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(54) ENCODING OF DATA FOR PROCESSING IN A SPATIAL AND TEMPORAL MEMORY SYSTEM

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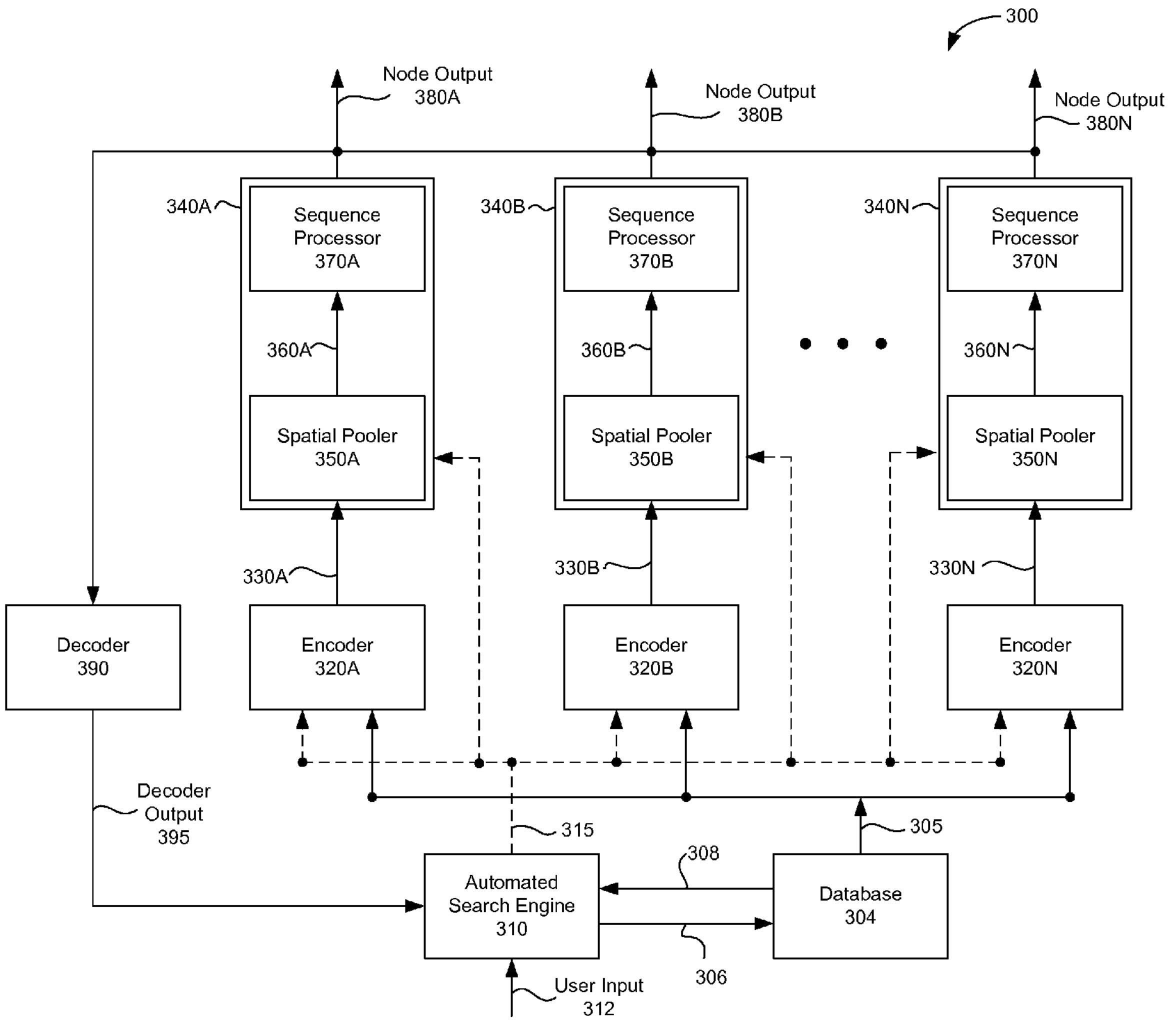
(57) **ABSTRACT**

A spatial and temporal memory system (STMS) processes input data to detect whether spatial patterns and/or temporal sequences of spatial patterns exist within the data, and to make predictions about future data. The data processed by the STMS may be retrieved from, for example, one or more database fields and is encoded into a distributed representation format using a coding scheme. The performance of the STMS in predicting future data is evaluated for the coding scheme used to process the data as performance data. The selection and prioritization of STMS experiments to perform may be based on the performance data for an experiment. The best fields, encodings, and time aggregations for generating predictions can be determined by an automated search and evaluation of multiple STMS systems.



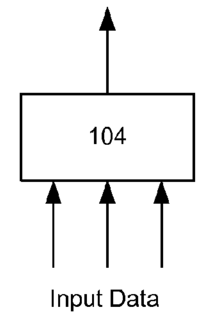


FIG. 1A

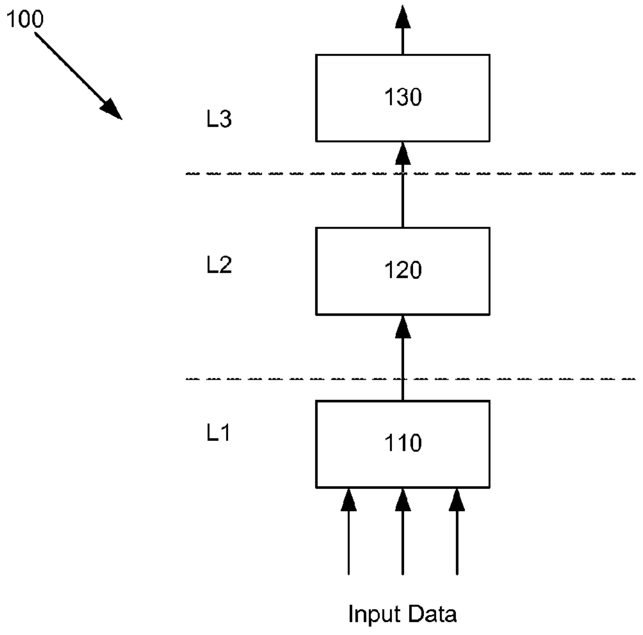


FIG. 1B

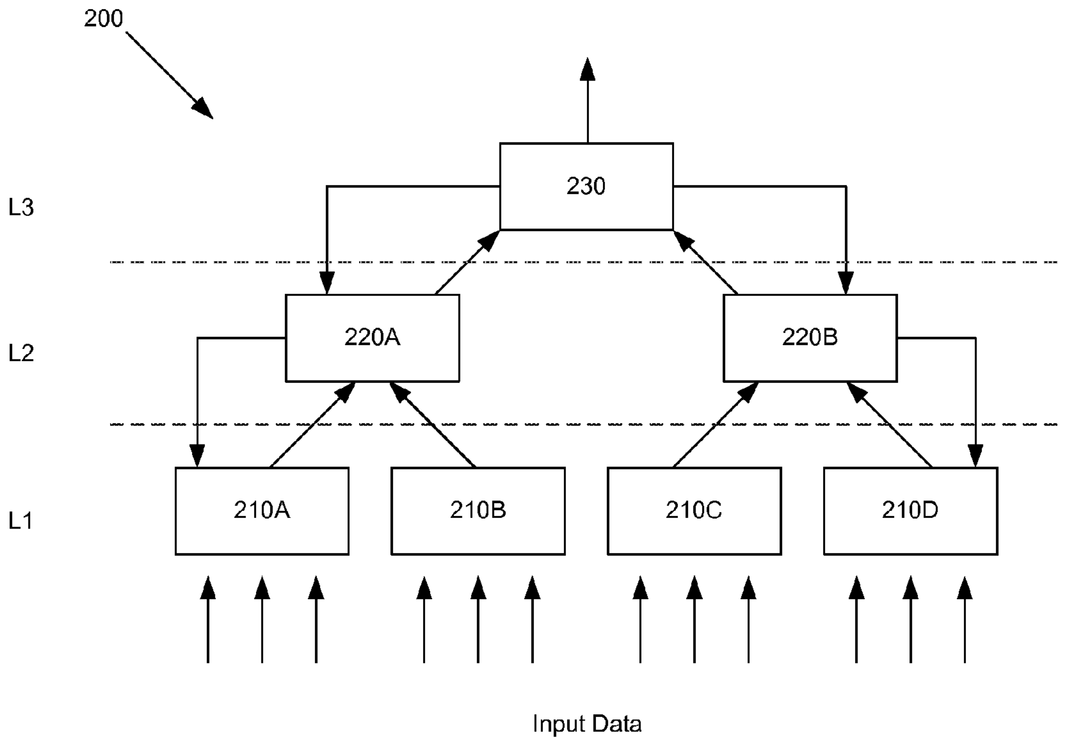


FIG. 2

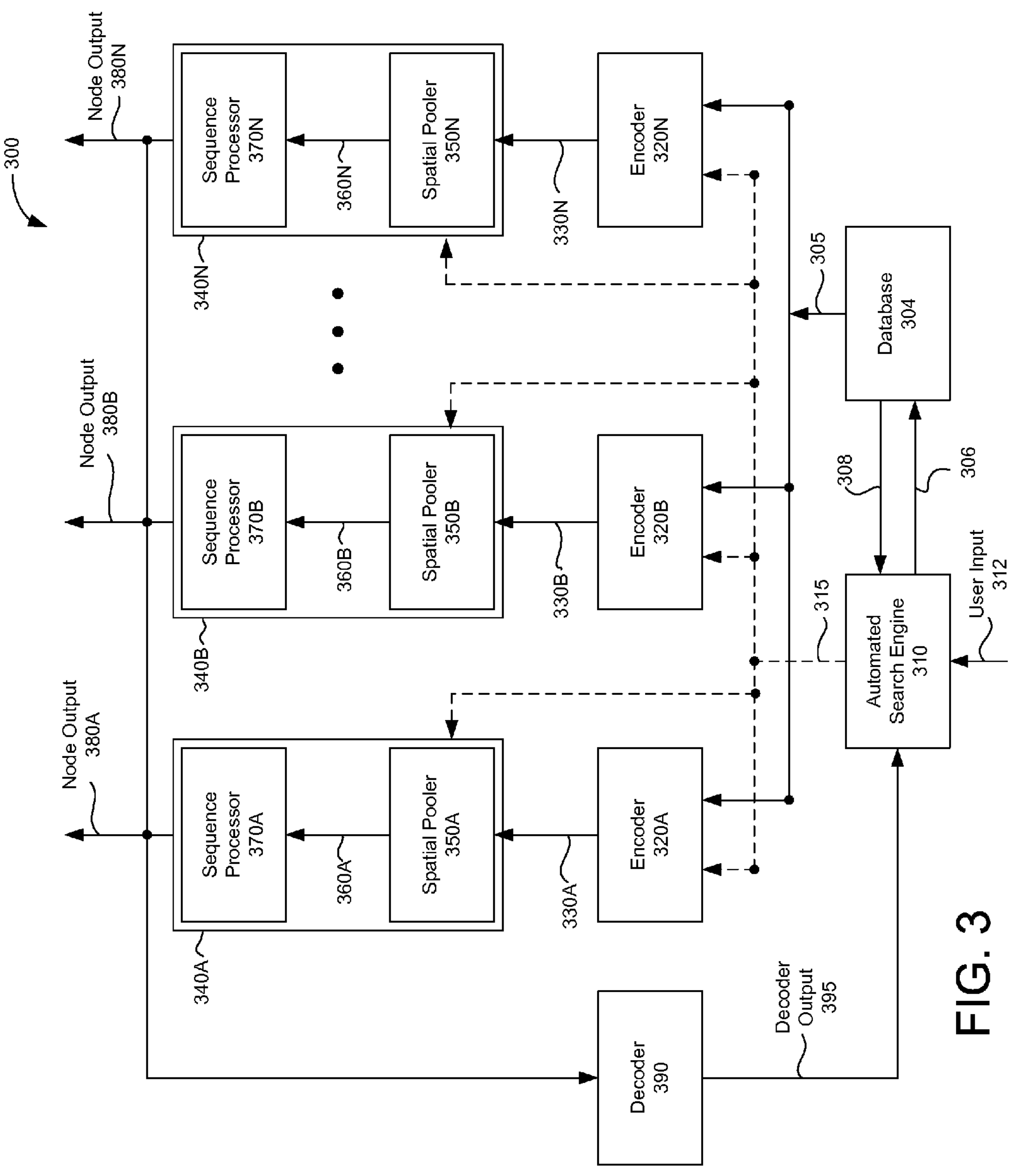

300
Node Output 380A
Node Output 380B
Node Output 380N
Sequence Processor 370A
Sequence Processor 370B
Sequence Processor 370N
360A
360B
360N
Spatial Pooler 350A
Spatial Pooler 350B
Spatial Pooler 350N
340A
340B
340N
330A
330B
330N
Encoder 320A
Encoder 320B
Encoder 320N
Decoder 390
Decoder Output 395
Database 304
305
306
308
315
Automated Search Engine 310
User Input 312

FIG. 3

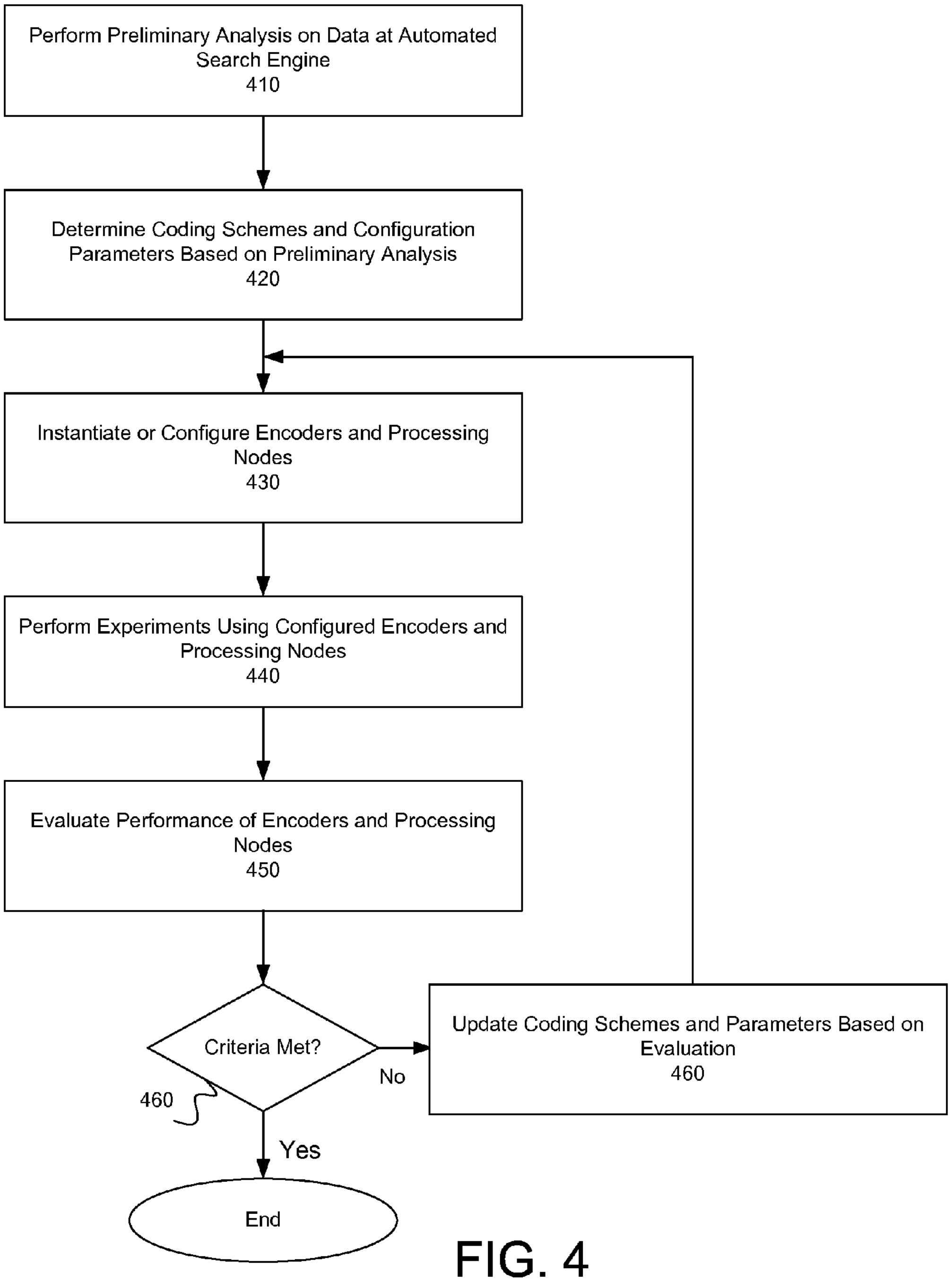

Perform Preliminary Analysis on Data at Automated Search Engine
410
Determine Coding Schemes and Configuration Parameters Based on Preliminary Analysis
420
Instantiate or Configure Encoders and Processing Nodes
430
Perform Experiments Using Configured Encoders and Processing Nodes
440
Evaluate Performance of Encoders and Processing Nodes
450
Criteria Met?
460
No
Update Coding Schemes and Parameters Based on Evaluation
460
Yes
End

FIG. 4

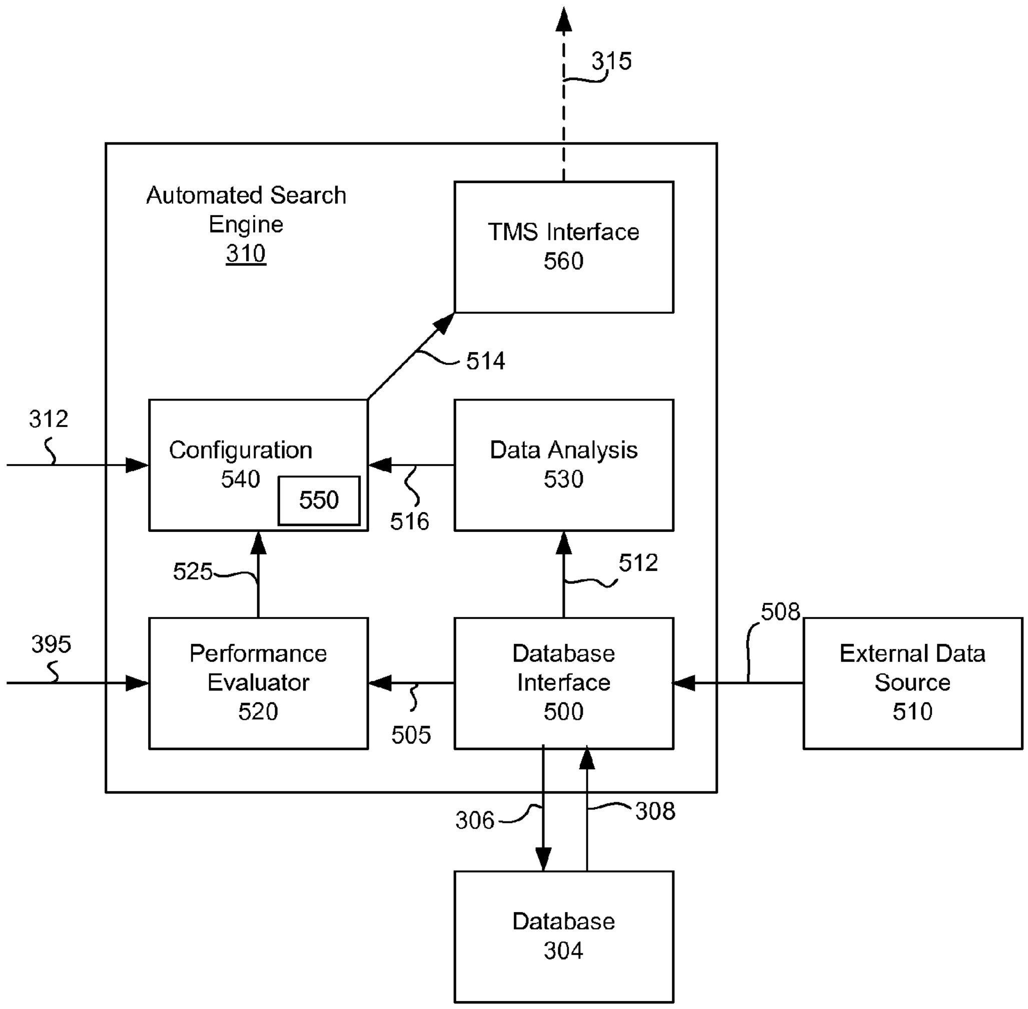

315
Automated Search Engine 310
TMS Interface 560
514
312
Configuration 540
550
Data Analysis 530
516
525
512
508
395
Performance Evaluator 520
Database Interface 500
External Data Source 510
505
306
308
Database 304

FIG. 5

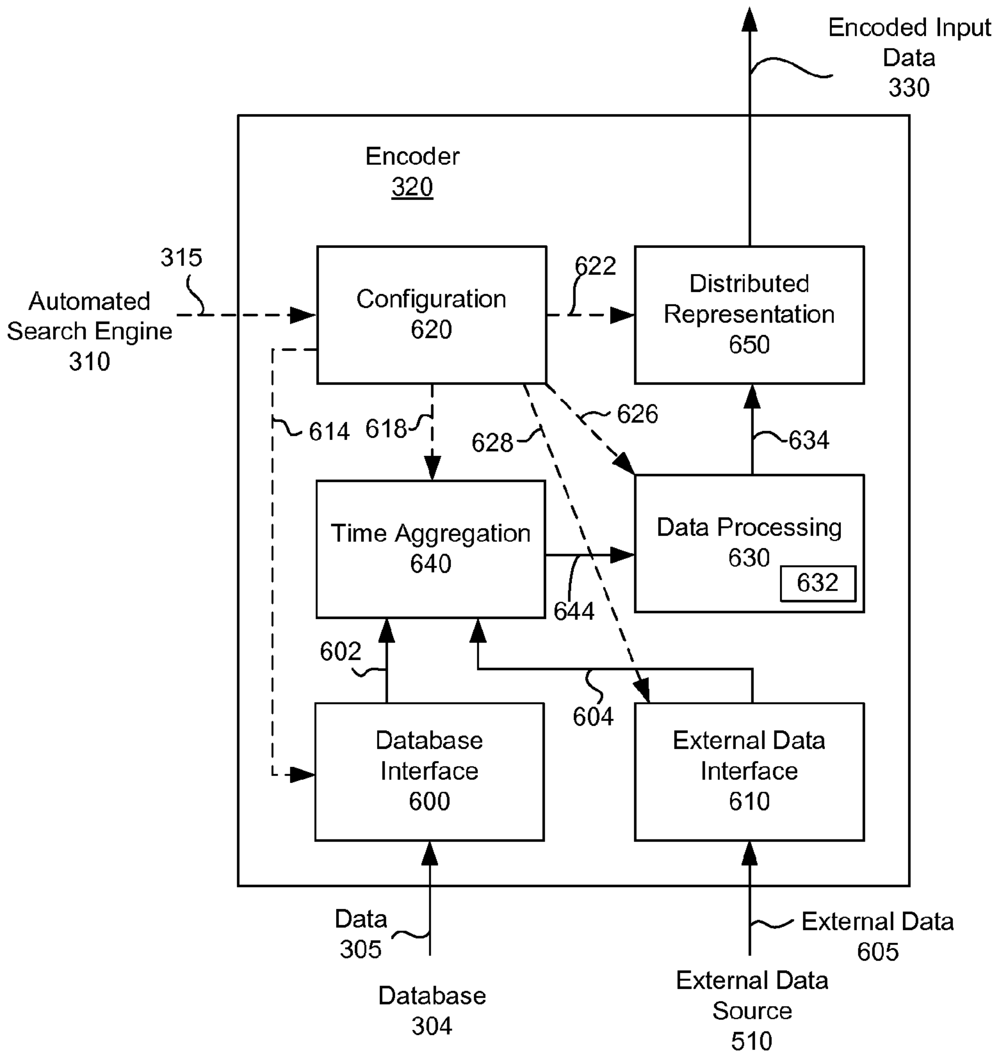

Encoded Input Data 330
Encoder 320
315
Automated Search Engine 310
Configuration 620
622
Distributed Representation 650
614
618
628
626
634
Time Aggregation 640
Data Processing 630
632
644
602
604
Database Interface 600
External Data Interface 610
Data 305
Database 304
External Data 605
External Data Source 510

FIG. 6A

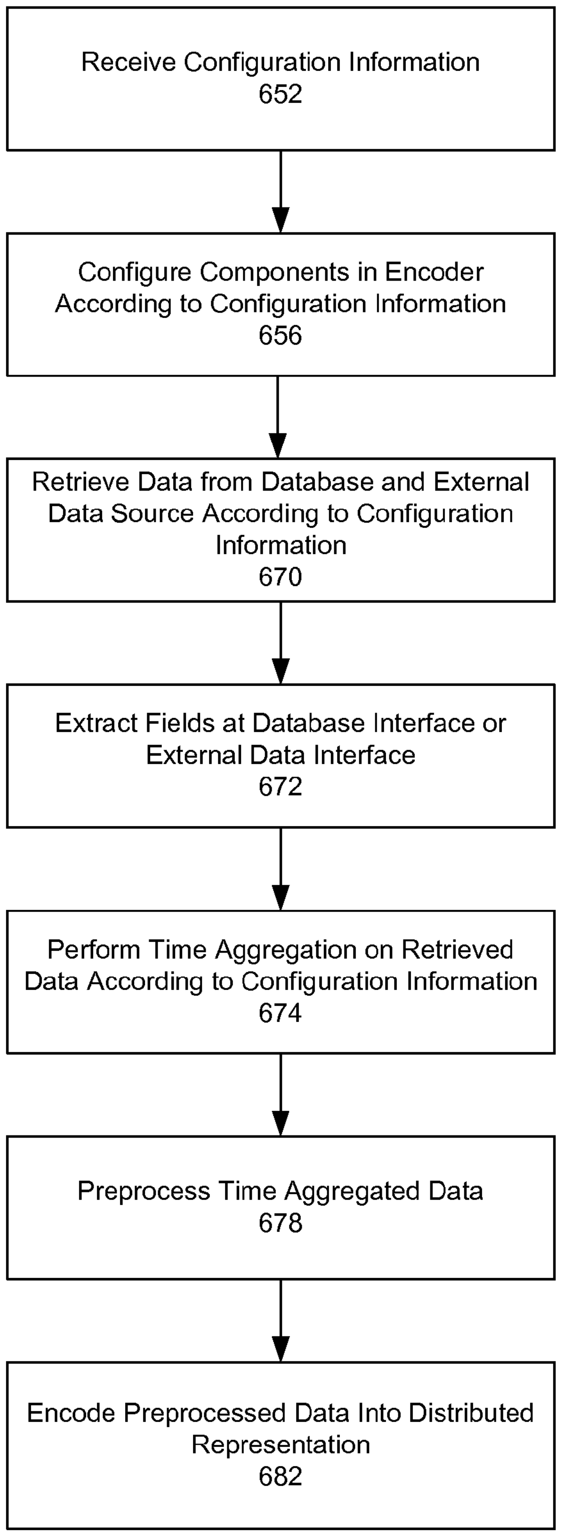

Receive Configuration Information
652
Configure Components in Encoder According to Configuration Information
656
Retrieve Data from Database and External Data Source According to Configuration Information
670
Extract Fields at Database Interface or External Data Interface
672
Perform Time Aggregation on Retrieved Data According to Configuration Information
674
Preprocess Time Aggregated Data
678
Encode Preprocessed Data Into Distributed Representation
682

FIG. 6B

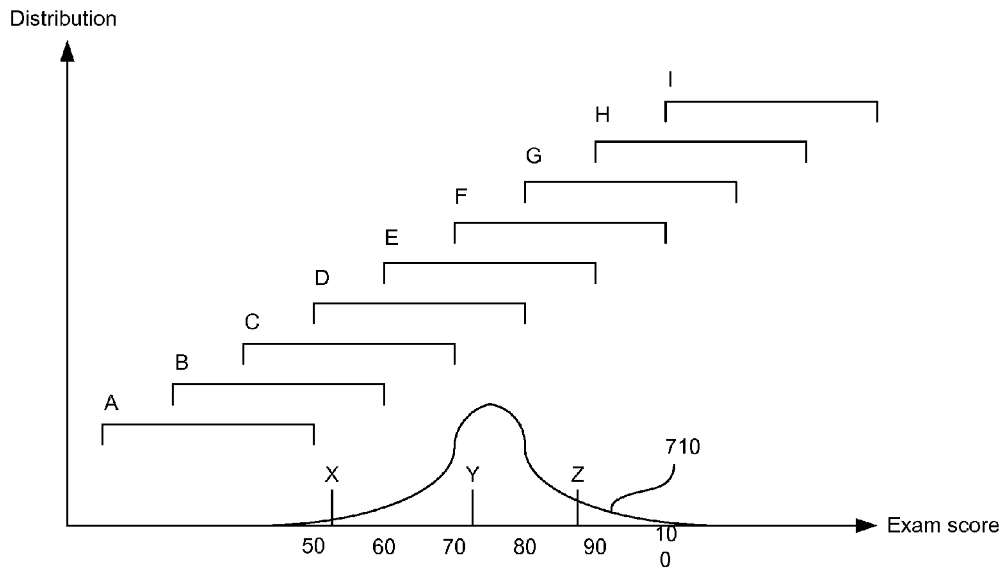

Distribution
I
H
G
F
E
D
C
B
A
710
X
Y
Z
Exam score
50
60
70
80
90
10
0

FIG. 7

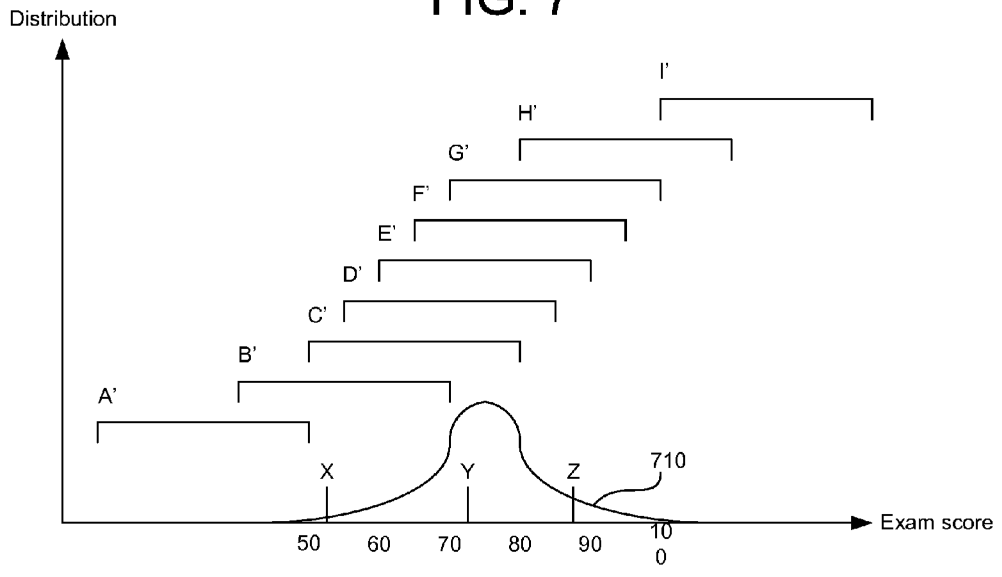
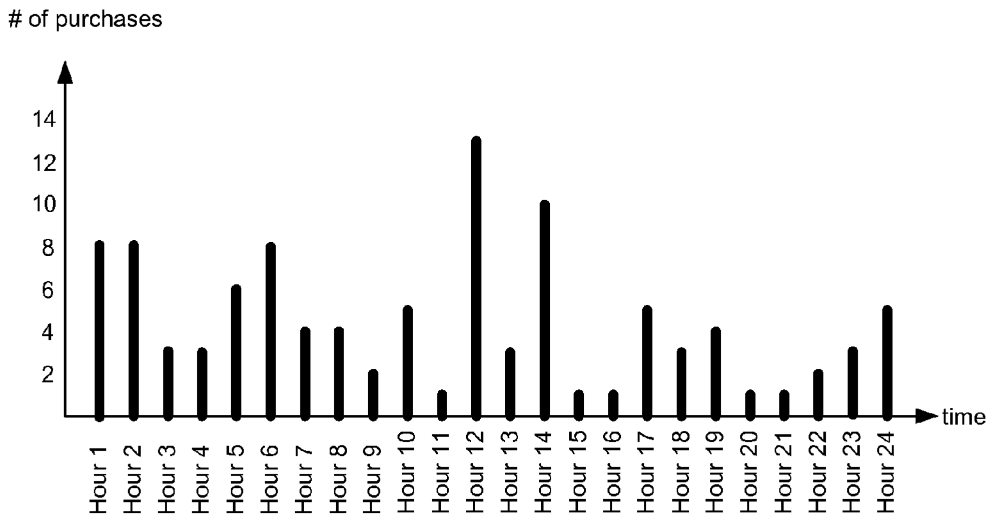
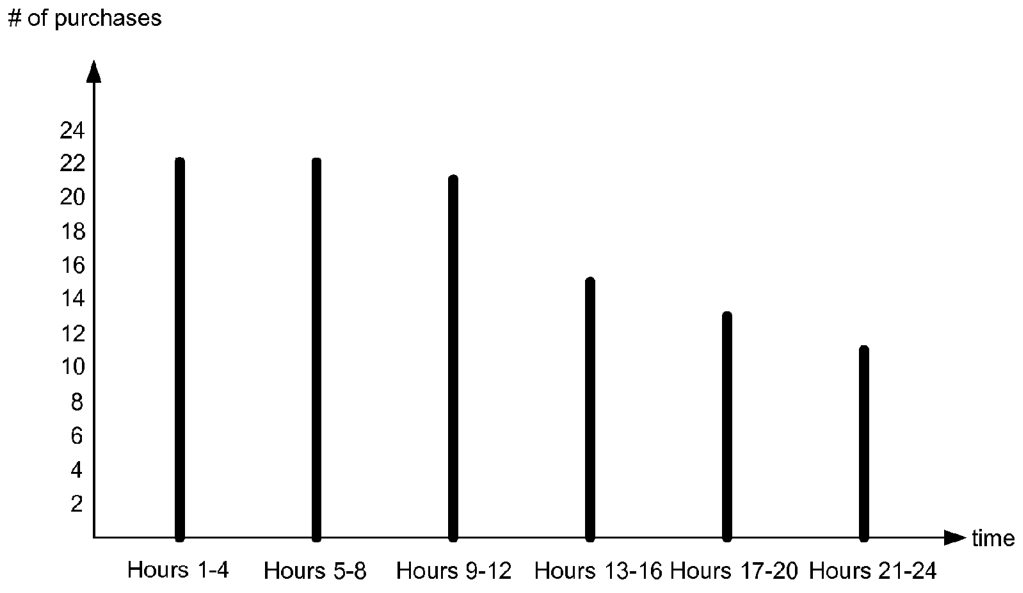

Distribution
I'
H'
G'
F'
E'
D'
C'
B'
A'
710
X
Y
Z
Exam score
50
60
70
80
90
10
0

FIG. 8



# of purchases
14
12
10
8
6
4
2
time
Hour 1
Hour 2
Hour 3
Hour 4
Hour 5
Hour 6
Hour 7
Hour 8
Hour 9
Hour 10
Hour 11
Hour 12
Hour 13
Hour 14
Hour 15
Hour 16
Hour 17
Hour 18
Hour 19
Hour 20
Hour 21
Hour 22
Hour 23
Hour 24

FIG. 9



# of purchases
24
22
20
18
16
14
12
10
8
6
4
2
time
Hours 1-4
Hours 5-8
Hours 9-12
Hours 13-16
Hours 17-20
Hours 21-24

FIG. 10

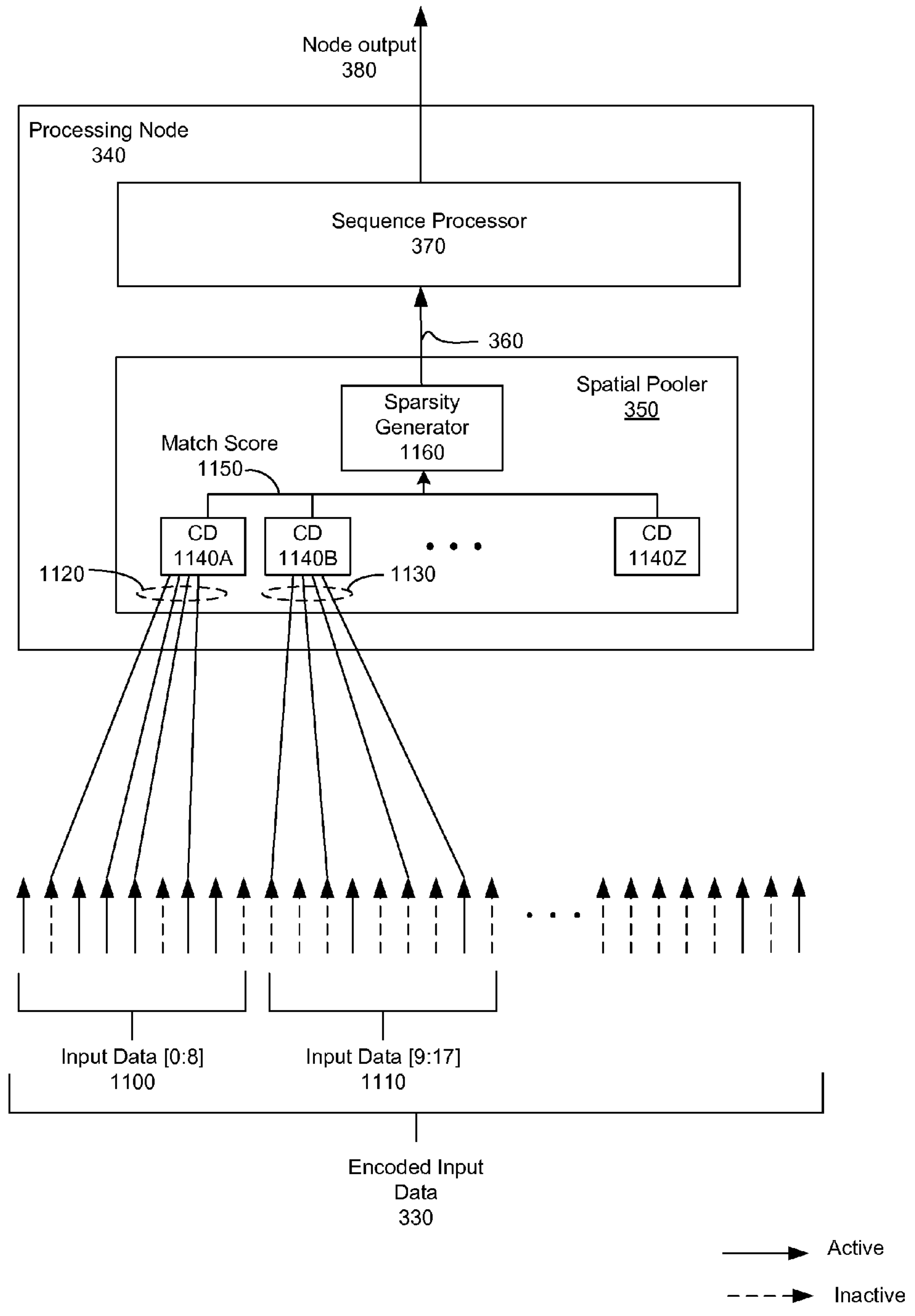

Node output
380
Processing Node
340
Sequence Processor
370
360
Spatial Pooler
350
Sparsity
Generator
1160
Match Score
1150
CD
1140A
CD
1140B
CD
1140Z
1120
1130
Input Data [0:8]
1100
Input Data [9:17]
1110
Encoded Input
Data
330
Active
Inactive

FIG. 11

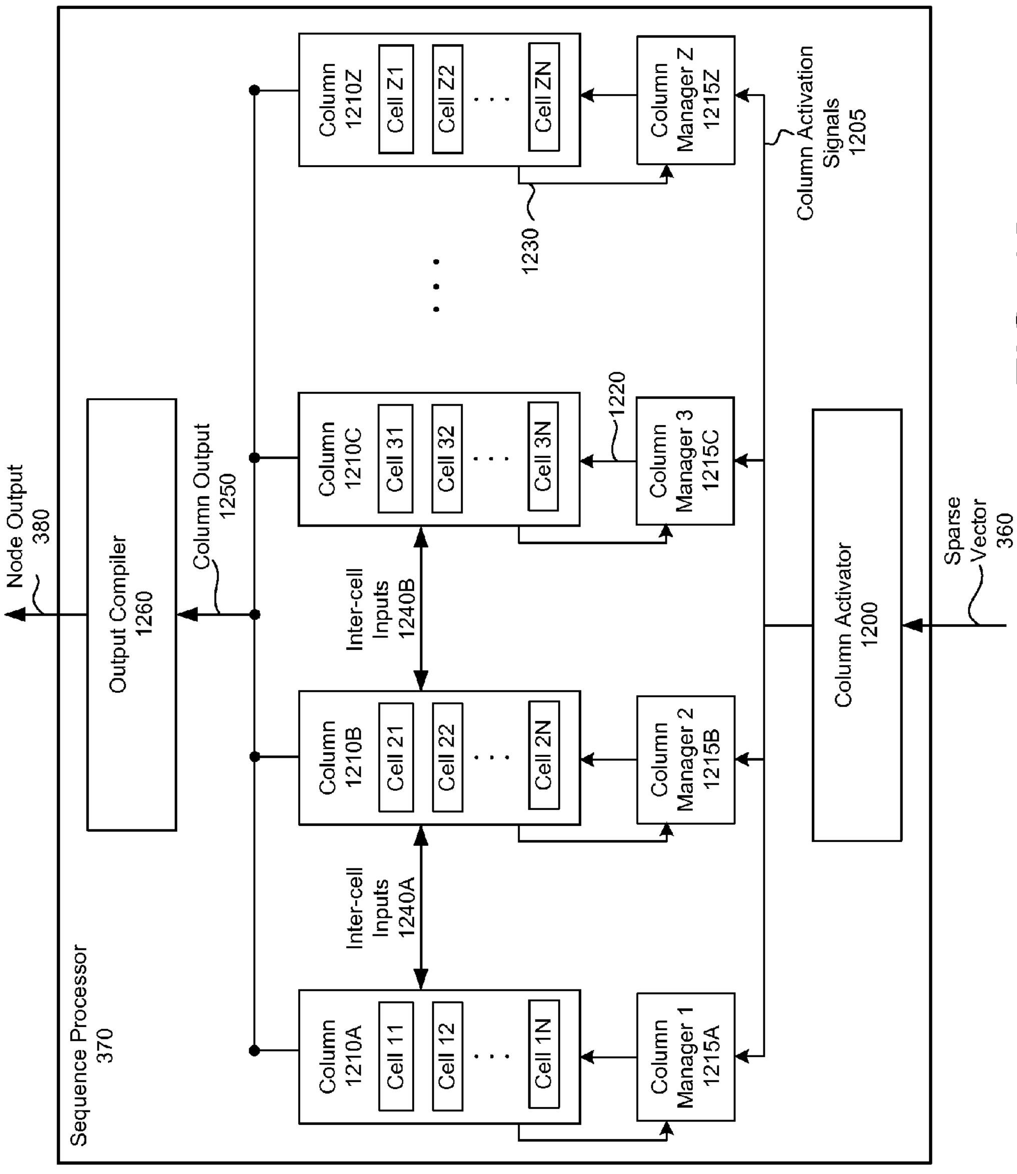

Sequence Processor 370
Node Output 380
Output Compiler 1260
Column Output 1250
Column 1210A
Cell 11
Cell 12
. . .
Cell 1N
Inter-cell Inputs 1240A
Column 1210B
Cell 21
Cell 22
. . .
Cell 2N
Inter-cell Inputs 1240B
Column 1210C
Cell 31
Cell 32
. . .
Cell 3N
1220
Column 1210Z
Cell Z1
Cell Z2
. . .
Cell ZN
1230
Column Manager 1 1215A
Column Manager 2 1215B
Column Manager 3 1215C
Column Manager Z 1215Z
Column Activation Signals 1205
Column Activator 1200
Sparse Vector 360

FIG. 12

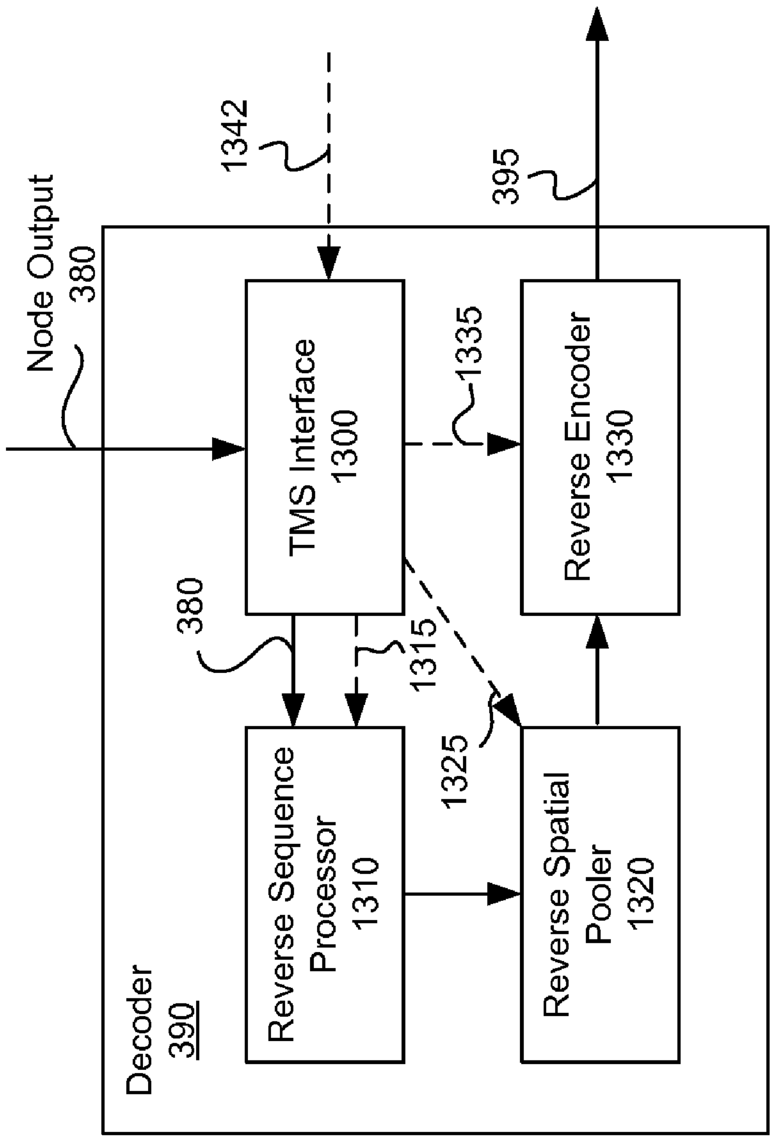

Node Output
380
1342
395
Decoder
390
TMS Interface
1300
Reverse Encoder
1330
1335
380
1315
1325
Reverse Sequence
Processor
1310
Reverse Spatial
Pooler
1320

FIG. 13

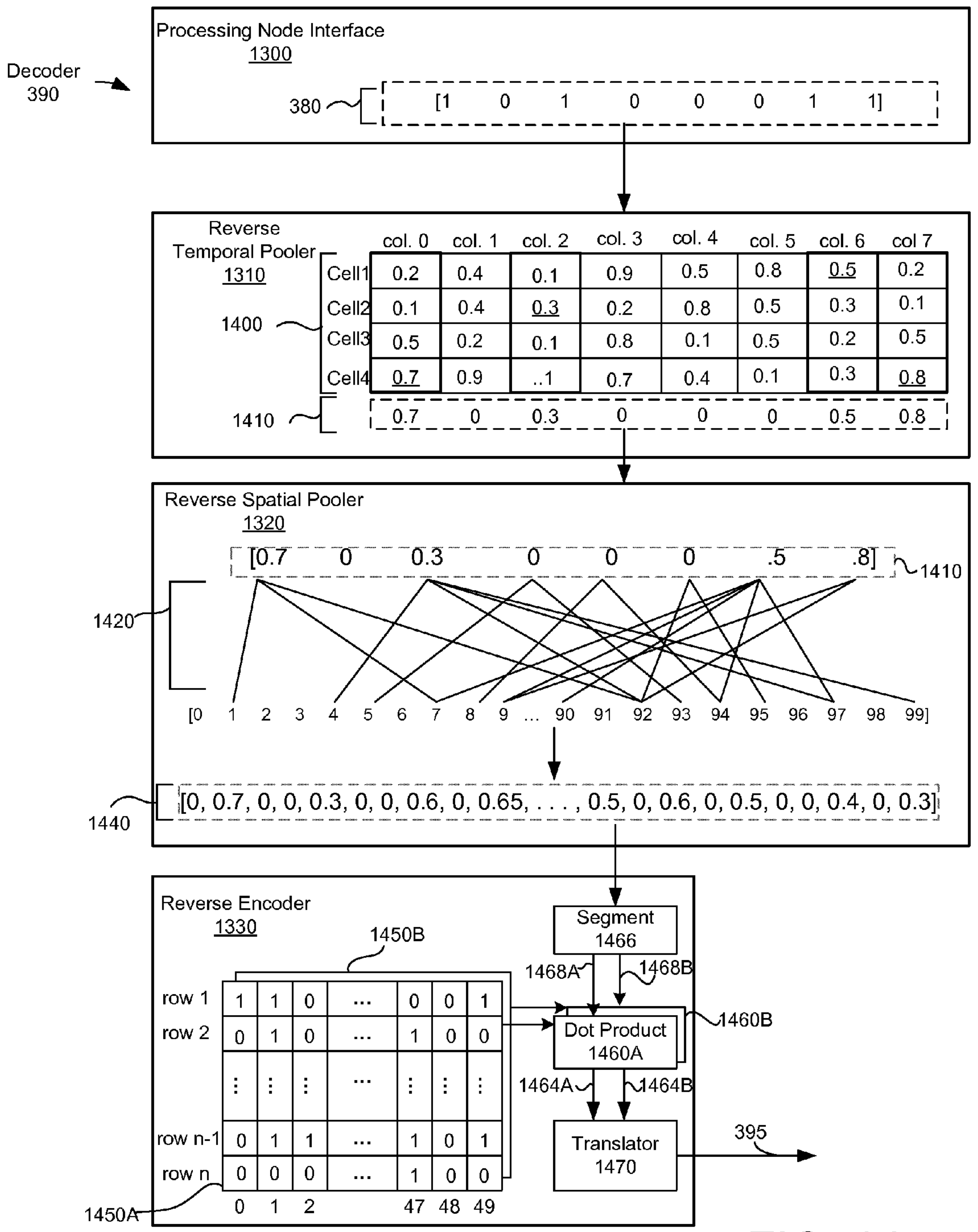

Decoder 390
Processing Node Interface 1300
380
[1 0 1 0 0 0 1 1]
Reverse Temporal Pooler 1310
1400
col. 0 col. 1 col. 2 col. 3 col. 4 col. 5 col. 6 col 7
Cell1 0.2 0.4 0.1 0.9 0.5 0.8 0.5 0.2
Cell2 0.1 0.4 0.3 0.2 0.8 0.5 0.3 0.1
Cell3 0.5 0.2 0.1 0.8 0.1 0.5 0.2 0.5
Cell4 0.7 0.9 ..1 0.7 0.4 0.1 0.3 0.8
1410
0.7 0 0.3 0 0 0 0.5 0.8
Reverse Spatial Pooler 1320
[0.7 0 0.3 0 0 0 .5 .8]
1410
1420
[0 1 2 3 4 5 6 7 8 9 ... 90 91 92 93 94 95 96 97 98 99]
1440
[0, 0.7, 0, 0, 0.3, 0, 0, 0.6, 0, 0.65, . . . , 0.5, 0, 0.6, 0, 0.5, 0, 0, 0.4, 0, 0.3]
Reverse Encoder 1330
1450B
row 1 1 1 0 ... 0 0 1
row 2 0 1 0 ... 1 0 0
row n-1 0 1 1 ... 1 0 1
row n 0 0 0 ... 1 0 0
0 1 2 47 48 49
1450A
Segment 1466
1468A
1468B
Dot Product 1460A
1460B
1464A
1464B
Translator 1470
395

FIG. 14

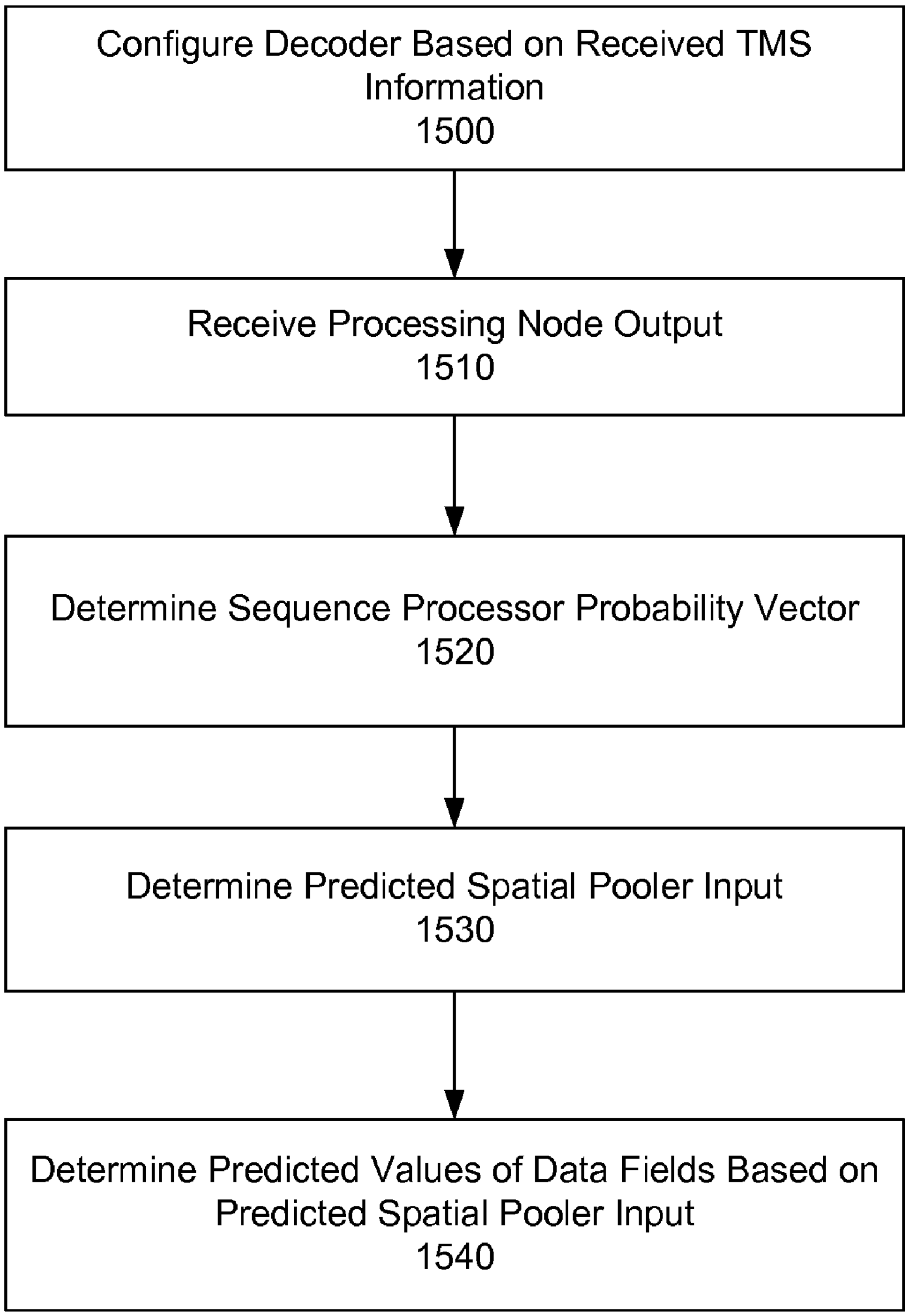

Configure Decoder Based on Received TMS Information
1500
Receive Processing Node Output
1510
Determine Sequence Processor Probability Vector
1520
Determine Predicted Spatial Pooler Input
1530
Determine Predicted Values of Data Fields Based on Predicted Spatial Pooler Input
1540

FIG. 15

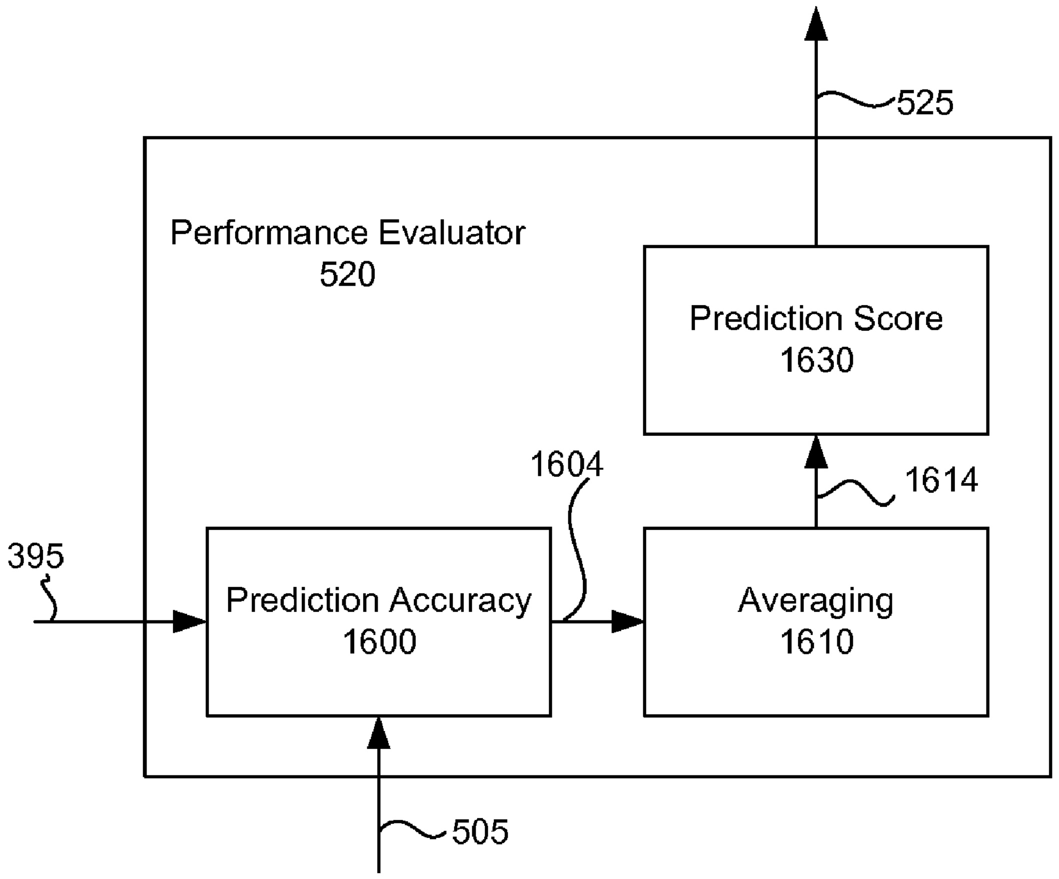

525
Performance Evaluator
520
Prediction Score
1630
1604
1614
395
Prediction Accuracy
1600
Averaging
1610
505

FIG. 16

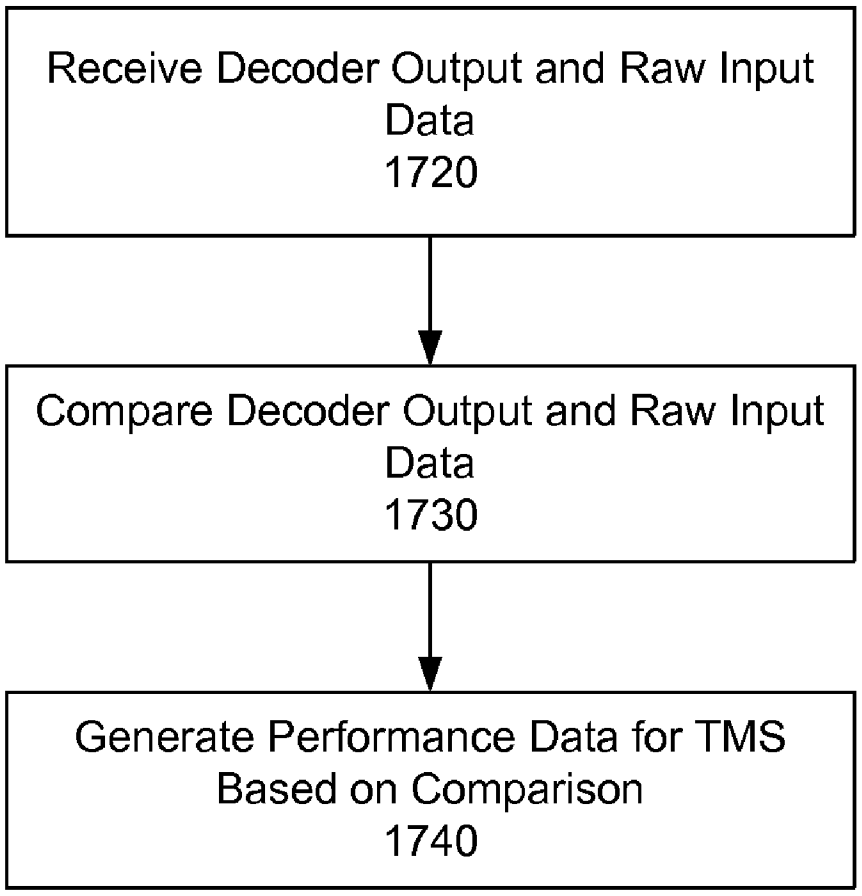

Receive Decoder Output and Raw Input Data
1720
Compare Decoder Output and Raw Input Data
1730
Generate Performance Data for TMS Based on Comparison
1740

FIG. 17

ENCODING OF DATA FOR PROCESSING IN A SPATIAL AND TEMPORAL MEMORY SYSTEM

RELATED APPLICATIONS

[0001] This application is related to U.S. patent application Ser. No. ______, entitled "Automated Search for Detecting Patterns And Sequences in Data Using A Spatial and Temporal Memory System" (Atty. Ref. 25172-18641), filed XX XX, 2011; U.S. patent application Ser. No. ______, entitled "Assessing Performance in A Spatial and Temporal Memory System" (Atty. Ref 25172-18642), filed XX XX, 2011; and U.S. patent application Ser. No. 13/046,464, entitled "Temporal Memory Using Sparse Distributed Representation" (Atty. Ref 25172-18193), filed Mar. 11, 2011. All of the foregoing applications are incorporated herein in their entirety by reference for all purposes.

BACKGROUND

[0002] 1. Field of the Disclosure

[0003] The present invention relates to spatial and temporal memory system processing, and more specifically to automatically searching for spatial patterns and temporal sequences of spatial patterns using multiple configurations of a machine learning system.

[0004] 2. Description of the Related Arts

[0005] Predictive analytics refers to a variety of techniques for modeling and data mining current and past data sets to make predictions. Predictive analytics allows for the generation of predictive models by identifying patterns in the data sets. Generally, the predictive models establish relationships or correlations between various data fields in the data sets. Using the predictive models, a user can predict the outcome or characteristics of a transaction or event based on available data. For example, predictive models for credit scoring in financial services factor in a customer's credit history and data to predict the likeliness that the customer will default on a loan.

[0006] Commercially available products for predictive analytics include products from IBM SSPS, KXEN, FICO, TIBCO, Portrait, Angoss, and Predixion Software, just to name a few. These software products use one or more statistical techniques such as regression models, discrete choice models, time series models and other machine learning techniques to generate useful predictive models. However, most of these software products are complex to use, often requiring weeks of training, mathematical expertise and complex data management. Hence, generating a useful predictive model is a daunting and expensive task for many enterprises.

[0007] Most predictive analytics products come with a toolbox of mathematical techniques that the user can choose to apply to the data sets. Depending on which techniques the user applies and how the data sets are encoded, these predictive analytic products may or may not yield use predictions. Determining the techniques to apply and the coding scheme used by a machine learning system is important to optimize the effectiveness of the machine learning system.

SUMMARY

[0008] Embodiments relate to a method and system for encoding data. Data is retrieved from one or more fields of data in one or more data sources, such as a database. The data in each field is encoded into a distributed representation format. Spatial patterns and temporal sequences of spatial patterns in the encoded input data may be identified by a spatial and temporal memory system's processing node. Predictions of future spatial patterns in the encoded input data may be made by the spatial and temporal memory system based on the identified spatial patterns and temporal sequences of spatial patterns in the encoded input data.

[0009] Embodiments relate to a method and system for evaluating the predictive performance of a spatial and temporal memory system. A spatial and temporal memory system output is generated in response to receiving input data representing a spatial pattern at a first time. The spatial and temporal memory system output includes a prediction of input data representing a spatial pattern at a second time subsequent to the first time or a prediction of a missing piece of information when other parts are known. Input data representing a spatial pattern at the second time is received. The performance of the spatial and temporal memory system is evaluated by comparing the prediction of the input data representing a spatial pattern at the second time with the received input data representing a spatial pattern at the second time.

[0010] Embodiments relate to a method and system for searching for temporal sequences of spatial patterns in data or for spatial patterns in each record of data. A plurality of spatial and temporal memory systems are generated according to configuration information. A subset of input data is provided to each spatial and temporal memory system, and two or more of the spatial and temporal memory systems are provided with different fields of input data, and/or different encodings of the fields, and/or different time aggregations of the data. Temporal sequences of spatial patterns are identified at each spatial and temporal memory system based on the provided subset of input data.

[0011] The features and advantages described in the specification are not all inclusive and, in particular, many additional features and advantages will be apparent to one of ordinary skill in the art in view of the drawings and specification. Moreover, it should be noted that the language used in the specification has been principally selected for readability and instructional purposes, and may not have been selected to delineate or circumscribe the inventive subject matter.

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] The teachings of the embodiments of the present invention can be readily understood by considering the following detailed description in conjunction with the accompanying drawings.

[0013] FIG. **1**A is a conceptual diagram of a single Spatial and Temporal Memory System (STMS) processing node in a non-hierarchical system, according to one embodiment.

[0014] FIG. **1**B is a conceptual diagram illustrating a Hierarchical Spatial and Temporal Memory System (HTMS) including three layers of processing nodes, according to one embodiment.

[0015] FIG. **2** is a conceptual diagram illustrating an HTMS with multiple processing nodes at lower levels, according to one embodiment.

[0016] FIG. **3** is a block diagram illustrating an automated search system using STMSs, according to one embodiment.

[0017] FIG. **4** is a flowchart illustrating an overall automated search process, according to one embodiment.

[0018] FIG. **5** is a block diagram illustrating an automated search engine of the automated search system, according to one embodiment.

[0019] FIG. **6**A is a block diagram illustrating a STMS encoder, according to one embodiment.

[0020] FIG. **6**B is a flowchart illustrating the process of encoding data retrieved from database based on configuration information, according to one embodiment.

[0021] FIG. **7** is a graph illustrating an example scheme for encoding entries in a database, according to one embodiment.

[0022] FIG. **8** is a graph illustrating another example scheme for encoding entries in a database, according to one embodiment.

[0023] FIG. **9** is a graph illustrating data values over an example time frame, according to one embodiment.

[0024] FIG. **10** is a graph illustrating aggregated data values of the time frame of FIG. **9**, according to one embodiment.

[0025] FIG. **11** is a block diagram illustrating a processing node of a STMS, according to one embodiment.

[0026] FIG. **12** is a block diagram illustrating a sequence processor of a STMS, according to one embodiment.

[0027] FIG. **13** is a block diagram illustrating a decoder of an automated search system, according to one embodiment.

[0028] FIG. **14** is a conceptual diagram illustrating a process of decoding a node output, according to one embodiment.

[0029] FIG. **15** is a flowchart illustrating a process of decoding a processing node output, according to one embodiment.

[0030] FIG. **16** is a block diagram illustrating a performance evaluator in an automated search engine, according to one embodiment.

[0031] FIG. **17** is a flowchart illustrating a process of evaluating the performance of a STMS, according to one embodiment.

DETAILED DESCRIPTION OF EMBODIMENTS

[0032] In the following description of embodiments, numerous specific details are set forth in order to provide more thorough understanding. However, note that the present invention may be practiced without one or more of these specific details. In other instances, well-known features have not been described in detail to avoid unnecessarily complicating the description.

[0033] A preferred embodiment is now described with reference to the figures where like reference numbers indicate identical or functionally similar elements. Also in the figures, the left most digits of each reference number corresponds to the figure in which the reference number is first used.

[0034] Reference in the specification to "one embodiment" or to "an embodiment" means that a particular feature, structure, or characteristic described in connection with the embodiments is included in at least one embodiment. The appearances of the phrase "in one embodiment" in various places in the specification are not necessarily all referring to the same embodiment.

[0035] Some portions of the detailed description that follows are presented in terms of algorithms and symbolic representations of operations on data bits within a computer memory. These algorithmic descriptions and representations are the means used by those skilled in the data processing arts to most effectively convey the substance of their work to others skilled in the art. An algorithm is here, and generally, conceived to be a self-consistent sequence of steps (instructions) leading to a desired result. The steps are those requiring physical manipulations of physical quantities. Usually, though not necessarily, these quantities take the form of electrical, magnetic or optical signals capable of being stored, transferred, combined, compared and otherwise manipulated. It is convenient at times, principally for reasons of common usage, to refer to these signals as bits, values, elements, symbols, characters, terms, numbers, or the like. Furthermore, it is also convenient at times, to refer to certain arrangements of steps requiring physical manipulations of physical quantities as modules or code devices, without loss of generality.

[0036] However, all of these and similar terms are to be associated with the appropriate physical quantities and are merely convenient labels applied to these quantities. Unless specifically stated otherwise as apparent from the following discussion, it is appreciated that throughout the description, discussions utilizing terms such as "processing" or "computing" or "calculating" or "determining" or "displaying" or "determining" or the like, refer to the action and processes of a computer system, or similar electronic computing device, that manipulates and transforms data represented as physical (electronic) quantities within the computer system memories or registers or other such information storage, transmission or display devices.

[0037] Certain aspects of the embodiments include process steps and instructions described herein in the form of an algorithm. It should be noted that the process steps and instructions of the embodiments could be embodied in software, firmware or hardware, and when embodied in software, could be downloaded to reside on and be operated from different platforms used by a variety of operating systems.

[0038] Embodiments also relate to an apparatus for performing the operations herein. This apparatus may be specially constructed for the required purposes, or it may comprise a general-purpose computer selectively activated or reconfigured by a computer program stored in the computer. Such a computer program may be stored in a computer readable storage medium, such as, but is not limited to, any type of disk including floppy disks, optical disks, CD-ROMs, magnetic-optical disks, read-only memories (ROMs), random access memories (RAMs), EPROMs, EEPROMs, magnetic or optical cards, application specific integrated circuits (ASICs), or any type of media suitable for storing electronic instructions, and each coupled to a computer system bus. Furthermore, the computers referred to in the specification may include a single processor or may be architectures employing multiple processor designs for increased computing capability.

[0039] The algorithms and displays presented herein are not inherently related to any particular computer or other apparatus. Various general-purpose systems may also be used with programs in accordance with the teachings herein, or it may prove convenient to construct more specialized apparatus to perform the required method steps. The required structure for a variety of these systems will appear from the description below. In addition, embodiments are not described with reference to any particular programming language. It will be appreciated that a variety of programming languages may be used to implement the teachings as described herein, and any references below to specific languages are provided for disclosure of enablement and best mode of the embodiments.

[0040] In addition, the language used in the specification has been principally selected for readability and instructional purposes, and may not have been selected to delineate or circumscribe the inventive subject matter. Accordingly, the disclosure set forth herein is intended to be illustrative, but not limiting, of the scope, which is set forth in the claims.

[0041] Embodiments relate to encoding various types of data into a distributed representation format for processing by a STMS. Input data to the STMS may be in a format incompatible for processing by STMS. Hence, an encoder receives the input data in a raw form and converts the input data into a distributed representation form. Different coding schemes may be applied to different data sets and data types to increase the performance of the STMS. In one embodiment, the coding schemes are iteratively modified to increase the performance of the STMS for a given data set. Other aspects of the STMS may also be iteratively modified to improve performance.

[0042] Embodiments also relate to assessing the performance of the STMS. A STMS may exhibit different performance characteristics based on the configuration or parameters of the STMS or based on the coding scheme used, which includes factors such as the encoding used, the time aggregations applied, and the input data that the STMS encodes and processes. The performance of the STMS may be assessed by determining the accuracy of the prediction of the STMS. Performance data representing the predictive performance of the STMS are generated as a result of the assessment. In one embodiment, the predictive performance of the STMS is assessed by comparing predicted input data with actual input data for one or more time steps. Based on the performance data, a desirable combination of coding schemes, node configurations and node parameters may be selected for processing further input data.

[0043] Embodiments also relate to identifying useful relationships between different data fields in a data set using a STMS. The STMS is capable of identifying temporal relationships in data in addition to identifying spatial patterns in the data set. Using the capability of the STMS to identify spatial patterns and temporal sequences, the STMS can more accurately determine relationships in data and make better predictions of future data. Further, different combinations of coding schemes, STMS configurations and STMS parameters may be used to identify useful patterns or sequences in the data.

[0044] A STMS as described herein refers to hardware, software, firmware or a combination thereof that is capable of learning and detecting spatial patterns and temporal sequences of spatial patterns in input data. The STMS stores temporal relationships in sequences of spatial patterns and generates useful information based on the stored relationships. The useful information may include, for example, predictions of spatial patterns to be received, predictions of missing parts of spatial patterns received, identifications of spatial patterns or a higher level causes associated with the spatial patterns in input data. The STMS includes at least one processing node and an encoder. The processing node may be embodied, for example, as described in U.S. patent application Ser. No. 13/046,464 entitled "Temporal Memory Using Sparse Distributed Representation, filed on Mar. 11, 2011 (hereinafter referred to as "the '464 application"), which is incorporated by reference herein in its entirety. In one embodiment, a spatial pooler in the STMS receives input data in a distributed representation and processes the input data for learning and/or predicting.

[0045] A distributed representation described herein refers to a format for representing data. Data in a distributed representation form has a limited number of elements which may number in hundreds to thousands. In a distributed representation form, different data are represented by different combinations of active and inactive elements. Each element in a distributed representation can in theory be assigned an independent meaning or attribute. Thus, a distributed representation is a set of attributes that represent a data element. A special case of the distributed representation form is the sparse distributed representation form, where the number of active (or inactive) elements is comparatively smaller than the total number of elements.

[0046] An coding scheme as described herein refers to a methodology for converting data in a first format to a second format. The first format may be incompatible for processing by a STMS, so conversion to a second format that is compatible for processing by the STMS is required prior to processing by the STMS. The coding scheme may define, among other parameters, the following: (i) the selection of a subset of data fields, (ii) the selection of a subset of data within each data field, (iii) the aggregation of data over certain time intervals, (iv) the conversion of the format from one format to another format (e.g., to a distributed representation format) and (v) the processing or supplementing of data from one source based on data from another data source.

[0047] An experiment as described herein refers to a process of configuring a STMS and processing data using the configured STMS. For each experiment, the STMS is configured to use a particular coding scheme to encode input data with the STMS's encoder into a format for processing by the STMS's processing node and operates with certain node parameters.

[0048] Performance data as described herein refers to data representing the quantification of the predictive performance of a STMS. Performance data may indicate the percentage of accurate predictions made by the STMS or the deviation of a predicted numeric value of input data compared to an actual numeric value in the input data.

[0049] An automated search as described herein refers to the performing of a plurality of experiments to identify predictive models that produce predictions of future data based on a set of given data. The experiments may be performed sequentially or in parallel.

[0050] Node parameters as described herein refer to configurable parameters that affect the operation of a STMS. The configuration parameters may include, for example, the number of processing nodes and their connective relationships, the number of cells or columns in the sequence processors of the processing nodes, the rate of learning and forgetting to prune or expand co-occurrences and sequences, and the permissible range of density (or sparsity) of sparse vectors generated by spatial poolers.

Architecture of a Spatial and Temporal Memory System

[0051] A STMS stores common spatial patterns in a stream of distributed representations, learns temporal relationships in sequences of the spatial patterns, and generates useful information based on the stored relationships. The useful information may include, for example, predictions of spatial patterns to be received, predictions of part of a spatial pattern that is missing, identifications of spatial patterns or temporal sequences, or grouping patterns and sequences by similarity. A STMS may include a plurality of processing nodes or a single processing node, and may be of a non-hierarchical structure or of a hierarchical structure. A STMS with multiple processing nodes structured in a hierarchical manner is hereinafter referred to as Hierarchical Spatial and Temporal Memory System (HTMS).

[0052] FIG. **1**A is a conceptual diagram of a non-hierarchical STMS including a single processing node **104**, according to one embodiment. The processing node **104** receives input data, determines spatial patterns and temporal sequences in the input data and generates an output. The output of the processing node **104** is based on the spatial and temporal relationships between spatial patterns in the input data. The output may include a prediction of future spatial patterns and/or may indicate how well the prediction matched a subsequent spatial pattern in the input data.

[0053] FIG. **1**B is a conceptual diagram illustrating an HTMS including three layers of processing nodes, according to one embodiment. In an HTMS, multiple processing nodes learn, predict and infer input at different levels of abstraction. An example HTMS **100** of FIG. **1**B comprises three levels where each of level L1, L2 and L3 include one processing node **110**, **120** and **130**, respectively. HTMS **100** has three levels L1, L2, L3, with level L1 being the lowest level, level L3 being the highest level, and level L2 being an intermediate level between levels L1 and L3. HTMS **100** processes the input data, and outputs a signal that includes a prediction of future spatial patterns in the input and/or indicates how well the prediction matched a subsequent spatial pattern in the input.

[0054] The processing nodes of the HTMS may be arranged so that the number of processing nodes decreases as the HTMS level increases. FIG. **2** is a diagram illustrating HTMS **200** having three levels L1, L2, L3, with level L1 being the lowest level, level L3 being the highest level, and level L2 being an intermediate level between levels L1 and L3. HTMS **200** is hierarchically structured so that the processing nodes cover a larger input space as the level ascends. Level L1 has nodes **210**A, **210**B, **210**C and **210**D; level L2 has nodes **220**A and **220**B; and level L3 has node **230**. Nodes **210**A, **210**B, **210**C, **210**D, **220**A, **220**B, and **230** are hierarchically connected in a tree-like structure such that each processing node has several children nodes (that is, nodes connected at a lower level) and one parent node (that is, node connected at a higher level).

[0055] Further, HTMS **200** propagates bottom-up signals up the hierarchy as well as propagates top-down signals down the hierarchy. That is, each processing node **210**A, **210**B, **210**C, **210**D, **220**A, **220**B, and **230** may be arranged to (i) propagate information up the HTMS hierarchy to a connected parent node, and (ii) propagate information down the HTMS hierarchy to any connected children nodes. In one embodiment, information propagated down the HTMS hierarchy includes performance data describing the success of a particular experiment. In another embodiment, information propagated down the HTMS hierarchy includes predictions of what sequences the child node is likely to receive next.

[0056] The number of levels or the arrangement of processing nodes in FIGS. **1**A, **1**B and **2** are merely illustrative. Many variants of a STMS system may be developed and deployed depending on the specific application.

[0057] A STMS includes one or more processing nodes and an associated encoder. Some of many functions performed by a processing node include, for example, spatial pooling and temporal processing. The spatial pooling described herein refers to the process of mapping distributed input patterns onto a set of coincidence detectors each of which learns common spatial co-occurrences in the input patterns. The temporal processing may include, but is not limited to, learning temporal sequences, performing inference, recognizing temporal sequences, predicting temporal sequences, labeling temporal sequences and temporal pooling. The learning of temporal sequences described herein refers to one or more of initializing, expanding, contracting, merging and splitting temporal sequences. The prediction described herein refers to assessing the likelihood that certain spatial patterns will appear subsequently in the input data. The temporal pooling described herein refers to processing input data to provide an output that is more stable and invariable over time compared to spatial patterns in the input data. Hardware, software, firmware or a combination thereof for performing the spatial pooling is hereinafter referred to as a spatial pooler. Hardware, software, firmware or a combination thereof for performing the temporal processing is hereinafter referred to as a sequence processor. The sequence processor may perform one or more of learning temporal sequences, performing inference, recognizing temporal sequences, predicting temporal sequences, labeling temporal sequences and temporal pooling.

[0058] In one embodiment, one or more STMSs receive input data representing images, videos, audio signals, sensor signals, data related to network traffic, financial transaction data, communication signals (e.g., emails, text messages and instant messages), documents, insurance records, biometric information, parameters for manufacturing process (e.g., semiconductor fabrication parameters), inventory patterns, energy or power usage patterns, data representing genes, results of scientific experiments or parameters associated with operation of a machine (e.g., vehicle operation) and medical treatment data. The STMS may process such inputs and produce an output representing, among others, identification of objects shown in an image, identification of recognized gestures, classification of digital images as pornographic or non-pornographic, identification of email messages as unsolicited bulk email ('spam') or legitimate email ('non-spam'), prediction of a trend in financial market, prediction of failures in a large-scale power system, identification of a speaker in an audio recording, classification of loan applicants as good or bad credit risks, identification of network traffic as malicious or benign, identity of a person appearing in the image, processed natural language processing, weather forecast results, patterns of a person's behavior, control signals for machines (e.g., automatic vehicle navigation), gene expression and protein interactions, analytic information on access to resources on a network, parameters for optimizing a manufacturing process, predicted inventory, predicted energy usage in a building or facility, web analytics (e.g., predicting which link or advertisement that users are likely to click), identification of anomalous patterns in insurance records, prediction on results of experiments, indication of illness that a person is likely to experience, selection of contents that may be of interest to a user, indication on prediction of a person's behavior (e.g., ticket purchase, no-show behavior), prediction on election, prediction/detection of adverse events, a string of texts in the image, indication representing topic in text, prediction of sales, prediction of needed resources such as number of employees needed on any day or the amount of raw materials needed in a future time period, and a summary of text or prediction on reaction to medical treatments. The underlying representation (e.g., photo, audio, sales data, and etc.) can be stored in a non-transitory storage medium.

[0059] For the sake of simplicity, the following embodiments are described primarily with reference to a non-hierarchical STMS. However, similar or same principle and operations as described herein are equally applicable to an HTMS.

Overall Structure and Operation of an Automated Search System

[0060] FIG. **3** is a block diagram illustrating an automated search system **300**, according to one embodiment. The automated search system **300** may include, among other components, a database or other source of data records **304**, an automated search engine **310**, encoders **320**A through **320**N (hereinafter collectively referred to as the "encoders **320**"), processing nodes **340**A through **340**N (hereinafter collectively referred to as the "processing nodes **340**"), and decoder **390**. One or more of these components in automated search system **300** may be combined into a single module or be divided into multiple modules. Further, each component may be embodied in a single hardware device or may be distributed across multiple hardware devices.

[0061] The automated search engine **310** includes hardware, software, firmware or a combination thereof that manages the overall process of an automated search. The automated search engine **310** may perform, among others, the following functions: (i) receiving and processing a user input **312**, (ii) determining an order of experiments, (iii) selecting coding schemes for encoders **320**, and (iv) configuring the processing nodes **340**. The automated search engine **310** may iteratively perform multiple experiments on data from database **304** in parallel, in series or a combination thereof until predetermined criteria are met. An example of the automated search engine **310** is described below in detail with reference to FIG. **5**.

[0062] The decoder **390** includes hardware, software, firmware or a combination thereof that decodes the node outputs **380**A through **380**N (hereinafter collectively referred to as "node outputs **380**"). The decoder **390** stores parameters of the processing nodes and processes the node outputs **380** to produce the decoder output **395**, which may be used to determine the accuracy of predictions made by the processing nodes **340**, as described below in detail with reference to FIG. **13**.

[0063] Each of the processing nodes **340** in combination with an encoder **320** constitutes a distinct STMS for performing predictions. An example of the processing node **340** is described below in detail with reference to FIG. **11**. Although only non-hierarchical STMSs, each with a single node, are illustrated in FIG. **3**, hierarchically structured STMS with multiple processing nodes may also be used in the automated search system **300**.

[0064] Encoder **320** includes hardware, firmware, software or a combination thereof for encoding data **305** (retrieved from, for example, database **304**) into a format (e.g., distributed representation form) according to a coding scheme. Each encoder **320** is included in a STMS to encode data for processing by an associated processing node **340**. In one embodiment, each encoder **320** is instantiated and configured by the automated search engine **310** to implement the experiments managed by the automated search engine **310**. An example embodiment of an encoder **320** is described below in detail with reference to FIG. **6**A. Although FIG. **3** displays only one encoder **320** for each processing node **340**, the automated search system **300** may assign one encoder **320** to multiple processing nodes **340**.

[0065] The database **304** provides data for analysis and/or processing by the automated search system **300**. Database **304** feeds data **305** to the encoders **320** for conversion into a format compatible for processing with the processing nodes **340**. Database **304** may be embodied on a computing device using conventional technology or technology to be developed in the future. In addition to or alternatively to receiving data **305** from database **304**, the automated search system **300** may receive data from other sources such as point of sale (POS) devices, sensor devices, live or real-time data streams, or external databases (hereinafter referred to as an "external data source").

[0066] The Encoders **320** utilize one or more coding schemes to encode data **305** into encoded input data **330** in a distributed representation form compatible for processing by processing nodes **340**. An encoder **320** retrieves entries from one or more select data fields of the database **304** according to a coding scheme. Each encoder **320** may retrieve data from distinct sets of data fields. For example, encoder **320**A may retrieve entries from a first data field, encoder **320**B may retrieve entries from second and third data fields, encoder **320**C may retrieve entries from fourth and sixth data fields, and so forth. In one embodiment, the encoders **320** select the data fields retrieved by each encoder **320**. In an alternative embodiment, automated search engine **310** selects the data fields each encoder **320** retrieves.

[0067] In one embodiment, the encoders **320** select a coding scheme to use in encoding data **305**, or use a default coding scheme for encoding data **305**. Alternatively, the encoders **320** may receive a coding scheme from the automated search engine **310**. For example, the automated search engine **310** configures or instantiates one or more encoders **320** to encode data **305** using one or more coding schemes. In one embodiment, the automated search engine **310** selects a default coding scheme for use in configuring the encoders **320**, or selects a coding scheme according to a maintained experiment order. Alternatively, as discussed below in detail with reference to FIG. **4**, the automated search engine **310** may select a coding scheme based on the performance of previously selected coding schemes. In addition, coding schemes may be selected based on analysis of the contents of database **304** or based on analysis of selected data fields. For example, the automated search engine **310** analyzes the data stored in two data fields in database **304** to select coding schemes for encoding the data of the two data fields.

[0068] Each of the processing nodes **340** may include, among other components, a spatial pooler (one of spatial poolers **350**A through **350**N, hereinafter "spatial pooler **350**") which outputs a sparse vector **360** (one of sparse vectors **360**A through **360**N) to a sequence processor (one of sequence processors **370**A through **370**N, hereinafter "sequence processor **370**"). A processing node **340** receives encoded input data **330** (one of encoded input data **330**A through **330**N, hereinafter "encoded input data **330**") from an encoder **320**, and the processing node's spatial pooler **350** performs spatial pooling on the encoded data **330** to produce a sparse vector **360**. The sequence processor **370** of the processing node **340** receives the sparse vector **360**, performs sequence processing and produces a node output **380**. The node output **380** includes, among others, a prediction of data to be subsequently received at the processing node **340** or alternately a prediction of part of the data missing in the current input. The detailed operation of the processing nodes **340** is described below in detail with reference to FIGS. **12** and **13**.

Example Operation of an Automated Search System

[0069] Each STMS in the automated search system **300** analyzes, learns and makes predictions based on different perspectives of input data depending on the configuration of the encoders **320** and the processing nodes **340**. A STMS may identify and learn different relationships in data **305** than a different STMS (e.g., a combination of processing node **340**B and encoder **340**B) due to different coding schemes and configurations (e.g., various node parameters). By analyzing, leaning and making predictions on different perspectives of input data, multiple STMSs may identify different patterns and sequences in the input data, and produce useful predictions that would otherwise not be available by using a single STMS. The automated search system **300** automatically experiments with different coding schemes and configurations to determine one or more predictive models describing the input data.

[0070] FIG. **4** is a flowchart illustrating an overall automated search process, according to one embodiment. The automated search engine **310** issues a request **306** and retrieves a subset of entries **306** in the database **304** and/or the external data source **510** for preliminary analysis. The automated search engine **310** performs **410** preliminary analysis of the subset of entries **410**, which may take into account, for instance, the data field type, the data category, the data content, and the data trends or behavior. Based on the preliminary analysis, the automated search engine **310** determines **420** coding schemes and node parameters of the STMSs. The automated search engine **320** can take other factors (e.g., user input) in determining the coding schemes and the node parameters for use by the STMSs.

[0071] In one embodiment, multiple sets of coding schemes and parameters are determined to instantiate or configure multiple sets of encoders and STMSs for operation in parallel, as illustrated in FIG. **3**. In another embodiment, a single coding scheme is determined to instantiate or configure a single STMS at a time. In this embodiment, multiple sets of encoders and STMSs are instantiated or configured in series.

[0072] The determined coding scheme may indicate, among others, which data fields are to be included in each of encoded input data **330**A through **330**N. For example, a first coding scheme may cause an encoder to include converted versions of first and second data fields in the encoded input data while a second coding scheme may cause another encoder to include converted versions of first and third data fields in the encoded input data. A STMS using the first coding scheme may identify spatial and temporal relationships between data entries in first and second data fields whereas a STMS using the second coding scheme may identify spatial and temporal relationships between data entries in first and third data fields.

[0073] The automated search engine **310** instantiates or configures **430** encoders **320** and corresponding processing nodes **340** according to the determined coding schemes and configuration parameters. The automated search system **300** performs **440** experiments using encoders and processing nodes instantiated or configured by the automated search engine **310**. Each experiment includes the process of selectively converting one or more data fields into encoded data input **330**, and then feeding the encoded data input **330** to the STMS's processing nodes. In response to receiving the encoded data input **330**, each STMS generates a node output **380**. More than one set of encoders and processing nodes can be operated simultaneously to expedite the automatic search process.

[0074] Each of the node outputs **380**A through **380**M includes information representing predicted input data. Node outputs **380** are provided to the decoder **390** to obtain decoder outputs **395**. The decoder outputs **395** are fed to the automated search engine **310** to evaluate **450** the predictive performance of STMSs.

[0075] If it is determined **460** that the experiments satisfy predetermined criteria (e.g., reaching a limit of allocated computer time, or accuracy above a particular threshold), a desired predictive model (in the form of the coding scheme used by the encoder and the associated processing node configuration and parameters) is obtained and the process ends. Conversely, if the experiments do not satisfy the predetermined criteria, the coding schemes and parameters are updated **460** based on the evaluation. The process proceeds to instantiating or configuring **430** STMSs and repeats the subsequent steps.

[0076] The processors and their sequences described in FIG. **4** are merely illustrative. Additional steps may be added or omitted from the processes described in FIG. **4**. For example, a predetermined number of encoders and STMSs may be instantiated or configured **430** in parallel, and updating **460** may not be iteratively performed even when the predetermined criteria are not met.

[0077] In one embodiment, the automated search engine **310** maintains a priority or selection of experiments, each experiment associated with a different coding scheme and/or node parameters. The automated search engine **310** modifies priority or selection of experiments based on the predictive performance of STMSs in experiments that were previously performed. Optimization algorithms or other heuristic algorithms may be used to achieve coding schemes, node parameters or a combination thereof exhibiting higher predictive performance in an efficient manner.

[0078] In one embodiment, processing by a STMS is terminated if the performance of the STMS remains low or receives one or more error signals indicating certain types of errors are generated in the STMS. The automated search engine may attempt to debug the errors or launch a new STMS to perform another experiment. In this way, less computing or storage resources are wasted on the STMS that is unlikely to be productive.

Example Architecture of an Automated Search Engine

[0079] FIG. **5** is a block diagram illustrating an automated search engine **310**, according to one embodiment. The automated search engine **310** manages an overall process of instantiating and configuring STMSs (i.e., sets of encoders **320** and processing nodes **340**), performs experiments using the STMSs, evaluates the performance of the STMSs, and identifies one or more STMSs yielding useful predictions. Automated search engine **310** may include, among other components, database interface **500**, performance evaluator **520**, data analysis module **530**, configuration module **540**, and STMS interface **560**.

[0080] The database interface **500** includes hardware, software, firmware or a combination thereof for retrieving data from a database **304** for preliminary analysis and for use in evaluating predictions made by STMSs. Database interface **500** may also request and receive data **508** from an external data source **510** to supplement or as an alternate to data in the database **304**. The external data source **510** may include point of sale (POS) devices, web resources, sensor signals and data provided by users or data vendors. In one embodiment, the database interface **500** stores information on how to correlate certain data fields in the database **304** with data available from the external data source **510**. For example, the database interface **500** stores information identifying that a data field on 'date' in the database **304** can be replaced with 'weather information' corresponding to date field data available from an external data source. The database interface **500** provides sampled data **512** to the data analysis module **530** for preliminary analysis, and also provides raw input data **505** to the performance evaluator **520** for evaluating the predictive performance of a STMS. The raw input data **505** represents fields of data from the database **304** or the external data source **510** that appears in a subsequent entry or time relative to data **305** causing a STMS to generate a decoder output **395** that is being compared with raw input data **505**.

[0081] The data analysis module **530** includes hardware, software, firmware or a combination thereof for performing preliminary analysis of sampled data **512** received from the database **304** and the external data source **510** via the database interface **500**. The sampled data **512** includes a subset of entries from the database **504** and subset of data available from the external database **510**. Based on, for example, data field types, the numerical range of values in the data, data trends or behavior, the data analysis module **530** generates and sends initial configuration information **516** to the configuration module **540**.

[0082] The performance evaluator **520** includes hardware, software, firmware or a combination thereof for evaluating the decoder output **395** to produce performance data **525** that indicates the capability or performance of a processing node **340** in making predictions, as described below in detail with reference to FIG. **16**.

[0083] The configuration module **540** includes hardware, software, firmware or a combination thereof for generating experiment parameters **514** based on one or more of user input **312**, performance data **525**, initial configuration information **516** and previously used experiment parameters. In one embodiment, the configuration module **540** uses an optimization algorithm to compute experiment parameters **514** for a next round of experiments or modifies experiment parameters **514** in a predetermined order of experiments. The configuration module **540** includes the coding scheme manager **550** for selecting coding schemes for a round of experiments. After the configuration module **540** determines one or more data fields to be retrieved at a STMS, the coding scheme manager **550** determines a data encoding for use by an encoder **320** and any parameters for applying the data encoding, as described below in detail in the section entitled "Coding Scheme Selection." The coding schemes selected by the coding scheme manager **550** are included in experiment parameters **514**.

[0084] Experiment parameters **514** define how the encoders **320** and the processing nodes **340** should be instantiated or configured in a current round of experiments. The experiment parameters **514** may define, for example, coding schemes and node parameters for each STMS. A coding scheme defines the manner in which an encoder converts the input data into encoded input data for processing by an associated processing node. The coding scheme defines, (i) the selecting of a subset of data fields, (ii) the selecting of a subset of data within each data field, (iii) the aggregating of data over a time frame, (iv) the conversion of the format from one format to another format (e.g., from a number, enumerated value, or date to a distributed representation format) and (v) the processing or supplementing of data from one source based on data from another data source (e.g., an external data source). The node parameters define, for example, the number of processing nodes and their connective relationships, the number of cells or columns in the sequence processors of the processing nodes, the activation of algorithms to prune or expand co-occurrences, and the permissible range of density (or sparsity) of sparse vectors generated by spatial poolers.

[0085] In one embodiment, user input **312** includes information to facilitate the automated search system **300** to learn and identify patterns and sequences in the input data. If a user knows that a particular set of data fields are likely to be correlated or a certain time aggregation is likely to result in meaningful predictions, the user may input user input **312** to the configuration module **540** to start initial experiments using the user defined parameters and configurations. The user input **312** may also identify an external data source **510** for processing or for supplementing the database **304**.

[0086] The STMS interface **560** includes hardware, software, firmware or a combination thereof for distributing configuration information **315** to one or more STMSs for a round of experiments. The STMS interface **560** receives the experiment parameters **514**, formats the experiment parameters into configuration information (a combination of a coding scheme and node parameters) for each STMS, and transmits the configuration information to each STMS. In one embodiment, multiple STMSs or STMS components are instantiated on computing devices dispersed in different locations. In such an embodiment, the STMS interface **560** converts the configuration information **315** for transmission over a network to the desired computing devices.

Example Architecture and Operation of an Encoder

[0087] FIG. **6**A is a block diagram illustrating an encoder **320** in a STMS, according to one embodiment. The encoder **320** retrieves data from sources, processes the data (as needed) and converts the data into a distributed representation form for feeding into one or more processing nodes **340**. The configuration of the encoder **320** may be reconfigured or updated after a round of experiments is terminated. Alternatively, the configuration of the encoder **320** may be continuously updated during experiments.

[0088] Encoder **320** may include, among other components, a database interface **600**, an external data interface **610**, a configuration module **620**, a data processing module **630**, a time aggregation module **640**, and a distributed representation module **650**. In some embodiments, the encoder **320** may contain fewer or additional modules, and certain functionalities of the encoder **320** may be performed external to the encoder **320**. For example, the functionality of the data processing module **630** or the time aggregation module **640** is performed by the automated search engine **310**. In some embodiments, the functionalities of the components of the encoder **620** may be combined into a single component. For example, the functionalities of the configuration module **620**, the data processing module **630**, the time aggregation module **640** and the distributed representation module **650** are combined into a single processing module.

[0089] The configuration module **620** receives configuration information **315** from the automated search engine **310** and configures other components of the encoder **320** by sending out configuration signals **614**, **618**, **622**, **626** and **628** to implement a coding scheme as identified in the configuration information **315**. Specifically, the configuration module **620** sends a database interface configuration signal **614** instructing the database interface **600** to retrieve certain field(s) of data from the database **304**. For this purpose, the database interface **600** sends queries to the database **304** and receives data **305** as a result. Depending on the data **305** received from the database **304**, the database interface **600** may further extract relevant fields or entries **602** from the data **305** and send them to the time aggregation module **640**.

[0090] A similar process is applicable to the external data interface **610**. That is, the configuration module **620** sends an external configuration signal **644** to configure the external data interface **610** to receive external data **605** from the external data source **510**. The external data interface **610** may further extract relevant fields or entries **604** from the external data **605** and send them to time aggregation module **640**.

[0091] The time aggregation module **640** performs time aggregations on the received data **602**, **604**, and sends the aggregated data **644** to the data processing module **630**. The time aggregation module **640** receives a time configuration signal **618** from the configuration module **620** to perform time aggregation, as described below in detail with reference to FIGS. **9** and **10**. Although the time aggregation module **640** is indicated as being placed between the data source interfaces (i.e., the database interface **600** and the external data interface **610**) and the data processing module **630**, the time aggregation module **640** may be placed between the data processing module **630** and the distributed representation module **650** to perform time aggregation on processed data. If no time aggregation is performed, the extracted fields or entries **602** and **604** may bypass the time aggregation module **640** and feed directly to the data processing module **630**.

[0092] The data processing module **630** performs data processing operations on the aggregated data **644** to generate processed data **630**, according to a preprocessing signal **626** received from the configuration module **620**. The preprocessing signal **626** defines how the data processing module **630** should preprocess data before sending the data to the distributed representation module **650**. The data processing module **630** stores functions **632** to preprocess aggregated data **644** or extracted fields or entries **602** and **604** before conversion to a distributed representation format. One or more functions **632** may be embodied as look-up tables or arithmetic processing units. Representative functions of the data processing module **630** include scalar multiplications and various filtering functions. The data processing module **630** may be bypassed if no further processing is to be performed on the aggregated data **644**. The data processing module **630** may also replace or supplant data in certain extracted data fields or entries **602** from the database **304** with data in extracted fields or entries **604** from the external data source **510**.

[0093] The distributed representation module **650** encodes processed data **634** (or aggregated data **644**, or extracted fields or entries **602** and **604**) to a distributed representation format. For each data field, the distributed representation module **650** converts data entries into a distributed representation format. The distributed representation module **650** then concatenates the converted data entries for different data fields, forming encoded input data **330**. In one embodiment, the distributed representation module **650** stores multiple mapping tables, with each table mapping possible values of each data field to certain distributed representation formats. Details of coding schemes are described in the subsequent section entitled "Coding Scheme Selection."

[0094] Concatenating encoded fields together has the benefit of, among other benefits, allowing a processing node to detect spatial patterns and temporal sequences across more than one data field. Table 1 illustrates an example where a first data field (Field 1) and a second data field (Field 2) each contains 4 data entries in a distributed representation format. The Concatenated Input Data column of Table 1 shows the resulting concatenation of Field 1 and Field 2. Underlined portions of the Concatenated Input Data column entries in Table 1 represent data associated with the entries of Field 2. It should be noted that typical distributed patterns will contain many more bits than in Table 1.

TABLE 1

Data field concatenation example.

	Field 1	Field 2	Concatenated Input Data
data[0]	0010110	$\underline{100}$	0010110$\underline{100}$
data[1]	0110010	$\underline{111}$	0110010$\underline{111}$
data[2]	1001011	$\underline{101}$	1001011$\underline{101}$
data[3]	0100110	$\underline{000}$	0100110$\underline{000}$

[0095] FIG. **6**B is a flowchart illustrating the process of encoding data retrieved from the database **304** and/or the external data source **510**, based on configuration information **315**, according to one embodiment. The encoder **320** receives **652** configuration information **315** from the automated search engine **310**. The encoder **320** then configures **656** components (e.g., the data interface **600**, the external data interface **610**, the time aggregation module **640**, the data processing module **630** and the distributed representation module **650**) according to the configuration information **315**. The configuration information **315** may indicate the inactivation of one or more of the components in the encoder **320**. For example, the time aggregation module **640** or the data processing module **630** is deactivated. In case any of the components are inactive, data may bypass these inactive modules and feed directly to the module subsequent to the inactive modules.

[0096] After the database interface **600** and the external data interface **610** are configured according to configuration information **315**, the database interface **600** interacts with the database **304** or the external data source **510** to retrieve **670** data **305**. The external data interface **610** may also interact with the external data source **510** to retrieve **670** external data **605** from the external data source **510**, as determined by configuration information **315**.

[0097] The database interface **600** or the external data interface **610** may further extract **672** the selected fields **602** and **604** from data **305** and external data **605**. If applicable, time aggregation is performed **674** on the extracted fields **602** and **604**. In addition, preprocessing is performed **678** on the extracted fields **602** and **604** or the aggregated data **644**, if applicable.

[0098] After performing extraction, time aggregation and/or data preprocessing, the resulting data is encoded **682** into a distributed representation form. Encoding **682** may include concatenating multiple encoded data fields into a single binary vector.

[0099] The processes illustrated in FIG. **6**B are merely illustrative. One or more of (i) extracting **672** fields or entries, (ii) performing **674** time aggregation and (iii) preprocessing **678** of data may be omitted. Further, steps may be performed in alternative orders or in parallel. Moreover, different fields of data may undergo different processing. For example, one field may be retrieved from the database **304** and then directly encoded into a distributed representation form while another field may undergo time aggregation or preprocessing before being encoded into a distributed representation form.

Coding Scheme Selection

[0100] Data for analysis may include data fields of various formats. Example data formats include integers, floating-point values, Boolean values and alphanumeric strings. However, a processing node in a STMS may be compatible with only a certain type of data format (e.g., a distributed representation). Hence, in order to process data in a format that is not compatible for processing by a processing node, the data is converted to a compatible data format using a coding scheme, as described herein.

[0101] Generally, coding schemes may be classified into the following three separate categories: (i) category coding schemes for converting data of enumerated types (e.g., alphanumeric strings, integers with limited values, or Boolean values) into a distributed representation, (ii) scalar coding schemes for converting scalar data (e.g., integers and floating-point values) to a distributed representation, and (iii) hybrid coding schemes. The hybrid coding schemes use a combination of category coding schemes and scalar coding schemes to encode a data field. Data used in hybrid coding schemes may be available from a single data source (e.g., a database **304**) or available from multiple sources (e.g., a database **304** and an external data source **510**).

[0102] An example of category coding scheme for encoding time entries into a distributed representation is described herein with reference to Table 1. In this example, suits of cards in a series of cards withdrawn from a card deck are converted to a distributed representation of 5 bits:

TABLE 1

Encoding example by card type.

bit[0]	Club
bit[1]	Diamond
bit[2]	Heart
bit[3]	Spade
bit[4]	Other cards

Using the coding scheme of Table 1, a card of a club suit is converted to a distributed representation of "10000," a card of a diamond suit is converted to "01000," a card of a heart suit is converted to "00100," a card of a spade suit is converted to "00010," and a card not belonging to any of these suits (e.g., joker card) is converted to "00001."

[0103] Table 1 shows a simple encoding scheme using very few bits and where each encoded value is represented by a single bit and there is no overlap between the different encodings. Generally a distributed encoding would use tens or hundreds of bits of which some small percentage are set to "1". In such an encoding scheme the number of different values can be much greater than the number of bits used to represent them. In such a scheme any two randomly chosen encodings would likely share just a few bits in common. Further, it is possible to assign meanings to the individual bits such that encodings with similar meanings would have an overlap that is greater than chance. In this way the STMS can recognize patterns based on the meanings of the encodings.

[0104] An example of a scalar coding scheme is described herein with reference to Table 2. In this example, the price of an item is converted to a distributed representation of 6 bits using a non-overlapping price range. For example, a data entry indicating a price of $25 is encoded to "000100" and data entry indicating a price of $45 is encoded into "010000."

TABLE 2

Encoding example for prices.

bit[0]	$0.00-$10.00
bit[1]	$10.00-$20.00
bit[2]	$20.00-$30.00
bit[3]	$30.00-$40.00
bit[4]	$40.00-$50.00
bit[5]	$50.00-$110.00

[0105] An alternative scalar coding scheme using overlapping ranges is described herein with reference to Table 3. In this example, encoded data in a distributed representation include bits representing overlapping ranges. For example, a coding scheme produces a distributed representation of 6 bits where each bit represents the following price ranges:

TABLE 3

Encoding example for prices.

bit[0]	$0.00-$30.00
bit[1]	$10.00-$40.00
bit[2]	$20.00-$60.00
bit[3]	$40.00-$75.00
bit[4]	$55.00-$100.00
bit[5]	$70.00-$110.00

Using this example encoding, the price $35 is encoded as the distributed representation "000110", and the price $59 is encoded as the distributed representation "011100". By overlapping numeric ranges corresponding to active bits, encoded data entries with similar numerical values have more bits in common than encoded data entries with dissimilar numeral values. Among other advantages, using data encoded with overlapping numeric ranges facilitates the processing node **340** in learning and classifying spatial co-occurrences in the input data. The same concept of overlapping ranges can be applied to distribute representations using tens or hundreds of bits.

[0106] FIG. **7** is a graph illustrating an example of a scalar coding scheme using overlapping ranges (i.e., buckets), according to one embodiment. Bits of a distributed representation with overlapping ranges may be visualized using overlapping buckets. The embodiment of FIG. **7** displays an example distribution curve **710** of exam scores where buckets A through I are distributed evenly along the exam score axis. This scalar coding scheme produces a distributed representation bit for each of the 9 buckets, where the distributed representation bit is a "1" if a particular exam score falls within a particular bucket. For example, exam score X is encoded as the distributed representation "011100000", exam score Y is encoded as the distributed representation "000111000", and exam score Z is encoded as the distributed representation "000011100".

[0107] To provide better resolution for data in a particular range, buckets may be distributed unevenly, concentrating the distribution of the buckets around particular values. FIG. **8** is a graph illustrating another example scalar coding scheme for the same distribution curve **710** but with buckets A' through I' placed differently compared to the example of FIG. **7**. Since the exam scores are distributed along a bell curve centered at the exam score "75," a scalar coding scheme clustering buckets around a median exam score (e.g., around 75) provides better resolution of data compared the scalar coding scheme of FIG. **7**. In the coding scheme of FIG. **8**, exam score X is encoded as the distributed representation "011000000", exam score Y is encoded as the distributed representation "001111100", and exam score Z is encoded as the distributed representation "000011110". In one embodiment, a preliminary analysis performed by the data analysis module **530** of the automated search engine **310** includes identifying such a concentration of data values. Based on the identification, scalar coding schemes for the encoders **320** may be configured for more efficient operations.

[0108] An example of a hybrid coding scheme is described herein with reference to table 4. In this example, encoded data in a distributed representation form includes bits indicating disparate information about the same date where bits in encoded data represent the following:

TABLE 4

Encoding example for dates.

bits[6-0]	Day of the week: Mon = 0000001, Tues = 0000010, etc.
bit[18-7]	Month of the year: Jan = 000000000001, Feb = 000000000010, etc.
bit[19]	Holiday?: yes = 1, no = 0
bit[20]	First half of month?: yes = 1, no = 0
bits[23-21]	Weather?: rain = 001, cloudy, no rain = 010, sunny = 100

Using this example encoding, the date Dec. 28, 1981 is encoded as the distributed representation (assuming it was raining) "001001000000000000000001". The encoding scheme for Table 4 involves both category coding schemes and scalar coding schemes. That is, bits [**6-0**], [**19**], [**20**] and [**23-21**] are encoded using category encoding schemes whereas bit [**18-7**] are encoded using a scalar encoding scheme.

[0109] Another example of a hybrid coding scheme involves encoding data for a data field representing countries. Countries are an enumerated data type. However, scalar data associated the countries may be encoded using a category coding scheme or a scalar coding scheme. For example, the coding scheme may generate encoded data to include bits related to location of a country (e.g., "001" if the country is located within North America, and "010" if the country is located in Asia), bits representing the land size of the country, bits representing the population of the country, bits representing the type of government of the country, and bits representing major industries of the countries. In this example, the name of countries, the continental location of the countries and the major industries of the countries are encoded using a category coding scheme while the other data are encoded using a scalar coding scheme.

[0110] Some coding schemes may cascade multiple coding schemes or the preprocessing of data. Such coding schemes include a logarithmic coding scheme which converts input data into log values, and then encodes the log values to a distributed representation format using a scalar coding scheme.

[0111] A coding scheme also defines whether input data should be aggregated over a particular time interval. Either the preliminary analysis of data by the automated search engine **310** or the user input **312** may indicate that spatial patterns or temporal sequences are likely to be identifiable if the data was aggregated over particular time intervals. In such cases, the automated search engine **310** may indicate a time aggregation to be performed as part of a coding scheme, and an encoder may perform the time aggregation on data field entries as indicated by the coding scheme. The aggregation may be performed using different methods (e.g., summing, averaging, or multiplying values in data entries) depending on the nature of the data. The time interval for aggregation may be uniform or unequal depending on the application and the nature of input data.

[0112] FIG. **9** is a graph illustrating the number of purchases made hourly over a day. For example, in hour 2, 8 purchases were made and in hour 17, 5 purchases were made. FIG. **10** is a graph illustrating the number of purchases made in 4-hour time periods over a day for the same data set as FIG. **9**, according to one embodiment. A STMS using data aggregated over the 4-hour time periods may identify the general trend (e.g., decreasing purchases over time) which could not be identified in data that are not aggregated over time. By varying time aggregations, various spatial patterns or temporal sequences may be identified by STMSs that would otherwise be unidentifiable or difficult to identify.

[0113] As described above with reference to FIG. **5**, the automated search engine **310** is responsible for selecting or creating a coding scheme for each encoder **320**. Specifically, the configuration module **540** of the automated search engine **310** analyzes various factors such as the user input **312**, the initial configuration information **516** and the performance data **525** of previous experiments to determine coding schemes for a subsequent round of experiments. User input **312** may indicate a user preference of a particular coding scheme or certain processing node parameters (e.g., the use of a category coding scheme or a scalar coding scheme and time aggregation parameters).

[0114] Initial configuration information **516** is generated as result of the preliminary analysis by the data analysis module **530** taking into account data types in the data fields of the database **304**, the general range of values in certain data fields of the database **304**, and the distribution or trend of fluctuation in the data values in the data fields of the database **304**. Initial configuration information **516** may also indicate the preprocessing of data before the conversion to a distributed representation form, such as: (i) the conversion of integer values to floating point values, (ii) the identification of data corresponding to the data entries of the database **304** using a look-up table, (iii) the multiplication by a scalar value, and (iv) the application of a function or transform to the data (e.g., a linear, logarithmic, or dampening function, or a Fourier transform) to change the range of data values. Alternatively, the configuration module **540** may store and use default coding schemes for an initial round of experiments without performing preliminary analysis.

[0115] Performance data **525** indicative of predictive performance of a STMS in a round of experiments may be taken into account to configure STMSs for further rounds of experiments. Various types of optimization algorithms may be used to improve configurations of STMSs over multiple rounds of experiments or to prematurely end experiments that do not look promising.

Example Functions and Operations of a Processing Node

[0116] FIG. **11** is a block diagram illustrating a processing node **340** of a STMS, according to one embodiment. The functions and operations of the processing node **340** are described in further detail in the '464 application, and are briefly described herein for the sake of brevity. As shown in FIGS. **1** and **2**, processing nodes **340** may operate as standalone nodes or may operate as part of a hierarchy of processing nodes to detect spatial patterns and temporal sequences, and to perform predictions or inference based on the learned patterns and temporal sequences.

[0117] The processing node **340** may include, among other components, a spatial pooler **350** and a sequence processor **370**. The spatial pooler **350** receives encoded input data **330**, performs spatial pooling, and outputs a sparse vector **360** to the sequence processor **370**. The sparse vector **360** includes information about co-occurrences (stored spatial patterns that were learned from the data) detected in the encoded input data **330**. The sequence processor **370** receives the sparse vector **360** from the spatial pooler **350**, performs temporal processing, and outputs a node output **380**. The node output **380** includes information on the detected temporal sequences of spatial patterns and the prediction of temporal sequences in the encoded input data **330**.

[0118] Spatial pooling is the process of forming a sparse distributed representation from a distributed input pattern. The output bits of the spatial pooler are learned common co-occurrences of input bits. Referring to FIG. **11**, the spatial pooler **350** may include, among other components, a sparsity generator **1360** and a plurality of co-occurrence detectors (CDs) **1140**A through **1140**Z (hereinafter referred to as "CDs **1140**"). In one embodiment, each CD **1140** is mapped to a subset of elements in the encoded input data **330**. As illustrated in FIG. **11** by lines extending from the CD **1140**A to a subset **1120** of arrows representing input data bits, the CD **1140**A is mapped to receive a subset **1120** of elements from bits [**0**:**8**] of the encoded input data **330**. Similarly, the CD **1140**B is mapped to receive a subset **1130** of elements from bits [**9**:**17**] of the encoded input data **330**. In order for the CDs **1140** and the spatial pooler **350** to operate, the encoded input data **330** is in a distributed representation form to indicate which of the elements in the encoded input data **330** are active and which are inactive. In FIG. **11** the input bits to each CD are shown as separate and non-overlapping subsets of the encoded input data **330**. This is for clarity only. Generally, the input bits to each CD are overlapping and intermixed.

[0119] The CDs **1140** detect similarity between the spatial patterns of the received subset of elements of the encoded input data **330** and the stored spatial patterns (i.e., co-occurrences), and generate match scores **1350** indicating the degree of detected similarity. In one embodiment, a higher match score indicates greater overlap between the subset of elements of the encoded input data **330** and the associated co-occurrences of each CD **1140**. The match scores **1150** are provided to the sparsity generator **1360**. In response, the sparsity generator **1160** generates the sparse vector **360** in a sparse distributed representation form.

[0120] The sparsity generator **1160** collects the match scores **1350** from the CDs **1140**, and selects a number of CDs **1140** based on their match scores and the match scores of nearby CDs **1140** that satisfy conditions to generate the sparse vector **360**. In one embodiment, when a CD becomes dominant (i.e., the CD has a high match score), the CD inhibits the selection of other CDs within a predetermined range (hereinafter referred to as "an inhibition range"). The inhibition range may extend only to CDs immediately adjacent to the dominant CD or may extend to CDs that are separated from the dominant CD by a predetermined distance. Alternatively, the sparsity generator **1160** may select a subset of CDs with the highest match scores among all CDs in the processing node.

[0121] In one embodiment, the sparse vector **360** may contain one vector element for each CD **1140**. In this embodiment, if a CD is selected by the sparsity generator **1160**, the vector element associated with the CD becomes active. For example, if the spatial pooler **350** contains ten CDs **1140**, and the sparsity generator **1160** selects the first CD and the fourth CD based on the associated match scores **1150**, the sparse vector **360** is (1, 0, 0, 1, 0, 0, 0, 0, 0, 0), where the first and fourth elements are one but other elements are zero. The density (or sparsity) of the sparse vector **360** representing the ratio of selected CDs among all CDs **1340** is governed by the inhibition range and the match score selection threshold value. In another embodiment the CDs output a scalar value and each element in the output **360** of the sparsity generator **1160** is a scalar.

[0122] As the inhibitory range of a dominant CD increases, the density of the sparse vector **360** decreases. Further, as the selection threshold value increases, the density of the sparse vector **360** increases. Conversely, as the inhibitory range of a dominant CD decreases, the density of the sparse vector **360** increases. Also, as the selection threshold value decreases, the density of the sparse vector **360** decreases. The combination of the inhibitory range and the selection threshold value maintains the density (or sparsity) of the sparse vector **360** within a certain range. Alternatively, a fixed number of CDs may be selected from all CDs **1340** based on the match scores **1350**.

[0123] FIG. **12** is a block diagram illustrating a sequence processor **370** of a processing node, according to one embodiment. The sequence processor **370** may include, among other components, a column activator **1200**, column managers **1215**A through **1215**Z (hereinafter collectively referred to as "column managers **1215**") coupled to columns **1210**A through **1210**Z (hereinafter collectively referred to as "columns **1210**"), and an output compiler **1260**. The sequence processor **370** receives the sparse vector **360** from the spatial pooler **350**, performs temporal processing, and outputs a node output **380**. Temporal processing includes various time-based processing of sequential spatial patterns such as the recognizing, predicting or labeling of temporal sequences. The sequence processor **370** learns and stores the transitions between the spatial patterns as represented by the sparse vector **360**. Based on the learned transitions, the sequence processor **370** recognizes and predicts subsequent sparse vectors **360**.

[0124] The sequence processor **370** performs temporal processing by selectively activating cells (and columns **1210**), and learning the previous states of cell activations. The cells learn to anticipate spatial patterns in the encoded input data **330** and activate before the corresponding spatial patterns actually appear in the encoded input data **330**. When a cell becomes active, the cell sends out inter-cell inputs **1240** to other cells to indicate the activation state of the cell. A basic idea behind implementing temporal processing is to have a learning cell, upon activation, detect and store the identities of other active cells. The stored active cells may be currently active and/or may have been previously active. When a cell detects the activation of a threshold number of stored cells via inter-cell inputs **1240**, the cell becomes active and the column **1210** containing the cell outputs an active column output **1250**.

[0125] Based on the connections to other cells, a cell may be activated in advance before receiving column activation signals **1205** indicating a corresponding column to be activated, or a "prediction". In one embodiment, with exposure to repeated temporal sequences, the cells make connections to earlier activation states of other cells; hence, the cells become activate earlier in time and make longer term predictions. For each cell, the sequence processor **370** may tally a cell confidence score indicating how likely the advanced activation of the cell will be followed by a column activation signal. In one embodiment the confidence score is calculated by determining the percentage of times a predicted cell was followed by a column activation. A high confidence score indicates that early activation of the cell is very likely to be predictive of a corresponding spatial pattern whereas a low confidence score indicates that early activation of the cell was not as often followed by a corresponding spatial pattern.

[0126] In some embodiments, a column of the sequence processor **370** is activated when any cell in the column is activated. In such embodiments, a column confidence score may be adopted to indicate the predictive performance at the column level. The column confidence score indicates how likely the advanced activation of the column (based on early or predictive activation of any cells in the column) will be subsequently followed by a column activation signal indicating the activation of the cell.

[0127] The column activator **1200** receives the sparse vector **360** from the spatial pooler **350**. In response, the column activator **1200** generates column activation signals **1205** indicating which columns to activate based on the sparse vector **360**. Each column **1210** is connected to an associated column manager **1215** and contains a number of cells. Each column manager **1215** receives the column activation signal **1205**, determines activation states of cells in the column (based on the activation signal **1205**), and sends a select signal **1220** to activate one or more cells in the column **1210**. The activated cells then learn a temporal sequence by making connections to active cells in other columns **1210** through inter-cell inputs **1240**. Although not shown in FIG. **12**, inter-cell inputs **1240** may exist between each pair of columns and even between cells in the same column. The column activator **1200** receives the sparse vector **360**, determines which elements of the sparse vector **360** are active, and sends column activation signals **1205** to corresponding columns **1210** to activate these columns **1210**. In one embodiment, the output compiler **1260** collects the outputs from the columns **1210** and concatenates these outputs as the node output **380**.

Decoding of Node Output

[0128] The decoding of the node output **380** herein refers to converting the node output **380** into values or parameters predicted to be received at a corresponding STMS. The predicted values or parameters may be entry values for data fields in the database **304**, values of the external data **605**, or intermediate values or parameters generated at different stages of processing at a STMS. The decoding may be performed for various reasons, including for determining the accuracy of prediction at a STMS, as described in the section entitled "Performance Evaluation of a Spatial and Temporal Memory System," and for generating a prediction to be used by a person or program.

[0129] Decoding can be performed at different levels of STMS processing. The complete decoding of the node outputs **380** may be advantageous, for among other reasons, because errors or irregularities at the encoders **320** or the spatial poolers **350** will have less effect on the decoded data. Corruption of data and any inadequate processing by the encoders **320** or the spatial poolers **350** may be removed or reduced when the reverse processing of the encoders **320** and the spatial poolers **350** is performed. Complete decoding is also useful to output a prediction in the form of the original data. Partially decoding the node outputs **380** to the sparse vector **360** format (hereinafter referred to as a "sequence probability vector") or to the encoded input data **330** format (hereinafter referred to as a "predicted spatial pooler input") may also be performed. Partially decoding the node outputs **380** consumes less computing resources and can also be used to identify issues with the encoders **320** and the spatial poolers **350**.

[0130] FIG. **13** is a block diagram illustrating the decoder **390**, according to one embodiment. The decoder **390** may include, among other components, a STMS interface **1300**, a reverse sequence processor **1310**, a reverse spatial pooler **1320**, and a reverse encoder **1330**. The STMS interface **1300** receives and caches the node output **380**. The node output **380** includes predictions on input data to be subsequently received at the STMS. The STMS interface **1300** then forwards the node output **380** to the reverse sequence processor **1310** for processing. For simplicity, the decoder **390** will be described in terms of receiving a single node output **380** from a single processing module **340**, but it should be noted that a decoder **390** may receive and decode node outputs **380** from any number of processing modules **340**. In addition, although only one decoder **390** is illustrated in FIG. **3**, any number of decoders **390** may be implemented in the automated search system **300**. More than one decoder may be provided in the automated search system **300** to decode node outputs **380** from different STMSs.

[0131] In one embodiment, the STMS interface **1300** receives STMS information **1342** from the STMS whose node output **380** is being decoded. The STMS information **1342** includes information associated with the learned patterns and sequences at the STMS and the coding schemes for the encoder of the STMS. The STMS interface **1300** analyzes the STMS information and sends out the sequence processor information **1315**, the spatial pooler information **1325**, and the encoder information **1335** to the reverse sequence processor **1310**, the reverse spatial pooler **1320** and the reverse encoder **1330**, respectively. The sequence processor information **1315** may include, among other information, the sequence processor configuration parameters (e.g., the number of sequence processor cells and columns), the data stored in the temporal memory segments, and any other information related to the operation of the sequence processor **370**. The spatial pooler information **1325** may include, among other information, the spatial pooler configuration parameters (e.g., the number of co-occurrence detectors), the mappings between CDs **1340** and the subsets of elements in the encoded input data **330**, and any other information related to the operation of the spatial pooler **350**. The encoder information **1335** may include, among other information, information related to the coding schemes and any other information related to the operation of the encoder **320**. The sequence processor **1310**, the reverse spatial pooler **1320** and the reverse encoder **1330** are configured accordingly to decode the node output **380**.

[0132] FIG. **14** is a conceptual diagram illustrating a process of decoding the node output **380**, according to one embodiment. In the example of FIG. **14**, the decoder **390** decodes the node output **380** generated by a sequence processor of a processing node having 8 columns, each column including 4 cells. The reverse temporal pooler **1310** copies the same column and cell structure of the counterpart processing node. Hence, the reverse temporal pooler **1310** also has 8 columns, each column including 4 cells.

[0133] As described above with reference to FIG. **11**, a cell confidence score indicates how likely the advanced activation of the cell will indeed be followed by a column activation signal in the sequence processor **370**, indicating the activation of the column. For decoding, the confidence scores **1400** of cells are copied from the sequence processor **370** of a corresponding processing node and stored in the reverse temporal pooler **1310**. In this example, a confidence scores takes a value not over 1 and not less than 0, and represents the percentage of time that the prediction of the cell output was accurate. For example, a confidence score of 0.7 indicates that the advanced activation of the corresponding cell in a column was followed by encoded input data activating the column 70% of the time.

[0134] In one embodiment, the reverse temporal pooler **1310** determines the highest cell confidence scores in the active columns and determines the sequence probability vector **1410**. The sequence probability vector **1410** is similar to the sparse vector **360** fed to the sequence processor **370** in a processing node with the exception that the active elements in the sequence probability vector **1410** are represented in probability values rather than integer values of 1 or 0 to account for the fact that the sequence probability vector **1410** is a predicted sparse vector derived from the node output **380** rather than an actual sparse vector **360** generated from the encoded input data **330**. Sequence probability vector **1410** is assembled by assigning the column confidence scores of active columns (having a "1" value in the corresponding elements of the node output **380**) to the corresponding elements in the sequence probability vector **1410** while assigning a value of zero to the elements of the sequence probability vector **1410** corresponding to the inactive elements in the node output **380**.

[0135] In the example of FIG. **14**, the elements of the node output **380** associated with the columns 0, 2, 6 and 7 are active and the other active node elements are inactive. For the active columns, the highest cell confidence score for all cells in the column is taken as the column confidence score. For example, for column 0, cell 4 has the highest cell confidence score of 0.7, and hence, the column confidence score for column 0 is set to 0.7. For column 2, cell 2 has the highest confidence score of 0.3, and hence, the column confidence score for column 2 is set to 0.3. After determining the column confidence scores, the reverse temporal pooler **1310** generates the sequence probability vector **1410** by assigning the column confidence scores to elements corresponding to the active columns while assigning zeros to the inactive columns. In the example of FIG. **14**, the sequence probability vector **1410** is (0.7, 0, 0.3, 0, 0, 0, 0.5, 0.8).

[0136] In an alternative embodiment, all cell confidence scores **1400** of a column are added or averaged to obtain a column confidence score of the same column instead of taking the highest cell confidence score of cells in the column.

[0137] The reverse spatial pooler **1320** receives the sequence probability vector **1410** and determines the predicted spatial pooler input **1440** based on the mappings **1420** between the elements of the sequence probability vector **1410** and the elements of the predicted spatial pooler input **1440**. The predicted spatial pooler input **1440** is similar to the encoded input data **330** fed to the spatial pooler **350** except that the elements in the predicted spatial pooler input **1440** are represented in probability values rather than an integer value of 0 or 1 to account for the fact that the predicted spatial pooler input **1440** is a prediction of the encoded input data to the spatial pooler **350** rather than the actual encoded input data. The mapping between the elements of the sequence probability vector **1410** and the elements of the predicted spatial pooler input **1440** are the same as mappings between the CDs in the spatial pooler **350** and the encoded input data **330** (refer to FIG. **11**).

[0138] One way of generating the predicted spatial pooler input **1440** is to assign an average value of the sequence probability vector elements mapped to a spatial pooler input element as the value for the same spatial pooler input element. Taking the example of the mapping **1420** in FIG. **14**, bit [**0**] of the predicted spatial pooler input **1440** is not mapped to any non-zero elements of the sequence processor probability vector **1410**. Hence, bit [**0**] of the predicted spatial pooler input **1440** takes a value of zero. Bit [**1**] of the predicted spatial pooler input **1440** is mapped only to the first element of the sequence processor probability vector **1410** (having a value of 0.7), and hence, the value of 0.7 is assigned to bit [**1**] of the predicted spatial pooler input **1440**. Similarly, bit [**4**] of the predicted spatial pooler input **1440** is mapped only to the third element of the sequence probability vector **1410** (having a value of 0.3), and hence, the value of 0.3 is assigned to bit [**4**] of the predicted spatial pooler input **1440**. On the other hand, bit [**7**] of the predicted spatial pooler input **1440** is mapped to both the first element (having value of 0.7) and the 99th element (having value of 0.5) of the sequence probability vector **1410**, and hence, the value of 0.6 (the average of 0.7 and 0.5) is assigned to bit [**7**] of the predicted spatial pooler input **1440**. The reverse spatial pooler **1320** populates all the bits of the predicted spatial pooler input **1440** by averaging values of the elements in the sequence probability vector **1410** mapped to each bit of the predicted spatial pooler input **1440**.

[0139] The reverse spatial pooler **1320** may apply functions other than the determining the average to elements of the sequence processor probable vector **1410** to produce elements of the predicted spatial pooler input **1440**. In one embodiment, the reverse spatial pooler **1320** determines values for each element in the predicted spatial pooler input **1440** by taking the maximum value of the sequence processor probability vector elements mapped to the element of the predicted spatial pooler input **1440**. Alternatively, the reverse spatial pooler **1320** may determine values for each element in the predicted spatial pooler input **1440** by taking the sum, the average or the median value of the sequence processor probability vector elements mapped to the element of the predicted spatial pooler input **1440**. The reverse encoder **1330** receives the predicted spatial pooler input **1440** and produces the decoder output **395**. The decoder output **395** will be a predicted version of the data **634**. In one embodiment, the reverse encoder **1330** may include, among other components, a segment module **1466**, one or more decoder tables **1450**A and **1450**B (hereinafter collectively referred to as "decoder tables **1450**"), one or more dot product modules **1460**A and **1450**B (hereinafter collectively referred to as "dot product modules **1460**"), and an input translator **1470**. The segment module **1466**, the decoder table **1450**, the dot product module **1460** and the translator **1470** may be configured or instantiated based on the encoder information **1335** received at the reverse encoder **1330**. The number of decoder tables **1450** and dot product modules **1460** may differ depending on the number of encoded data fields concatenated in a corresponding encoder.

[0140] When a corresponding encoder concatenates encoded vectors of multiple fields, the segment module **1466** segments the predicted spatial pooler input **1440** into multiple segments, each corresponding to a data field of the data **305** (or the external data **605**). As described above with reference to FIG. **6**, the distributed representation module **650** concatenates encoded data for each data field into the encoded input data **330**. The segment module **1466** reverses this process and segments the predicted spatial pooler input **1440** into multiple segments. Taking the example of FIG. **14**, a counterpart encoder of the decoder **390** receives two data fields of 50 bits each and concatenates the encoded data fields. The segment module **1466** splits the predicted spatial pooler input **1440** into the segments **1468**A and **1468**B and provides the segments **1468**A and **1468**B to the corresponding dot product modules **1460**A and **1460**B. If a corresponding encoder generates the encoded input data **330** for a single data field without concatenation with vectors of another field, then segmentation of the predicated spatial pooler input **1440** does not occur.

[0141] Each decoder table **1450** is used for decoding a segment of the predicted spatial pooler input **1440** corresponding to a data field. As set forth above in the section entitled "Coding Scheme Selection," each data field of the data **305** and/or the external data **605** is encoded in a different manner. The decoder table **1450** for each segment has a number of columns corresponding to the number of elements in the segment and a number of rows corresponding to each possible unique output data **330** that can be generated for a corresponding data field by a corresponding encoder **320**

[0142] In one embodiment, each element in the decoder table **1450** has a binary value of 0 or 1. Referring to FIG. **6**, the decoder table **1450** is obtained by copying mapping information (e.g., a mapping table) in the encoder **320**, indicating the mapping between values of entries in a data field with a vector in a distributed representation format in the distributed representation module **650** (refer to FIG. **6**). Each row of the decoder table **1450** represents an output vector of encoded input data produced at the distributed representation module **650** in response to receiving a data field value in the processed data **634** (or the aggregated data **644**, or the extracted fields **602** and **604**, depending on whether preprocessing or time aggregation is performed). In the example of FIG. **14**, the decoder table **1450**A has n rows and 50 columns. Hence, the distributed representation module **650** corresponding to the reverse encoder **1330** produces n discrete segments of the encoded input data **330**, with each segment having 50 elements.

[0143] Each dot product module **1460** receives a segment of the predicted spatial pooler input **1440** and performs a dot product operation between a segment of the predicted spatial pooler input **1440** and each row of the decoder table **1450**. Specifically, the dot product module **1460**A computes dot product values for each row of the decoder table **1450**A by performing dot product operations between the segment **1464**A and the row of the decoder table **1460**B. The dot product module **1460**A then determines an index of the row **1464**A that results in the highest dot product value. Similarly, the dot product module **1460**B computes dot products values for the rows of the decoder table **1450**B and the segment **1464**B, producing an index of the row **1464**B that results in the highest dot product value. The dot product modules **1460**A, **1460**B then send the selected table row indices **1464**A and **1464**B to the translator **1470**.

[0144] The translator **1470** receives the row indices **1464**A and **1464**B, identifies the values corresponding to the indices **1464**A and **1464**B, and produces a decoder output **395**. In one embodiment, the translator module **1470** outputs a decoder table row index as the decoder output **395**. In one embodiment, the translator **1470** retrieves the data values corresponding to the received row indices. Such data values represent the predicted values of the data fields fed to the encoder of a corresponding STMS. For example, the encoder **320** receives a scalar value (e.g., 85.27), and encodes the scalar value to an encoded data input segment (e.g., (1, 0, 0, 1, 1, 0, 1)). In this example, a decoder table of a corresponding decoder contains a row with a vector corresponding to the encoded data input segment (e.g., (1, 0, 0, 1, 1, 0, 1)). If the value predicted by the STMS is the same or a similar scalar value (e.g., 85.27), the dot product value for a row (e.g., the 5*th* row) corresponding to the similar scalar value (e.g., 85.27) results in the highest dot product value. The input translator **1470** then identifies the scalar value (e.g., 85.27) by determining a value corresponding to the row (e.g., the 5*th* row). The translator **1470** may output any format of the data value as part of the decoder output **395**.

[0145] In one embodiment, the translator **1470** determines and outputs a range of values for a decoding table row index. For example, if an encoder table has n rows, each representing a range of x, the translator **1470** generates (i) data values between 0 and x in response to receiving a first row index, (ii) data values between x and 2x in response to receiving a second row index, and so forth. Alternatively, the translator **1470** may output midpoint values of the range, values determined by a predetermined function, or a random value within the range.

[0146] FIG. **15** is a flowchart illustrating a process of decoding a processing node output **380**, according to one embodiment. The STMS interface **1300** receives STMS information **1342** from a STMS and configures **1500** the decoder **390** to decode the node output **380**. Specifically, the STMS interface **1300** generates and outputs the sequence processor information **1315**, the spatial pooler information **1325**, and the encoder information **1335** to the reverse sequence processor **1310**, the reverse spatial pooler **1320** and the reverse encoder **1330**, respectively, and configures these components for decoding the node output **380**.

[0147] The decoder **390** receives **1510** the node output **380** generated by the STMS at the STMS interface **1300**. The reverse temporal pooler **1310** determines **1520** the sequence probability vector **1410** by analyzing the cell confidence scores of the columns indicated as being active by the node output **380**.

[0148] The reverse spatial pooler **1320** then processes **1530** the sequence probability vector **1410** and outputs the predicted spatial pooler input **1440**. The reverse encoder **1330**

determines **1540** the predicted values of the data fields based on the predicted spatial pooler input **1440**. Specifically, the segment module **1446** divides up the predicted spatial pooler input **1440** into multiple segments **1468**A and **1468**B corresponding to each data field. The dot product operations are performed on the multiple segments **1468**A and **1468**B at the dot product modules **1460**A and **1460**B using the decoder tables **1450**A and **1450**B to determine the indices of rows having the highest dot product values. The indices **1464**A and **1464**B are sent to the translator **1470** where corresponding values of the predicted data fields are determined based on the indices **1464**A and **1464**B.

[0149] The process of FIG. **15** is merely illustrative. Some of the steps, such as the configuring **1500** and the receiving **1510** steps, can be performed in parallel. Further, additional steps may be performed to verify the accuracy of the decoding at various levels or to enhance the performance of the decoder **390**.

[0150] Although the embodiments described above with reference to FIGS. **13** through **15** fully decode the node output **380** to the format of the data fields received at a corresponding STMS, partial decoding may be performed to produce the sequence probability vector **1410**, the predicted spatial pooler input **1440** or any other information derived therefrom as the decoder output **395**.

Performance Evaluation of a Spatial and Temporal Memory System

[0151] The predictive performance of a STMS may be evaluated in various ways. One way of evaluating the predictive performance is to decode the node output **380** of a STMS, and compare the decoded node output with input data subsequently received at the STMS. The decoded node output may be in the form of the decoder output **395**, described above in detail with reference to FIGS. **13** and **14**.

[0152] FIG. **16** is a block diagram illustrating the performance evaluator **520** in an automated search engine **300**, according to one embodiment. One of the many functions of the performance evaluator **520** is to compare the decoder output **395** and the raw input data **505** to determine the performance data **525**. As discussed above with reference to FIG. **5**, the configuration module **540** receives the performance data **525** and selects a coding scheme based on the performance data **525**.

[0153] The performance evaluator **520** may be one of many components in the automated search engine **310** as illustrated in FIG. **5**, or the performance evaluator **520** may operate as a stand-alone module. The performance evaluator **520** may include, among other components, a prediction accuracy module **1600**, an averaging module **1610**, and a prediction score module **1630**. The prediction accuracy module **1600** receives and performs a comparison between the decoder output **395** and the raw input data **505**, and outputs the result of the comparison **1604** to the averaging module **1610**. The raw input data **505** represents the fields of data from the database **304** or the external data source **510** that appear in a subsequent entry or time relative to the data **305**. That is, the decoder output **395** represents a prediction of future raw input data **505**. By comparing the decoder output **395** and the raw input data **505**, the predictive performance of the STMS can be determined.

[0154] The averaging module **1610** tracks the comparison result **1604**, computes the average score **1614** of the prediction based on the comparison result **1604**, and sends the computed average score **1614** to the prediction score module **1630**. The prediction score module **1630** further processes or formats the averaged score **1614** to generate the performance data **525**. The processing performed at the prediction score module **1630** can normalize the average scores for different types of data being compared at the prediction accuracy module **1600** so that the performance of STMSs can be assessed in a consistent manner across data of different types and varying ranges.

[0155] In one mode of operation, the prediction accuracy module **1600** outputs a "0" if the decoder output **395** and the raw input data **505** are not identical, regardless of the degree of similarity between the decoder output **395** and the raw input data **505**. Such a comparison scheme is applicable, for example, in cases where a category encoding scheme is used by the encoder **320**. When a category encoder is used, the degree of difference in the data may not have a useful meaning. Hence, whether the decoder output **395** and the raw input data **505** are identical may be the sole factor in evaluating the predictive performance of a STMS using a category encoding scheme.

[0156] In another mode of operation, the prediction accuracy module **1600** outputs a result **1604** representing the similarity between the decoder output **395** and the raw input data **505**. The differences may be represented in terms of percentages, in absolute terms, in logarithmic terms or in other suitable manners. When a scalar coding scheme is used for a data field, the similarity or difference between the decoder output **395** and the raw input data **505** has a useful meaning. That is, the difference between the decoder output **395** and the raw input data **505** is inversely related to the accuracy of the prediction of future input data. For a scalar coding scheme, the prediction accuracy module **1600** produces a value representing a difference between the decoder output **395** and the raw input data **505** as the comparison result **1604**.

[0157] When the decoder output **395** represents a range of predicted values, the prediction accuracy module **1600** can generate a value representing the range (e.g., a median value or an average value) for comparison with the raw input data **505**.

[0158] In one embodiment, the prediction accuracy module **1600** receives more than one decoder output **395** and corresponding raw input data **505** simultaneously, and performs multiple comparisons simultaneously.

[0159] In one embodiment, the prediction score module **2030** outputs the performance data **525** for more than one coding scheme. For example, the prediction score module **2030** outputs the prediction scores for two or more coding schemes based on a single comparison by the prediction accuracy module **1600**, or outputs the prediction scores for two or more coding schemes based on running averages of the prediction accuracy for the two or more coding schemes.

[0160] FIG. **17** is a flowchart illustrating a process of evaluating the performance of a STMS, according to one embodiment. The performance evaluator **520** receives **1720** the decoder output **395** and the raw input data **505**. The performance evaluator **520** then compares **1730** the decoder output **395** and the raw input data **505**. Based on the comparison results, the performance evaluator **520** generates **1740** the performance data **525**. The process of generating the performance data **525** may include, among other steps, the averaging and the normalizing of values representing the comparison results.

[0161] Upon reading this disclosure, those of skill in the art will appreciate still additional alternative designs for processing nodes. Thus, while particular embodiments and applications have been illustrated and described, it is to be understood that the invention is not limited to the precise construction and components disclosed herein and that various modifications, changes and variations which will be apparent to those skilled in the art may be made in the arrangement, operation and details of the method and apparatus disclosed herein without departing from the spirit and scope of the present disclosure.

What is claimed is:

1. A method of processing data, comprising
retrieving at least one field of data from one or more data sources including a plurality of records of data;
converting the at least one field of data into encoded input data in a distributed representation format at an encoder; and
detecting spatial patterns or temporal sequences of spatial patterns in the encoded input data at a processing node.

2. The method of claim **1**, further comprising configuring the encoder and the processing node to perform conversion and processing according to configuration information.

3. The method of claim **2**, wherein the one or more data sources comprises one or more of: a database, an external data source, and a data stream.

4. The method of claim **3**, further comprising supplanting or adding data from the external data source to a field of data of the database.

5. The method of claim **1**, wherein converting the at least one field comprises:
converting an entry of a first data field into first encoded data in a distributed representation format;
converting an entry of a second data field into second encoded data in a distributed representation format; and
concatenating the first encoded data and the second encoded data to form the encoded input data.

6. The method of claim **1**, wherein the at least one field of data includes an entry represented by a scalar value, and wherein the conversion comprises determining whether the scale value is within one or more buckets, wherein each bucket defines a numerical range.

7. The method of claim **6**, wherein at least two buckets have overlapping numerical ranges.

8. The method of claim **1**, wherein converting the at least one field comprises:
preprocessing entries in the at least one field of data; and
determining vectors in a distributed representation format corresponding to the preprocessed values.

9. The method of claim **8**, wherein the preprocessing values comprises performing time aggregation on a subset of the values to generate the preprocessed values.

10. A system for processing data, the system comprising:
a data retrieving module configured to retrieve at least one field of data from one or more data sources including a plurality of records of data;
an encoder configured to convert the at least one field of data into encoded input data in a distributed representation format; and
a processing node configured to detect spatial patterns or temporal sequences of spatial patterns in the encoded input data.

11. The system of claim **10**, further comprising a configuration module configured to configure the encoder and the processing node to perform conversion and processing according to configuration information.

12. The system of claim **11**, wherein the one or more data sources comprises one or more of: a database, an external data source, and a data stream.

13. The system of claim **12**, further comprising supplanting or adding data from the external data source to a field of data of the database.

14. The system of claim **10**, wherein converting the at least one field comprises:
converting an entry of a first data field into first encoded data in a distributed representation format;
converting an entry of a second data field into second encoded data in a distributed representation format; and
concatenating the first encoded data and the second encoded data to form the encoded input data.

15. The system of claim **10**, wherein the at least one field of data includes an entry represented by a scalar value, and wherein the conversion comprises determining whether the scale value is within one or more buckets, wherein each bucket defines a numerical range.

16. The system of claim **15**, wherein at least two buckets have overlapping numeral ranges.

17. The system of claim **10**, wherein converting the at least one field comprises:
preprocessing entries in the at least one field of data; and
determining vectors in a distributed representation format corresponding to the preprocessed values.

18. The system of claim **17**, wherein the preprocessing values comprises performing time aggregation on a subset of the values to generate the preprocessed values.

19. A non-transitory computer-readable storage medium storing executable computer program instructions for processing data, the instructions comprising instructions for:
retrieving at least one field of data from one or more data sources including a plurality of records of data;
converting the at least one field of data into encoded input data in a distributed representation format at an encoder; and
detecting spatial patterns or temporal sequences of spatial patterns in the encoded input data at a processing node.

20. The non-transitory computer-readable storage medium of claim **19**, further comprising configuring the encoder and the processing node to perform conversion and processing according to configuration information.

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