 1
Doc 2
Client B
Doc 3
Client C
Contract Family 2
Doc 4
Client D
1368

SYSTEM AND METHOD FOR ANALYSIS AND DETERMINATION OF RELATIONSHIPS FROM A VARIETY OF DATA SOURCES

CROSS-REFERENCE TO RELATED APPLICATION

This application is a continuation-in-part of and claims the benefit of the filing date of U.S. patent application Ser. No. 16/159,088, filed on Oct. 12, 2018, which claims the benefit of the filing date of, and incorporates by reference thereto in its entirety, U.S. Provisional Patent Application Ser. No. 62/572,266, filed on Oct. 13, 2017.

FIELD OF THE INVENTION

The present invention relates to systems and methods for analyzing data from a variety of data sources, and generating responses to specific questions based on the analyzed data.

BACKGROUND

The digitization of labor continues to progress as advancements in machine learning, natural language processing, data analytics, mobile computing and cloud computing are used in various combinations to replace certain processes and functions. Basic process automation can be implemented without significant IT investment as solutions may be designed, tested and implemented for a relatively low cost. Enhanced process automation incorporates more advanced technologies that enable the use of data to support elements of machine learning. Machine learning tools can be used to discover naturally-occurring patterns in data and to predict outcomes. And natural language processing tools are used to analyze text in context and extract desired information.

However, such digital tools are generally found in a variety of formats and coding languages and, therefore, are difficult to integrate and are also not often customized. As a result, such systems would not be able to provide automated solutions or answers to specific questions requiring analysis and processing of various types of input data e.g., structured data, semi-structured data, unstructured data, and images and voice. For example, such systems are currently unable to efficiently address questions such as "[w]hich of these 500 contracts fails to comply with new banking regulation XYZ?".

It would be desirable, therefore, to have a system and method that could overcome the foregoing disadvantages of known systems and that could apply automated and customized analysis to analyze documents, communications, text files, websites, and other structured and unstructured input files to generate output in the form of answers to specific questions and other supporting information.

SUMMARY

According to one embodiment, the invention relates to a computer-implemented system and method for analyzing data from a variety of data sources. The method may comprise the steps of: receiving, as inputs, data from the variety of data sources; converting the received data from each of the variety of data sources into a common data structure; identifying keywords in the received data; generating sentence or word embeddings based on the document corpus; receiving a selection of one or more labels based on

the generated sentence or word embeddings; adding the selected one or more labels to a model; training the model over the common data structure based on a configuration file; and generating a result in response to a user question based on the model, wherein the generating includes: retrieving related documents from the received data; determining which information should be reported from which of the retrieved related documents; and providing the result based on the determination and a graph schema associated with the related documents.

The invention also relates to computer-implemented system for analyzing data from a variety of data sources.

The exemplary document management workflow seamlessly integrates key tasks for document ingestion, prediction, consolidation, and analysis. The workflow enables users to answer specific questions about documents (e.g., contracts) and model relationships to other documents in order to build up a knowledge base. In particular, each step (e.g., ingestion, prediction, consolidation, and analysis) is integrated into an end-to-end workflow that is configurable with minimal effort or changes needed by a user. Each step builds upon previous steps to enable the analysis and extraction of information from documents. In this regard, other document management frameworks usually require a significant amount of "glue code" (e.g., code custom-made for a particular project) to pull the entire workflow together. On the other hand, with the present invention, users are able to configure each step without having to rewrite code, making the exemplary process easily reusable on a variety of projects.

Further, according to an embodiment, the exemplary workflow is able to handle various types of document analysis problems, e.g., by mapping the process to a specific problem/use case. The problem can originate from a variety of domains, e.g., clause/regulation compliance, procurement contracts, commercial leakage, contract risk analytics, etc. Further, the exemplary framework is flexible, enabling users to customize business logic rules, post-processing, and quality assessment tasks, and tailor them to the specific needs of the business use case and particular user. In other words, the exemplary process is fit to the document analysis problem, rather than trying to fit the problem into a standard, inflexible framework. Further, each part of the exemplary workflow (e.g., document processing, feature creation, model architecture, quality assessment, post-processing, and contract consolidation) can be associated with a default configuration, which can cover many specific questions. However, these default configurations can be easily modified to address new or unique questions. In addition, a Lume data structure perpetuates data and metadata throughout the exemplary process, thereby enabling a unified learning model. Further, because the process is fully integrated, documents (e.g., contracts) and their corresponding corollary documents can be processed in order to extract knowledge and answer specific questions about content within the document. Further, the exemplary process can resolve information across multiple documents using a graph-based reasoning framework. For example, a business logic layer can allow a subject matter expert to specify how document families are combined. Further, the graph-based reasoning framework can specify handling of conflicting clauses. In addition, inferences can also be made at the document family level or the individual document level.

Further, the present invention also provides for interchangeable model architectures, which can be switched in order to find the optimal model framework for extracting a particular clause with minimal human interaction. The framework-specific language can be included in the default configurations or customized configurations. Further, framework-specific features can be made available through the knowledge base. In addition, highly effective default options for particular problems minimize configurations by a user. Further, the interchangeable model architectures provide support for sequence labeling, classification, and deep learning models that can be swapped via customized configuration files, which can be used by non-experts.

Further, according to an embodiment, with the present invention, subject matter expertise can be encoded into the entire solution. For example, the present invention can digitize the completion of complex, manual tasks to enhance machine learning output. Further, post processing may be applied to clean or reformat high-confidence answers based on client specifications. In addition, post processing can also leverage subject matter expertise to generate downstream answers to questions that rely on multiple pieces of information from a document. Further, quality assessment steps are added to ensure that high-confidence answers conform to a client's specifications.

Further, according to an embodiment, the present invention also provides for the development of enriched, high quality training and testing datasets. For example, the present invention provides for curated subject matter expertise in the labeling of data. Further, the present invention leverages search, text similarity, and clustering techniques to get representative and diverse labeled datasets that are more efficient and effective in producing performant models. In addition, the datasets can also be incorporated with information from a framework-specific knowledge base. Further, the present invention also provides for the creation of custom word embeddings in order to better represent the specific domain in question. Further, at least one of a unified learning model or an active learning model can be leveraged in order to label particular document information. Lastly, the specific models and results from the exemplary framework can be stored in a third party storage device.

These and other advantages will be described more fully in the following detailed description.

BRIEF DESCRIPTION OF THE DRAWINGS

In order to facilitate a fuller understanding of the present invention, reference is now made to the attached drawings. The drawings should not be construed as limiting the present invention, but are intended only to illustrate different aspects and embodiments of the invention.

FIG. **1** is a functional block diagram for an analysis system according to an exemplary embodiment of the invention.

FIG. **2** is a diagram of the architecture of an analysis system according to an exemplary embodiment of the invention.

FIG. **3** is a representation of a standard data format for a converted file, referred to herein as Lume, according to an exemplary embodiment of the invention.

FIG. **4**A is a drawing depicting an example of a Lume structure and example levels according to an exemplary embodiment of the invention.

FIG. **4**B illustrates a larger view of the document with metadata depicted in FIG. **4**A.

FIG. **5** is a drawing depicting a Lume creation process from a Microsoft Word document according to an exemplary embodiment of the invention.

FIG. **6** is a drawing depicting a dataset creation process from a directory of Microsoft Word and text files according to an exemplary embodiment of the invention.

FIG. **7** is a flow diagram for the analysis system according to an exemplary embodiment of the invention.

FIG. **8** illustrates an example of a document to be ingested and analyzed by the analysis system according to an exemplary embodiment of the invention.

FIG. **9** is an example of expression, presented as expression strings shown in a table according to an exemplary embodiment of the invention.

FIG. **10** is an example of output from an intelligent domain engine in the form of predicted answers according to an exemplary embodiment of the invention.

FIG. **11** is an example of output from an intelligent domain engine in the form of support and justification for answers according to an exemplary embodiment of the invention.

FIG. **12** is a system diagram of the analysis system according to an exemplary embodiment of the invention.

FIG. **13** is a flow diagram for an analysis system according to an exemplary embodiment of the invention.

FIG. **14** is a flow diagram of the annotation step depicted in FIG. **13** according to an exemplary embodiment of the invention.

FIG. **15**A is an architectural diagram for the active learning step depicted in FIG. **13** according to an exemplary embodiment of the invention.

FIG. **15**B is a workflow diagram for the active learning step depicted in FIG. **13** according to an exemplary embodiment of the invention.

FIG. **16** is a diagram of the machine learning step depicted in FIG. **13** according to an exemplary embodiment of the invention.

FIG. **17** is a diagram of the consolidation step depicted in FIG. **13** according to an exemplary embodiment of the invention.

FIG. **18** is a diagram depicting graph schemas to represent multiple documents according to an exemplary embodiment of the invention.

DETAILED DESCRIPTION

Exemplary embodiments of the invention will now be described in order to illustrate various features of the invention. The embodiments described herein are not intended to be limiting as to the scope of the invention, but rather are intended to provide examples of the components, use, and operation of the invention.

According to one embodiment, the invention relates to an automated system and method for analysis of structured and unstructured data. The analysis system (sometimes referred to herein as the "System") may include a portfolio of artificial intelligence capabilities, including artificial intelligence domain expertise and related technology components. The System may include foundational capabilities such as document ingestion and optical character recognition (OCR), e.g., the ability to take documents and convert them into formats readable by a machine to perform analytics. According to a preferred embodiment, the System also includes machine learning components that provide the ability for the System to learn without being explicitly programmed (supervised and unsupervised); deep learning components that model high-level abstractions in data; and natural language processing (NLP) and generation, e.g., functionality to understand human speech or text and produce text or speech.

The System can also be designed to ingest and process various types of input data, including structured data (e.g., data organized in columns and rows such as transactional system data and Microsoft Excel files); semi-structured data (e.g., text not stored in a recognized data structure but that still contains some type of tabs or formatting, such as forms); unstructured data (e.g., text not stored in a recognized data structure, such as contracts, Tweets and policy documents); and images and voice (e.g., photographs or other visual depictions of physical objects and human voice data).

The System can be deployed to ingest, understand and analyze the documents, communications, and websites that make up the rapidly growing body of structured data and unstructured data. According to one embodiment, the System may be designed to: (a) read transcripts, tax filings, communications, financial reports, and similar documents and input files, (b) extract information and capture the information into structured files, (c) assess the information in the context of policies, rules, regulations, and/or business objectives, and (d) answer questions, produce insights, and identify patterns and anomalies in the information. The System can capture and store subject matter expertise; ingest, mine and classify documents using natural language processing (NLP); incorporate advanced machine learning and artificial intelligence methods; and utilize collaborative, iterative refinement with advisory and client stakeholders.

Examples of questions that the System can answer may include, for example, which documents comply with a certain policy or regulation, which assets are most risky, which claims warrant intervention, which customers are most/least likely to undergo attrition, which clients will have growing/shrinking wallet and market share, and which documents are experiencing a change in trend or meaning. Examples of policies or rules that the System can analyze may include, for example, new regulations, accounting standards, profitability targets, identification of accretive vs. dilutive projects, assessment of credit risk, asset selection, rebalancing a portfolio, or settlement outcomes, to name a few. Examples of documents that the System can analyze may include, for example, legal contracts, loan documents, securities prospectus, company financial filings, derivatives confirms and masters, insurance policies, insurance claims notes, customer service transcripts, and email exchanges.

FIG. **1** is a functional block diagram of a system for automated analysis of structured and unstructured data according to an exemplary embodiment of the invention. As shown in FIG. **1**, the System integrates a variety of data sources, domain knowledge, and human interaction, in addition to the algorithms that ingest and structure the content. The System includes a scanning component **10** to ingest a plurality of documents **5** such as contracts, loan documents, and/or text files, and to extract related data **6**. During the ingestion process, the System may incorporate OCR technology to convert an image (e.g., PDF image) into searchable characters and may incorporate NLP pre-processing to convert the scanned images into raw documents **11** and essential content **12**. In addition, the appropriate ingestion approach will be used to convert and preserve document metadata and formatting information. In many instances, the input unstructured data will reside in a multitude of documents which together form a corpus **15** of documents that is stored in a dataset.

The FIG. **1** example depicts a "Regulatory Rule Set" that has been implemented in a particular business context. One example of a regulatory rule set may be new or amended financial regulations, and a financial institution or company may need to ensure that its contracts comply with the new regulations. Manual review of the contracts to assess compliance with new regulations is one alternative, but that approach could well involve a very substantial time commitment and extensive costs for experts to review the contracts. Alternatively, the System can be configured to read the contracts, extract information and capture the information into structured files, assess the information in the context of the amended regulations and/or business objectives, and answer questions, produce insights, and identify patterns and anomalies in the contracts. Exemplary embodiments of the invention can thus automate the analysis of complex documents which can provide the benefits of enabling 100% coverage rather than traditional sampling approaches, reducing costs and development time needed to produce insights, enabling humans to achieve and manage precise consistency, leveraging the knowledge and expertise of subject matter experts (SMEs), and automatically creating audit logs describing how the data has been processed.

Referring to FIG. **1**, the regulatory rule set is used by subject matter experts in the manual review and are also translated into related semantics **21** and a determination strategy **22** in the machine review. Semantics **21** include domain knowledge embodied in an ontology or knowledge base consisting of entities, relationships and facts. The determination strategy **22** consists of business rules applied to the related semantics **21** to answer specific questions. This includes document-level assessments (such as compliant vs non-compliant), feature-level extraction (termination dates, key entities), inferred facts (such as utilizing extracted facts and the ontology to make inferences), or to identify risk (such as identify portions of the document that require further scrutiny). The machine learning review **25***a* analyzes dispositive features **26***a*, such as the specified contract terms, dates, entities, and facts, and undertakes an automated document analysis assessment **27***a* through the use of an intelligent domain engine (sometimes referred to herein as the "IDE"). The machine learning review **25***a* assists the machine compliance determination **28***a* by providing confidence scoring. In parallel, the manual review **25***b* of selected documents, conducted for example by a subject matter expert, analyzes dispositive features **26***b* and undertakes a document analysis assessment **27***b* and a manual compliance determination **28***b* for a sample of the contracts. The parallel manual and machine assessments are used to determine accuracy and confidence scoring **29**, which is then used as feedback **30** for the manual review and the machine review. The feedback **30** allows for the refinement of the machine review, such that each iteration can provide enhanced accuracy in the automated analysis and a corresponding increase in confidence scoring. Active learning methods are used to decrease the number of iterations needed to achieve a given accuracy.

Referring to FIG. **2**, the architecture of the System is depicted according to an exemplary embodiment of the invention. As mentioned previously, the System can support information extraction and data analysis on structured and unstructured data. The input data **210** may take the form of various files or information of different types and formats such as documents, text, video, audio, tables, and databases. As shown in FIG. **2**, the data to be analyzed can be input to a core document management system **220**.

According to a preferred embodiment of the invention, the input data **210** is transformed into a common data format **230**, referred to in FIG. **2** as "Lume." Lume may preferably be the common format for all components and data storage. As shown in FIG. **2**, the core document management system includes a document conversion system **240** (to convert documents to a Lume format **230**) and a document and corpus repository **220**. The document conversion system provides a utility for extracting document data and metadata and storing it in a format **240** used to perform natural language processing. The standardized Lume format **230** facilitates the processing and analysis of data in the Lumes because a multitude of components can then be easily applied to the Lumes and utilize upstream information for enhanced processing. In one application, a workflow of processing can be chained together to identify sentences, tokens, and other document structure; entity identification; annotation against a taxonomy or ontology; and the intelligent domain engine **251** can utilize this information to create derived and inferred features. Each of these components utilizes a Lume **240** as input, and Lume **240** as output, and the metadata can be inserted additively into the Lume. Other examples of components may include, for example, different engines, natural language processing (NLP) components **255**, indexing components, and other types of components (e.g., optical character recognition (OCR) **252**, machine learning **253**, and image processing **254**).

Components **250** read Lumes **240** and generate Lume Elements. The Lume Elements are then stored in stand-off annotation format (which is depicted by the database **220**, the parent class definition in the base data format **230**, and the specific instances of the formats in the application specific data formats **240**). As an example, the NLP component **255** processes a Lume **240** and adds additional Lume Elements to indicate human language specific constructs in the underlying data, including word tokens, part-of-speech, semantic role labels, named entities, co-referent phrases, etc. These elements can be indexed to provide users with the ability to quickly search for a set (or individual) Lume **240** or Lume Elements through a query language.

The Lume technology will be described further below with reference to FIGS. **3-6**.

FIG. **2** also illustrates that a number of machine learning (ML) components **253** can be incorporated into the System. For example, the System may include an ML conversion component, a classification component, a clustering component, and a deep learning component. The ML conversion component converts the underlying Lume representations into machine-readable vectors for fast analytic processing. The classification component maps a given set of input into a learned set of outputs (categorical or numeric) based on initial training and configuration. The clustering component produces groups of vectors based on a pre-determined similarity metric. The deep learning component is a specific type of machine learning component **253** that utilizes a many-layer network representation of nodes and connections to learn outputs (categorical or numeric).

FIG. **2** illustrates that the System may include a number of user interfaces **270** that enable different types of users to interact with the System. The IDE manager **273** allows users to modify, delete and add expressions to the System. The model manager **274** allows users to select machine learned models for execution in a pipeline. A search interface **272** (i.e., data exploration) allows users to find data loaded in the platform. The document & corpus annotator **271** (i.e., annotation manager) and editors allows users to manually create and modify annotations on a Lume and group Lumes into corpora for training and testing the System. Visual workflow interfaces **275** (i.e., workbench) provide a visual capability for building workflows, and can be used to create histograms and other statistical views of the data stored in the platform.

FIG. **3** illustrates properties and features of a Lume according to an exemplary embodiment of the invention. As shown in FIG. **3**, the "name" is a string comprising a non-qualified name of the document. The "data" is a string or binary representation of the document (e.g., serialized data representing the original data). The "elements" are an array of Lume Elements.

As shown in FIG. **3**, each Lume Element includes an element ID and an element type. According to a preferred embodiment of the invention, only an element ID and element type are required to define and create a Lume Element. The element ID is a string comprising a unique identifier for the element. The element type is a string that identifies the type of Lume Element. Examples of types of Lume Elements include a part-of-speech (POS) such as noun, verb, adjective; and a named-entity-recognition (NER) such as a person, place or organization. Additionally, file path and file type information can be stored as elements. The file path is a string comprising the full source file path of the document. The file type is a string comprising the file type of the original document.

Although not required, a Lume Element may also include one or more attributes. An attribute is an object comprised of key-value pairs. An example of a key-value pairs might be, for example, {"name":"Wilbur", "age":27}. This creates a simple, yet powerful format that allows the developer flexibility. The reason only the element ID and type are required, according to an exemplary embodiment of the invention, is that it provides flexibility to the developers to store information about a Lume in an element while also ensuring that it's accessible by ID or type. This flexibility allows users to determine how they would like to store relationships and hierarchies among elements according to their domain expertise. For example, elements can contain the necessary information for complicated linguistic structures, store relationships between elements, or refer to other elements.

According to an exemplary embodiment of the invention, the Lume Elements are used to store stand-off annotation format. That is, the elements are stored as annotations separately from the document text, rather than being embedded in the text. According to this embodiment, the System does not modify and can restore the original data.

According to a preferred embodiment, the Lume Elements are not stored in a hierarchical relationship to other Lume Elements, and document data and metadata are stored in a non-hierarchical fashion. Most known formats (other than Lume) are hierarchical, making them difficult to manipulate and convert. Lume's non-hierarchical format allows for easy access to any elements of the document data or its metadata, either at the document level or the text level. In addition, editing, adding, or parsing the data structure can be done via the operations on the elements without the need to resolve conflicts, manage the hierarchy or other operations that may or may not be required for the application. According to this embodiment, because it is a stand-off annotation format, the System can preserve an exact copy of the original data and support overlapping annotations. In addition, this allows for the annotation of multiple formats, such as audio, image and video.

The Lume technology can provide a universal format for document data and metadata. Once the Lume has been created, it can be used in each tool of a natural language processing pipeline without the need for writing format conversions to incorporate tools into the pipeline. This is because the basic conventions required to pass the data and metadata are established by the Lume format. The System provides utilities for extracting document data and metadata from a number of formats, including plain text and Microsoft Word. Format-specific parsers convert the data and metadata from these formats into Lume, and correspondingly write the modified Lume back to the format. The System can use the Lume technology to store information related to families of words to prepare them for natural language processing, such as preprocessing and stemming. In addition, the System can use the Lume technology to store information related to relationships, and graph structures in the document.

According to an exemplary embodiment of the invention, the System includes other components in addition to the Lume and Lume Elements. In particular, the System may be configured to include a dataset, a Lume Data Frame, an Ignite component, and an element index. A dataset is a collection of Lume objects that have a unique identifier. A dataset is typically used to designate training and testing sets for machine learning and can also be used for performing bulk operations on many documents. A Lume Data Frame is a specialized matrix representation of a Lume. Many machine learning and numerical operation components within the System can leverage this optimized format. The System may also include Ignite components that read Lume (or Lume Corpus) data and return Lume (or Lume Corpus) data, usually by processing existing Lume Elements or the original source data and adding new Lume Element objects. An element index is computer object representation of sets or elements and representations typically leveraged in Ignite for efficiency in Lume data and metadata retrieval. For example, some components may be optimized to work over character offsets and therefore an index on character offsets can speed up operations on those components.

According to an exemplary embodiment of the invention, the primary functionalities of the System include data representation, data modeling, discovery and composition, and service interoperability, described as follows.

Data Representation: Lume is the common data format used for storing and communicating analyses on the System. Lume takes a stand-off approach to data representation, e.g., results of analytics are stored as annotations independently of original data. According to one embodiment, Lume is implemented in Python and has computer-object representations as Python objects and is serialized as JavaScript Object Notation ("JSON") for inter-process communication. Lume may be designed for use with web-based specifications, such as JSON, Swagger (YAML), RESTful and will interface with the Python ecosystem, but it can also be implemented in, and support components written in Java and other languages.

Data Modeling: Lume can be designed to be simple and only enforce basic requirements on users of the System. Interpretations and business logic are left to the users of the System rather than requiring declarative representations of both data and processes. The System can be designed to leave the modeling informal and to leave the details for implementations in the processing components. This allows Lume to maintain a very simple specification, and allows it to be extended for specific applications without impeding other applications. For example, when searching the Lume is important, it is integrated with modules that index on top of the Lume structure. When working with a document object model (DOM) is important, the DOM parser stores the addition information in the form of Lume Elements and attributes into the Lume, and converts back out to a DOM model with this information.

Discovery and Composition: Lume may also have an additional design feature relating to analytic process provenance. The System workflows can require provenance information to promote repeatability and discovery of components. This provenance information is stored in Lume and can be enforced though provenance-enforcing workflows. For example, this can provide a check on each of the output Lumes to ensure that the correct processing steps were completed. In the validation stage, it can provide a means to track the provenance of the Lume Element that created the correct or incorrect metadata. Further, it can also track to ensure that all inputs are received as outputs.

Service Interoperability. The services provided by the System may require Swagger (YAML markup language) specifications, according to one embodiment of the invention. There may be many assumptions regarding business logic, order of operations and other data interpretations that are utilized to implement a System component. Identifying which components are interoperable may be achieved through the analysis of example workflows, rather than input and output specifications. In the System, a component may simply operate on a Lume and in the case of error return correct error codes and write the appropriate logging information.

FIG. **4**A illustrates an example of the Lume structure and the initial conversion of different types of files into Lumes. As shown in FIG. **4**A, dataset **410** refers to a body of different types of files or documents. These documents may initially be in different formats, e.g., such as Adobe portable document format (PDF), unstructured text files, Microsoft Word files, and HTML files.

FIG. **4**A also illustrates an example of defined elements for the Lume. For example, a first element **411** may correspond to the study director including contact information; a second element may correspond to the protocol manager including contact information **412**; a third element may correspond to the contract research organization (CRO) including contact information **413**, a fourth element may correspond to a research & development company **414**, and a fifth element **415** may correspond to a confidentiality notice for the document. FIG. **4**B illustrates a larger view of the document with metadata depicted in FIG. **4**A.

Also shown in FIG. **4**A are example levels of element types. For example, the System may provide functionality to enable the user to identify individual paragraphs, tokens or entities, each of which can be extracted from the Lume.

FIG. **5** provides further detail of an example of a Lume creation from a Microsoft Word document. As shown in FIG. **5**, the first step, i.e., step **501**, is to initialize the original document. Initialization entails storing the original data in the Lume object. The second step, i.e., step **502**, is to parse the document into elements in the Lume format. The step may include a loop **502***a* in which elements are created corresponding to metadata from the source document. This is performed by document specific components that ingest the specific format. In particular, during ingestion, (i) the original file is opened, (ii) the DOCX format is decompressed into an XML file, and then (iii) the XML file is read into a data structure for parsing. The parsing separates the data in the document from the metadata, and then stores the data in the "data" field of the Lume, and the metadata into Lume Elements. This will then be output as a LumeText. Examples of metadata stored are author, page, paragraph, and font information.

At the conclusion of the process shown in FIG. **5**, the input document has been converted into Lume, and the desired elements have been generated and stored.

FIG. **6** illustrates an example of applying the functionality of FIG. **5** to a corpus of documents. The first step in FIG. **6**, i.e., step **601**, comprises initializing the dataset. The subsequent steps in FIG. **6** entail application of the processes shown in FIG. **5** to each document in the dataset. As the Lumes in the dataset are converted to Lume format in step **602**, the results are stored in the dataset. The conversion includes the creation of the Lume data structure (i.e., loop **602***b*), the conversion of the format-specific metadata into Lume Elements (i.e., step **602***a*), and additional annotations that are needed, such as semantic annotation, natural language processing, creating domain-specific features, or a vectorization to a quantitative fingerprint. More specifically, in step **601**, the dataset documents are identified in the URI, and then the Lumes containing the file data is passed to **602**. Next, in **602***b*, the Lume is passed to the appropriate parser, which creates the appropriate data structure for parsing. In **602***a*, the parsing work through the document, parsing the data in the "data" field of the Lume, and the metadata into Lume Elements. This will then be output as a LumeText.

FIG. **7** is a process diagram that illustrates an example of a process for analyzing structured and unstructured data according to an exemplary embodiment of the invention. In step **710**, documents such as text, Microsoft Word, and/or Adobe PDF documents are ingested into the System. The documents are then converted in step **712** to Lume format as described above. An OCR process may be used in step **714** to convert an image file to characters. In step **716**, the documents are collected in a Dataset. In step **718**, the System identifies and annotates structural Lume Elements (e.g., see FIG. **6**). Once the documents have been converted into Lume format and the Lume Elements have been generated, natural language processing (NLP) routines or components can be applied in step **720** to the Lume formatted information.

In step **722**, a user of the System creates and inputs an ontology comprising a list of entities. According to one example, an ontology may describe the people and for which businesses they have been employees. The ontology can be useful for extracting people and businesses from documents in the platform, for example. Alternatively, the ontology can describe the different products of a company, the categories that they belong to, and any dependencies between them. Step **724** involves entity resolution and semantic annotation. Entity resolution determines which entities referred to in the data are actually the same real-world entities. This resolution is accomplished through the use of extracted data, ontologies and additional machine learning models. Semantic annotation relates phrases in the data to the formally-defined concepts defined on the ontologies. In the business employee example above, appearances of words "John Doe" will be identified, and connected with the employee John Doe in the ontology. This will enable downstream components to utilize additional information about John Doe, for example his title and function in the company.

In Step **726**, a user of the System creates expressions that are to be applied to the documents stored in the dataset. The expressions may be, for example, comma-separated-value (CSV) files that specify patterns to search for or other distinguishing features of documents. The expressions may incorporate the expertise and know-how of subject matter experts. For example, an expression may identify various specific words and relationships between words, or patterns, that identify particular contract clauses or clauses in a tax document. These expressions are used to search for and identify particular aspects, clauses, or other identifying features of a document. The expression may also leverage a machine learning operator, pre-trained sequence labeling component, or an algorithmic parser that acts as one of the operators into the IDE.

In step **728**, the expressions are input into an IDE, which reads the expressions and applies them to the dataset. According to one embodiment, the output may comprise predicted answers and support and justification for the answers. The IDE will be described further below in connection with FIGS. **8-12**.

In step **730**, the output of the IDE can be utilized to engineer additional features. This utilizes the previously created Lume Elements, and creates new Lume Elements corresponding to the additional features. The feature engineering can be thought abstractly as indicator functions over sets of Lume Elements to create features related to specific signals, for learning and inference tasks. In the general case, the feature engineering can generate additional categorical, or descriptive text features needed for sequence labelling, or sequence learning tasks. For example, the engineering can prepare features for custom entity tagging, identify relationships, or target a subset of elements for downstream learning.

In step **732**, machine learning algorithms or routines are applied to generate results from the Lume Elements created upstream. The machine learning can also be replaced by sequence labelling, or Bayesian network analysis. This creates machine-learned scoring, or probabilistic information on the accuracy of prior annotations, the relationships between elements, or in conjunction with new annotations or classification metadata. The results are analyzed in step **734**, where the results are provided to an analyst for review, either through a UI to inspect the annotations or a workbench to perform further analysis on the results. In step **736**, one or more iterations are performed to improve predictive accuracy. The steps of applying the expressions **728**, engineering features **730**, applying machine learning **732**, and reviewing results **734** may be repeated to improve accuracy. Once the accuracy has been improved to achieve a desired level, the results may be stored in a database in step **738**. Note that entity resolution and semantic resolution **724**, engineer features **730** and machine learning **734** will also be utilized within the Intelligent Domain Engine, but is separated in the case of large-scale processing pipelines.

According to an exemplary embodiment of the invention, the IDE comprises a platform for leveraging natural language processing, custom built annotation components, and manually encoded expressions to systematically classify and analyze a corpus of documents. The IDE can provide a platform for combining a company's cognitive/AI abilities with industry domain knowledge. Each document classification can be represented by a set of expressions that may include the features to be utilized, the patterns of the features to be identified, and reference location or scope information to focus the classification task. Expressions can be composed and work with Lume Elements and data contained in the Lume. The IDE can be designed to systematically evaluate expressions for each document in the corpus, producing specified results as well as annotated text supporting the classification determinations. Note that in this example, the IDE is utilized for natural language processing and text mining, however, the IDE framework applies to all Lume formats, such as images, audio, and video.

The IDE can provide a number of advantages. For example, the IDE can output annotated text to support classification decisions, in addition to an answer to a specific question. Annotations can be used to audit results and provide transparency. In addition, training an accurate machine learning model generally requires a large number of labeled documents. Using the IDE to integrate the domain knowledge with machine learning can reduce the number of documents needed to train an accurate model by an order of magnitude, by utilizing expert-derived features. This is because the machine learning problems involving unstructured data are generally overdetermined, and the ability to select accurate, and interpretable features requires more data than is generally available. For example, in documents, many tens of thousands of features can exist, including the dictionary of words, orthographic features, document structures, syntactic features, and semantic features. Furthermore, according to an exemplary embodiment of the invention, individuals such as subject matter experts (SMEs) who input expressions do not need computer coding skills, as expressions can be created using a domain specific language that can be codified in no-code environments, such as in spreadsheets (CSV or XLSX) or through an IDE user interface. Thereby the SME can create domain relevant features that can be leveraged for the machine training process. The IDE UI allows users to modify, delete and add expressions to the System and visualize elements created by executing the IDE. In addition, expressions can be designed to be interchangeable. They can be created for reuse in use cases throughout an industry or problem set. Additionally, the IDE can be designed to leverage the Lume format for storing and working with documents. This design allows the annotations and metadata to be inputs for the expressions, in addition to the textual features that exist in the document.

According to an exemplary embodiment of the invention, the process for creating and using an expression involves: (1) reviewing documents manually, (2) capturing patterns through expressions and creating custom built code that may leverage machine learning or statistical extraction, (3) loading expressions into the IDE and running the IDE, (4) building confusion matrices and accuracy statistics (i.e., by comparing the current results on an unseen set of documents, this creates an estimate of how well the expressions will generalize, and determines whether the System meets the performance requirements), (5) iterating and refining the foregoing steps, and (6) producing output, such as predicted answers and sections providing support and justification for answers.

According to one particular example, the IDE may be used to automatically determine answers to legal questions by analyzing documents such as investment management agreements or other legal documents. For the purpose of illustration, in this particular example suppose a company has 8 legal questions to answer in connection with 500 investment management agreements. An example question might be "Does the contract require notification in connection with identified personnel changes?" FIG. **8** depicts an example of sections of an investment management contract relevant to the legal question.

FIG. **9** illustrates examples of expressions according to one embodiment of the invention. As shown in FIG. **9**, the expressions may be detailed in a table format (such as CSV), rather than in code. In the FIG. **9** example, each expression has a "name," which may be useful when referencing other expressions. The name may also be used by the output file to create features. Each expression may also contain a "scope," which focuses and limits expressions to be applied. The scope itself is evaluated as an expression, and its results are used to limit the scope of the parent expression. For example, a scope expression may refer to Lume Elements (where it is pre-specified in the conversion to the Lume format or is created by another expression), or can be the result of an operator that identifies the appropriate clause in a contract. The expression also includes a "string" field which is where the expression is contained. The string field has a predetermined syntax. The string field can specify patterns to look for in the documents or logical operations. FIG. **9** shows examples of the string field.

The expression may also include a "condition" field, which is used to determine whether the particular expression should be evaluated or not. This is useful in enabling or disabling expressions for computational efficiency, or to implement control logic to enable or disable certain types of processing.

An expression may be used to search for patterns in documents, and the expression may encapsulate those patterns. Examples of such patterns include, for example, different ways to express a notification requirement and personnel changes. For example, there are many words for "personnel" such as "key person," "investment team," "professional staff" "senior staff" "senior officers," "portfolio manager," "portfolio managers," "investment managers," "key decision makers," "key employees," and "investment manager." Case sensitivity will matter in some cases. For example, "investment manager" may refer to an employee; whereas "investment manager" may refer to the client's investment organization. The order of words (indicating a subject-object relationship) will matter in some cases. For example, an investment manager notifying the client is not the same as the client notifying the investment manager. All of these types of patterns can be encapsulated in the expressions. Subject matter experts (SMEs) can encapsulate in the expressions their know-how in analyzing certain types of specialized document types.

FIG. **10** illustrates an example of one form of output from the IDE: predicted answers. It includes answers to each question for each document. For example, as shown in FIG. **10**, the output may comprise a table listing the filename of the input file, an answer to four questions that provide determinations on features of the contract. According to an embodiment, there may be many more questions or features that will be output from the IDE.

FIG. **11** illustrates an example of another form of out from the IDE: support and justification for the answers. In FIG. **11**, the user interface displays the actual contract language used by the IDE to support and justify its given answer. The actual contract language is presented so that a user can evaluate whether the IDE is correct. The System can utilize information stored in the Lume Element to highlight certain words in the text that specifically form the basis for the answer provided by the IDE. In this way, the IDE enables a human user to easily verify whether the answer is correct. It also facilitates the user's ability to understand any errors and to refine the expression to correct such errors.

FIG. **12** is a system diagram of the System according to an exemplary embodiment of the invention. As shown in FIG. **12**, the System may comprise a server **120** and associated database **122** along with the software and data that are used to run the System. The System may also include a scanner **126** used to scan and ingest original documents into the System. The server **120** and database **122** may be used to store the ingested documents, as well as to store the IDE, the Lumes and Lume Elements, and the other software and data used by the System. A user **125** such as a subject matter expert (e.g., tax professional) can access and use the server **120**, scanner **126**, and database **122** through a personal computing device **124**, such as a laptop computer, desktop computer, or tablet computer, for example.

The System may also be configured to allow one or more clients or other users to access the System. For example, as shown in FIG. **12**, a client **135** may use a personal computing device **134** and company server **130** to access the server **120** via network **110**. The client may also transmit client-specific data (e.g., a set of contracts to be analyzed) stored in a client database **132** to the System to be incorporated into the Dataset documents to be analyzed by the server **120** and stored in the database **122**. The server **120** shown in FIG. **12** can receive other documents, spreadsheets, pdf files, text files, audio files, video files, and other structured and unstructured data from other clients or users, represented generally by servers **140** and **150**.

Also shown in FIG. **12** is a network **110**. The network **110** may comprise any one or more of the Internet, an intranet, a Local Area Network (LAN), a Wide Area Network (WAN), an Ethernet connection, a WiFi network, a Global System for Mobile Communication (GSM) link, a cellular phone network, a Global Positioning System (GPS) link, a satellite communications network, or other network, for example. The other computing devices, such as servers, desktop computers, laptop computers, and mobile computers, may be operated by different individuals or groups, for example, and may transmit data such as contracts or insurance policies to the server **120** and database **122** via the network **110**. In addition, cloud-based architectures, with containerized or microservices-based architectures may also be used to deploy the System.

FIG. **13** is a flow diagram for an analysis system according to an exemplary embodiment of the invention. As depicted in the figure, a flow diagram **1300** includes a document ingestion step **1310**, a preprocessing step **1320**, an annotation step **1330**, an ML framework step **1340**, a post-processing step **1350**, and a multi-document consolidation step **1360**. As a result of these steps, the flow diagram **1300** can provide extracted document knowledge.

According to an embodiment, during step **1310**, data is ingested (i.e., input) from a variety of data sources, e.g., machine readable and/or non-machine readable PDFs, Word documents, Excel spreadsheets, images, HTML, etc. In particular, the raw data from the variety of data sources are converted to and stored in the same Lume data structure, thereby providing consistency across the different data types.

Further, according to an embodiment, during the preprocessing step **1320**, a number of tasks are performed in order to enrich the downstream modeling steps. For example, where necessary, optical character recognition (OCR) can be performed in order to convert text from non-machine-readable PDFs or images to machine-readable text. Further, additional Lume elements may be added to incorporate image-related features that can also be leveraged downstream. In addition, natural language processing tasks are also performed on the document text. For example, the words and sentences in the document text can be tokenized and/or lemmatized. Further, optional information, such as part of speech tagging or named-entity recognition, can also be included during this step to enrich the available information for subsequent modeling. Custom word embeddings can also be added to the token elements, in which the word embeddings are re-trained over the domain-specific document set and added to the tokenized word elements and/or sentence elements. According to an embodiment, the word embedding may re-trained with a large number of documents, e.g., greater than 50. Further, according to an embodiment, the added word embeddings may streamline annotation and smooth over OCR errors in feature creation and modeling. Further, in situations where documents are compiled into a single file (e.g., master service agreements and the corresponding multiple amendments that are usually stored within a single PDF), it may be necessary to split the file into the component documents. In these cases, a heuristic or trained model is utilized to split documents into their constituent parts. According to an embodiment, the document splitting is useful in cases where consolidation logic will be applied to sets of document families. In these situations, each document needs to be analyzed and considered separately in order to properly apply logic to the set of documents. For example, assuming a master service agreement has three amendments, the information, e.g., payment terms for a contract, across these related documents can be consolidated after preprocessing and model prediction have been run. However, only one of the documents, e.g., the most recent amendment, may include the most relevant information, e.g., payment terms for the contract. As such, contract consolidation can be used to apply logic across the set of documents and extract the most relevant information.

Further, according to an embodiment, during the annotation step **1330**, human knowledge and expertise can be incorporated into the process **1300**, wherein SMEs can label specific information in the document. This information can be specific phrases and/or text to extract, or labeling a specific clause or paragraph as a particular type, e.g., Type A, Type B, etc. According to an embodiment, such SME knowledge can be incorporated in a variety of ways, e.g., a web or Excel-based user interface. These annotations can then be added directly to the Lume data structure.

FIG. **14** is a flow diagram of the annotation step **1330**. After preprocessing is complete, the Lume data structure is ready for annotation. The data in the Lume contains the text of the document as well as elements describing its words, sentences, etc. The information in the Lume is then leveraged during the annotation step. In particular, annotations are added as elements which refer directly to the data (e.g., text) contained in the Lume. As depicted in the figure, at step **1331**, keywords/phrases and representative examples of document language are identified. According to an embodiment, the identification may be performed with an SME via a user interface. Further, the identified keyword/phrases and representative examples can be provided to a knowledge base **1334**. In addition, the identified keyword/phrases and representative examples can also be used to calculate embeddings of example sentences as depicted in step **1332**. Then, in step **1333**, the custom word embeddings are trained based on the calculated embeddings and SME knowledge, which can also be provided to the knowledge base **1334**. Further, as depicted in the figure, active learning steps may also be performed.

During active learning, a strategy is created in order to identify and streamline the data annotation and training set creation process. According to an embodiment, active learning leverages the word embeddings, sentence embeddings, and keywords to locate possible candidates of text in the broader dataset. In particular, a set of logical keyword searches as well as some examples of target text (e.g., example sentences of where the target information appears) are input for analysis. For example, in searching for candidates to annotate a contract term, keywords may include language such as “term,” “period,” “years,” or “months.” Further, sentence embeddings such as “[t]he Agreement will last for a term of 10 years” could be leveraged to find similar contextual language. This particular active learning strategy narrows down, with high probability, the search for annotations that are similar but not exact. The user can then review these results and use these candidate annotations to directly add labels to the Lume dataset of documents. Further, according to an embodiment, this active learning strategy is also for useful for balancing the training set with rare information, e.g., rare fields. Further, with active learning, diverse annotations can be generated and a representative dataset can be developed in a streamlined way and stored in the Lume with other metadata. In this way, annotations can be leveraged alongside the complementary information stored in the Lume.

According to an embodiment, as depicted in the figure, a particular active learning strategy (e.g., increasing data diversification, improving model informativeness, etc.) can be applied. For example, the similarity of sentence embeddings can be compared to an average. Then, in step **1336**, the user can review the results of the strategy, e.g., by confirming or rejecting the particular labels. The result is then incorporated into the Lume metadata. Further, the user may also refine the search or annotations, or add new data as needed. Then, as depicted by step **1337**, the confirmed labels are added to a model.

According to an embodiment, the exemplary framework combines both implicit and explicit knowledge transfer in a complementary manner. For example, implicit knowledge transfers, such as feature engineering in the form of IDE expressions, are used to support the explicit knowledge transfer, i.e., annotation through active learning. In other words, the IDE expressions can be used to provide the active learning algorithm the ability to supply candidates for the SME to label/review. Further, according to an embodiment, in the process of reviewing the candidates, the engineered features are also being updated/improved based upon the SME's observations. This cycle (e.g., IDE expression features ("explicit")→review of candidates ("implicit")→refinement of features based off observations ("explicit") →review of more candidates ("implicit")) repeats until the model meets the expected performance.

FIGS. **15**A and **15**B illustrate the interaction between the components in the active learning step depicted in FIG. **13**. According to an embodiment, the active learning step can utilize a user interface **1410**, an active learning application programming interface (API) **1420**, a database **1430**, a module management module **1440**, an Ignite platform **1450**, and a local platform **1460**. The API **1420** communicates with the model management module **1440**, which allows the user to run any number of experiments on a given dataset (e.g., changing hyperparameters or feature sets). Further, the API **1420** tracks performance metrics for the specific settings of that experiment. Further, the API **1420** can also interact with either the Ignite Platform (e.g., a cloud server running Ignite software to execute workflows) or a local platform (e.g., local server or a personal computing device running Ignite software to execute workflows) to interpret instructions for active learning. For example, if an SME were attempting to create a model to predict a "supplier name" from a plurality of contracts, then the SME can indicate to the model, e.g., via the user interface **1410**, that the supplier name can usually be located somewhere around the words "by," "between," "agreement," "inc.," etc. According to an embodiment, the SME can provide this information to the model in the form of IDE expressions. The active learning strategy then selects, with the API **1420**, annotation candidates that best fit the description of the IDE expressions, e.g., automatic annotations ("auto-annotations"). These candidates can be reviewed by the SME with the user interface **1410**, thus providing the model with implicit knowledge about a "supplier name." For example, an initial model, e.g., Model **1** in **15**B, can be trained on the reviewed examples (the candidates that were manually confirmed by the user) as well as additional auto-annotated examples from the active learning strategy. The model performance can then be evaluated on the test set. According to an embodiment, the manually-reviewed examples can be kept for future training; however, the auto-annotated examples will not be propagated through to additional model iterations. During this candidate review process, the SME might refine the IDE expressions based on the observed results (e.g., removing the word "by" and adding the word "company"). Once this refinement is complete, a Model **2** active learning strategy can be configured from the IDE expression refinements, which can be provided by the SME via user interface **1410**. Users can then manually review examples from this updated active learning strategy. As in the first iteration, the new model will be trained from both the manually-reviewed annotations (provided by the SME via user interface **1410**), and the auto-annotations (provided directly by the active learning prediction framework). This results in a new model version (e.g., from Model **1** to Model **2** in FIG. **15**B), which is then leveraged within the active learning prediction framework to create new candidates to review based on these refinements. The cycle will continue until the model has sufficient implicit and explicit knowledge to make predictions at an acceptable level of performance.

According to an embodiment, after the SME annotations have been incorporated in the Lume data structure, model training can begin with the ML framework **1340**. According to an embodiment, the ML framework **1340** consists of several components that work together to train or apply algorithms over the Lume data structures. For example, an information extraction component **1349** acts as an interactive layer with the machine learning component **1346**. Further, according to an embodiment, users can create a configuration file **1341**, which can be interpreted by the information extraction component **1349** before sending instructions to the machine learning component **1346**. According to an embodiment, the instructions in the configuration file **1341** include task type (e.g., train, validate, predict, etc.), algorithm type and package (e.g., regression algorithms such as sklearn logistic regression, recursive algorithms such as keras LSTM, etc.), and features (e.g., custom features, words embeddings, etc.). The machine learning component **1346** acts on the information passed to it from the configuration file **1341** by running training or prediction as instructed, and/or sending instructions to the regression or recursive algorithm. The machine learning component **1346** can also apply any labeling techniques that may be needed, such as BIO labeling, sliding windows, etc., as well as save or load the trained models. According to an embodiment, the regression and recursive algorithms receive data inputs from the machine learning component **1346**, perform training or prediction as instructed via the configuration file **1341**, and return the results (e.g., trained model or predictions) back to the machine learning component **1346**. Further, according to an embodiment, the process builder **1345** can enable all of the above tasks by acting as an API to build and translate instructions, which can be provided in the YAML format. For instance, if a user wants to use a different modeling package for training and prediction, then the user can provide the package and model type names in the YAML configuration to a framework **1347** of the process builder **1345**. The user can also use a module **1348** to customize any default modeling algorithms. Further, with the ML framework **1340**, minimal, if any, changes to the YAML file are needed to change the feature engineering and inclusion of/exclusion from model training. Further, differences in behaviors across models are isolated to the configuration YAML file, and are not mixed with the common code base. This enables the code base to remain "stable," while still allowing users the flexibility to make targeted modifications at any point and at any scope (e.g., fine-grained and/or coarse-grained modifications) to the workflow behavior of a particular model instance. In addition, because these modifications reside within the configuration file **1341** (and not code), they can be passed securely to a platform without the need for installing additional code to the deployment. For instance, the user could modify the model input to ignore punctuation marks, stop words, or add additional features such as word embeddings as well as determine if a word is capitalized. These changes can be executed by modifying the configuration YAML file, rather than changing the source code. The configuration file can then take the referenced features and generate a feature matrix from a training dataset.

FIG. **16** is a diagram of the machine learning step depicted in FIG. **13** according to an exemplary embodiment of the invention. According to an embodiment, the training of a model as well as the prediction from an existing model are performed using the same configuration file, e.g., configuration file **1341**. As depicted in the figure, during a training mode, target truth labels can be extracted from a training dataset, e.g., LumeDataset, and then provided to an initialized model. Further, features can also be extracted from the training dataset and then provided to the initialized model. A chosen model architecture, e.g., a third-party modeling package **1440** (e.g., sklearn, keras, etc.), then runs the model training steps, with the trained model then being saved to the database **1430**. Then, during a prediction mode, the trained model can be loaded from the database **1430** and run on the feature matrix set up from the configuration file as well as features extracted from a testing dataset in order to predict the results from the testing dataset. According to an embodiment, the training dataset is the data specifically used to develop the model but never to test the model performance; conversely, the testing dataset is used to test the model performance but never to train the model. However, both sets of data must be labeled.

According to an embodiment, many questions that can be asked of the documents involve explicit extraction of raw information from the text itself. However, for non-machine-readable documents where spelling errors are common and/or the formatting is inconsistent, additional processing is necessary. For example, dates may be written in many different ways in documents (e.g., 4/5/2010, 4.5.10, April 5th, 2010, the fifth of April 2010, etc.)—but the information still must be formatted consistently when reported for analysis. Thus, post-processing is required. In this regard, during the post-processing step **1350**, the user can customize particular tasks and functions to perform on the model results. Further, the post-processing step **1350** can also be used to impose certain business logic and conditioning on the results of the models. For example, certain business logic can be imposed if one field may be dependent on another—if the model predicts that there should be no auto-renewals in a contract, then there should be no result for the length of the auto-renewal term. As such, with the post-processing step **1350**, data can be provided in the format the user requires. Further, business logic can be imposed across a variety of model predictions in the event the results include fields that are interdependent.

Further, according to an embodiment, during the consolidation step **1360**, related documents are input and then business logic is performed by a graph consolidation engine **1361** (see FIG. **17**) to determine which information should be reported from which document. For example, for a master service agreement with multiple amendments, the information about contract term should be derived from the most recent amendment. According to an embodiment, this logic can be coded into the graph consolidation engine **1361** by the user. Further, the consolidation tasks can be implemented by a graph database **1370** (e.g., JanusGraph) to model the relationships between the documents. For example, as depicted in FIG. **17**, multiple documents **1362** and **1363** (or versions of same document, i.e., "Document **1**") can be input to the graph consolidation engine **1361** with updated or conflicting facts (e.g., facts A and B). For example, with regard to document **1362**, fact A="True" and fact B="1." On the other hand, in document **1363**, fact A="False" and fact B="2." In this regard, in order to resolve the conflicts between the documents **1362** and **1363**, the graph consolidation engine **1361** uses other model outputs found in the document, which can be retrieved from the graph database **1370**. The graph consolidation engine **1361** can then provide a consolidated output **1364** reflecting current true facts for Document **1**.

FIG. **18** is a diagram depicting graph schemas to represent multiple documents according to an exemplary embodiment of the invention. For example, as depicted in the figure, the documents **1366** (i.e., Doc **1**, Doc **2**, Doc **3**, and Doc **4**) can be represented with either a graph schema **1367** (i.e., graph schema A) or graph schema **1368** (i.e., graph schema B). According to an embodiment, the graph schemas **1367** and **1368** can be based on custom models for business cases as defined by SMEs. The graph schemas **1367** and **1368** can be generated via a configuration file, in which the SME can specify which information in a document can be used to determine the connections between the documents **1366** in the graph. This graph model can then be loaded into the graph database, with all the data loaded into the graph adhering to this graph model. Further, graph edges can be automatically and dynamically established based on the models processed. In this regard, with graph schema **1367**, the documents **1366** are connected by a shared document ID, e.g., "Contract Family 1." Further, with graph schema **1368**, Lumes are connected to a document root via related client names.

Further, according to an embodiment, the exemplary framework can answer questions about a document family using a graph query custom to a dynamic schema. For example, assuming the question was "Find the renewal period, prioritize amendments by newest," the exemplary framework would translate the query into a graph query and perform a traversal of the graph, finding only amendments and ordering them by "effective date model." The result is returned to the user with a full explanation of how consolidation was performed, but without need for understanding the underlying graph model. For example, the result can be: "Found X amendments, they had the following dates. They had the following renewal periods: Y. The best answer is Z." Further, if the question was "Lowest price is the valid price," the exemplary framework would translate the query into a graph query and perform a traversal of the graph, finding any document with a price and then finding the lowest price." In this regard, the result can be: "Found X documents with price. The values are [. . .]. The lowest values is Y."

Further, as depicted in FIG. **13**, the exemplary framework, e.g., flow **1300**, also includes a quality assessment (QA) component which implements QA checks after every step in the flow **1300** in order to enforce high quality and consistency. These checks can include (i) whether certain Lume Elements have been created and added to the Lume data structure as expected, (ii) whether all Lumes are passed successfully from step to step, and (iii) whether the right attribute keys and counts have been included at each step. Additionally, users may also configure and add their own custom quality assessment checks as needed.

It will be appreciated by those persons skilled in the art that the various embodiments described herein are capable of broad utility and application. Accordingly, while the various embodiments are described herein in detail in relation to the exemplary embodiments, it is to be understood that this disclosure is illustrative and exemplary of the various embodiments and is made to provide an enabling disclosure. Accordingly, the disclosure is not intended to be construed to limit the embodiments or otherwise to exclude any other such embodiments, adaptations, variations, modifications and equivalent arrangements.

The foregoing descriptions provide examples of different configurations and features of embodiments of the invention. While certain nomenclature and types of applications/hardware are described, other names and application/hardware usage is possible and the nomenclature is provided by way of non-limiting examples only. Further, while particular embodiments are described, it should be appreciated that the features and functions of each embodiment may be combined in any combination as is within the capability of one skilled in the art. The figures provide additional exemplary details regarding the various embodiments.

Various exemplary methods are provided by way of example herein. The methods described can be executed or otherwise performed by one or a combination of various systems and modules.

The use of the term computer system in the present disclosure can relate to a single computer or multiple computers. In various embodiments, the multiple computers can be networked. The networking can be any type of network, including, but not limited to, wired and wireless networks, a local-area network, a wide-area network, and the Internet.

According to exemplary embodiments, the System software may be implemented as one or more computer program products, for example, one or more modules of computer program instructions encoded on a computer-readable medium for execution by, or to control the operation of, data processing apparatus. The implementations can include single or distributed processing of algorithms. The computer-readable medium can be a machine-readable storage device, a machine-readable storage substrate, a memory device, or a combination of one or more them. The term "processor" encompasses all apparatus, devices, and machines for processing data, including by way of example a programmable processor, a computer, or multiple processors or computers. The apparatus can include, in addition to hardware, software code that creates an execution environment for the computer program in question, e.g., code that constitutes processor firmware, a protocol stack, a database management system, an operating system, or a combination of one or more of them.

A computer program (also known as a program, software, software application, script, or code) can be written in any form of programming language, including compiled or interpreted languages, and it can be deployed in any form, including as a standalone program or as a module, component, subroutine, or other unit suitable for use in a computing environment. A program can be stored in a portion of a file that holds other programs or data (e.g., one or more scripts stored in a markup language document), in a single file dedicated to the program in question, or in multiple coordinated files (e.g., files that store one or more modules, sub programs, or portions of code). A computer program can be deployed for execution on one computer or on multiple computers that are located at one site or distributed across multiple sites and interconnected by a communications network.

A computer may encompass all apparatus, devices, and machines for processing data, including by way of example a programmable processor, a computer, or multiple processors or computers. It can include, in addition to hardware, code that creates an execution environment for the computer program in question, e.g., code that constitutes processor firmware, a protocol stack, a database management system, an operating system, or a combination of one or more of them.

The processes and logic flows described in this document can be performed by one or more programmable processors executing one or more computer programs to perform functions by operating on input data and generating output. The processes and logic flows can also be performed by, and apparatus can also be implemented as, special purpose logic circuitry, e.g., an FPGA (field programmable gate array) or an ASIC (application specific integrated circuit).

Computer-readable media suitable for storing computer program instructions and data can include all forms of nonvolatile memory, media and memory devices, including by way of example semiconductor memory devices, e.g., EPROM, EEPROM, and flash memory devices; magnetic disks, e.g., internal hard disks or removable disks; magneto optical disks; and CD ROM and DVD-ROM disks. The processor and the memory can be supplemented by, or incorporated in, special purpose logic circuitry.

While the embodiments have been particularly shown and described within the framework for conducting analysis, it will be appreciated that variations and modifications may be affected by a person skilled in the art without departing from the scope of the various embodiments. Furthermore, one skilled in the art will recognize that such processes and systems do not need to be restricted to the specific embodiments described herein. Other embodiments, combinations of the present embodiments, and uses and advantages of the will be apparent to those skilled in the art from consideration of the specification and practice of the embodiments disclosed herein. The specification and examples should be considered exemplary.

What is claimed is:

1. A computer-implemented method for analyzing data from a variety of data sources, the method comprising:

receiving, as inputs, at least one specific question and data from the variety of data sources;

storing the data from the variety of data sources in a database;

applying an artificial intelligence process to the received data, the artificial intelligence process comprising the steps of:

converting the received data from each of the variety of data sources into a data structure that is common for a plurality of received data types;

identifying keywords in the received data;

generating sentence or word embeddings based on the identified keywords;

receiving a selection of one or more labels based on the generated sentence or word embeddings;

adding the selected one or more labels to a model;

training, via a machine learning algorithm of the artificial intelligence process, the model over the common data structure based on a configuration file; and

generating, by the trained model through the machine learning algorithm of the artificial intelligence process, a result in response to the at least one specific question, wherein the generating includes:

retrieving, from the database, one or more documents from the received data that, based on a decision made by the trained model, contain information that helps answer the at least one specific question;

determining the specific information from each of the one or more documents that helps answer the at least one specific question; and

providing the result based on the determination of specific information and a graph schema associated with the one or more retrieved documents; and

applying the answer to the specific question as feedback to the artificial intelligence process to improve the accuracy of the artificial intelligence process.

2. The method of claim **1**, wherein the variety of data sources includes at least one of a machine-readable document, non-machine readable document, spreadsheet, image, a Hypertext Markup Language file.

3. The method of claim **1**, further comprising:

splitting the received data into component documents, wherein the received data is split based on one of a heuristic model and a trained model.

4. The method of claim **1**, further comprising:

tokenizing at least one of word elements and sentence elements in the received data; and

adding default word embeddings to at least one of the tokenized word elements and sentence elements.

5. The method of claim **1**, wherein the configuration file includes instructions regarding at least one of a task type, algorithm type, and features.

6. The method of claim **5**, wherein (i) the task type is one of: train, validate, and predict, (ii) the algorithm type is one of a regression algorithm and a recursive algorithm, and (iii) the features include word embeddings.

7. The method of claim **1**, further comprising:

performing at least one quality assessment check.

8. The method of claim **1**, further comprising:

receiving, via a user interface, at least one expression;

providing the at least one expression to the model;

selecting, with an application programming interface, annotation candidates associated with the at least one expression; and

training the model based on the selected annotation candidates.

9. The method of claim **1**, wherein, during training, target truth labels and features are extracted from a training dataset, and then provided to the model.

10. A computer-implemented system for analyzing data from a variety of data sources, the system comprising:

a processor, wherein the processor is configured to:

receive, as inputs, at least one specific question and data from the variety of data sources;

store the data from the variety of data sources in a database;

apply an artificial intelligence process to the received data, the artificial intelligence process comprising the steps of:

convert the received data from each of the variety of data sources into a data structure that is common for a plurality of received data types;

identify keywords in the received data;

generate word or sentence embeddings based on the identified keywords;

receive a selection of one or more labels based on the generated word or sentence embeddings;

add the selected one or more labels to a model;

train, via a machine learning algorithm of the artificial intelligence process, the model over the common data structure based on a configuration file; and

generate, by the trained model through the machine learning algorithm of the artificial intelligence process, a result in response to the at least one specific question, wherein the generating includes:

retrieving, from the database, one or more documents from the received data that, based on a decision made by the trained model, contain information that helps answer the at least one specific question;

determining the specific information from each of the one or more documents that helps answer the at least one specific question; and

providing the result based on the determination of specific information and a graph schema associated with the one or more retrieved documents; and

apply the answer to the specific question as feedback to the artificial intelligence process to improve the accuracy of the artificial intelligence process.

11. The system of claim **10**, wherein the variety of data sources includes at least one of a machine-readable document, non-machine readable document, spreadsheet, image, a Hypertext Markup Language file.

12. The system of claim **10**, wherein the processor is further configured to:

split the received data into component documents, wherein the received data is split based on one of a heuristic model and a trained model.

13. The system of claim **10**, wherein the processor is further configured to:

tokenize at least one of word elements and sentence elements in the received data; and

add default word embeddings to at least one of the tokenized word elements and sentence elements.

14. The system of claim **10**, wherein the configuration file includes instructions regarding at least one of a task type, algorithm type, and features.

15. The system of claim **14**, wherein (i) the task type is one of: train, validate, and predict, (ii) the algorithm type is one of a regression algorithm and a recursive algorithm, and (iii) the features include word embeddings.

16. The system of claim **10**, wherein the processor is further configured to:

perform at least one quality assessment check.

17. The system of claim **10**, wherein the processor is further configured to:

receive, via a user interface, at least one expression;

provide the at least one expression to the model;

select, with an application programming interface, annotation candidates associated with the at least one expression; and

train the model based on the selected annotation candidates.

18. The system of claim **10**, wherein, during training, target truth labels and features are extracted from a training dataset, and then provided to the model.

19. A computer-implemented system for analyzing data from a variety of data sources, the system comprising:

an application programming interface; and

a processor, wherein the processor is configured to:
receive, as inputs, at least one specific question and data from the variety of data sources;
store the data from the variety of data sources in a database;
generate, by a trained model through the machine learning algorithm of an artificial intelligence process, a result in response to the at least one specific question, wherein the generating includes:
retrieving, from the database, one or more documents from the received data that, based on a decision made by the trained model, contain information that helps answer the at least one specific question;
determining the specific information from each of the one or more documents that helps answer the at least one specific question; and
providing the result based on the determination of specific information and a graph schema associated with the one or more retrieved documents; and
wherein the machine learning model is trained on annotation candidates provided by the application programming interface.

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