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(54) **PRIMARY KEY-FORIEGN KEY RELATIONSHIP DETERMINATION THROUGH MACHINE LEARNING**

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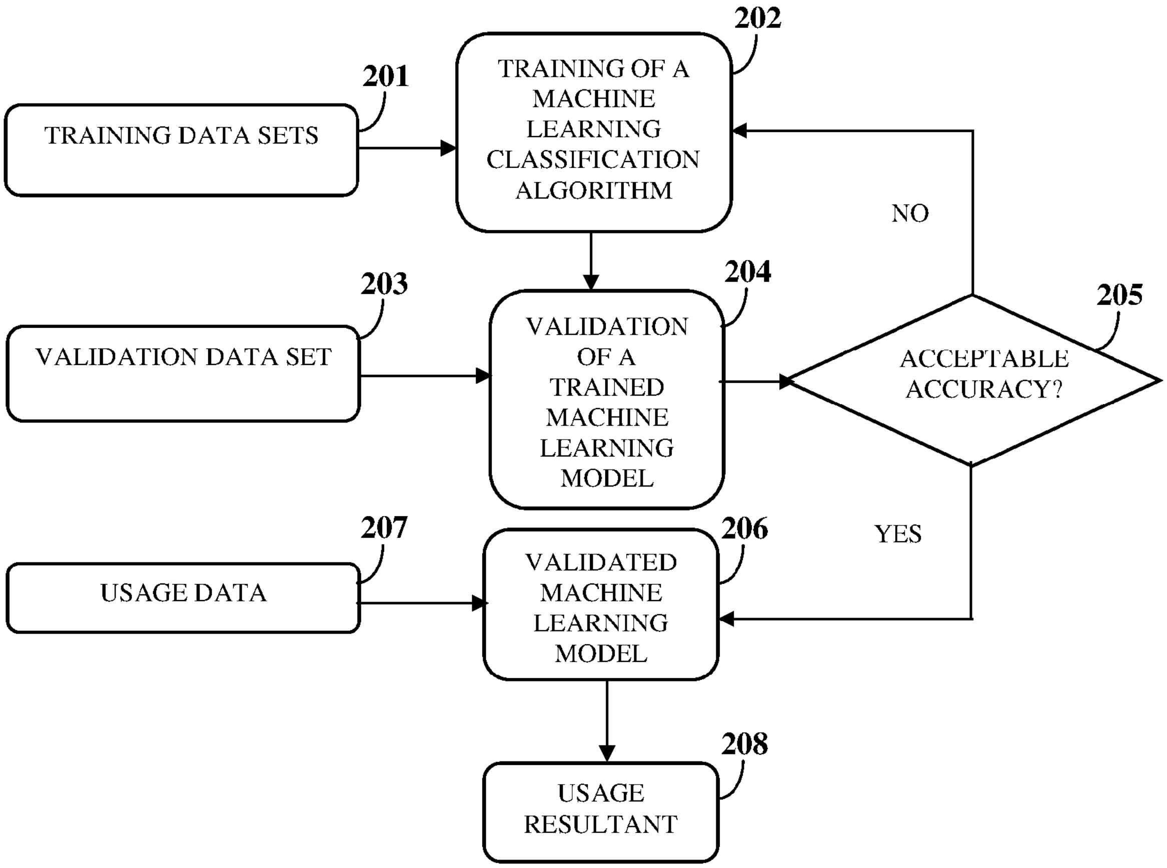
(52) **U.S. Cl.**

CPC ***G06N 99/005*** (2013.01); ***G06F 17/30292*** (2013.01)

(57) **ABSTRACT**

A method and a machine learning relationship determination system (MLRDS) for determining primary key-foreign key (PK-FK) relationships among data in tables of a target database through machine learning (ML) are provided. The MLRDS selects columns of the tables in the target database and identifies inclusion dependency (ID) pairs from the selected columns. The MLRDS receives training data and validation data from a source database, computes PK-FK features for the inclusion dependency pairs, the training data, and the validation data, and generates trained ML models and validated ML models using the PK-FK features. The MLRDS determines an optimum algorithm decision threshold for a selected machine learning classification algorithm (MLCA), using which the MLRDS determines a resultant on whether the inclusion dependency pair is a PK-FK pair or a non-PK-FK pair. The MLRDS performs majority voting on the resultant for multiple MLCAs to confirm the PK-FK relationships between the inclusion dependency pairs.


202
201
TRAINING DATA SETS
TRAINING OF A MACHINE LEARNING CLASSIFICATION ALGORITHM
NO
203
204
205
VALIDATION DATA SET
VALIDATION OF A TRAINED MACHINE LEARNING MODEL
ACCEPTABLE ACCURACY?
207
206
YES
USAGE DATA
VALIDATED MACHINE LEARNING MODEL
208
USAGE RESULTANT

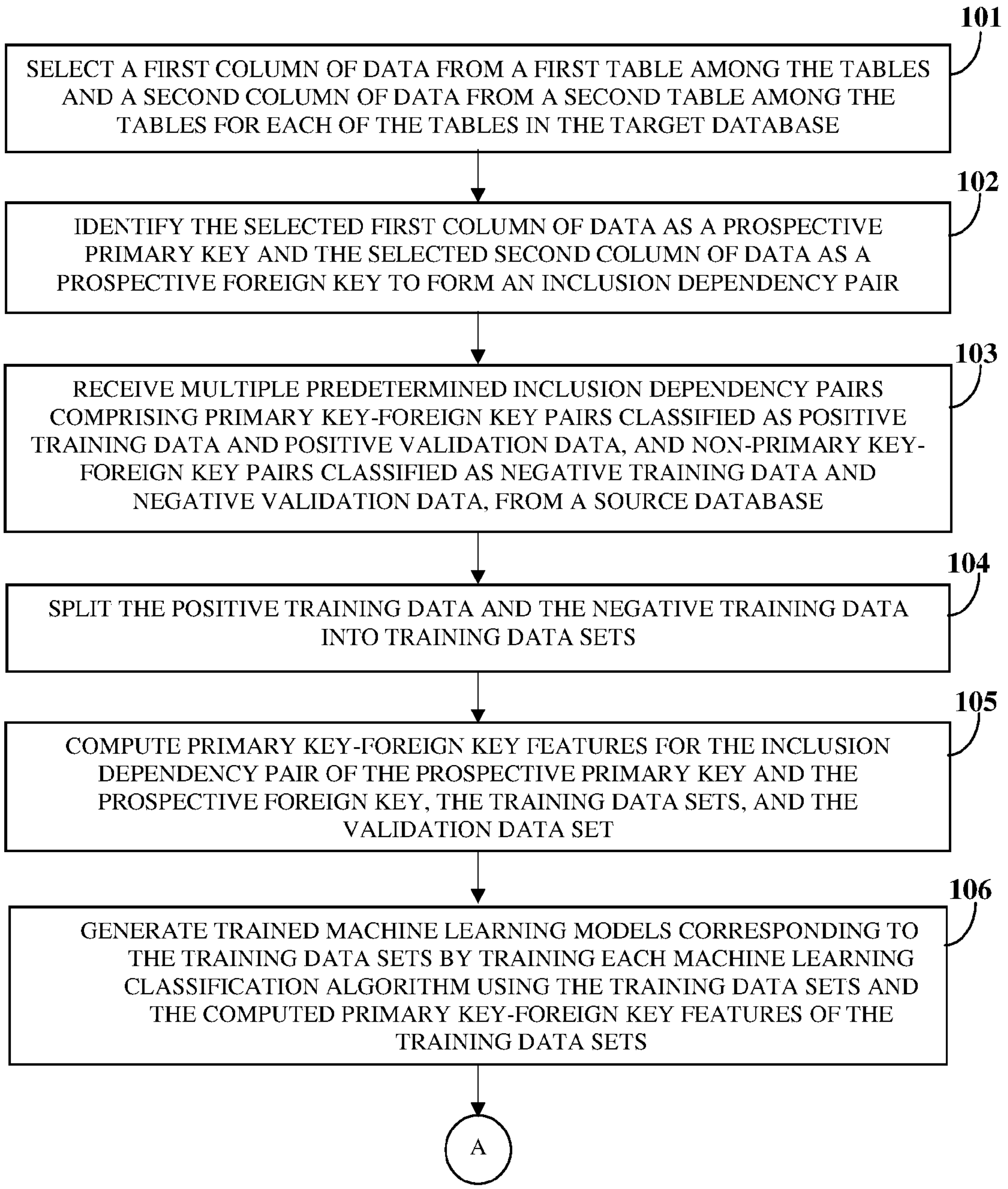

101
SELECT A FIRST COLUMN OF DATA FROM A FIRST TABLE AMONG THE TABLES AND A SECOND COLUMN OF DATA FROM A SECOND TABLE AMONG THE TABLES FOR EACH OF THE TABLES IN THE TARGET DATABASE
102
IDENTIFY THE SELECTED FIRST COLUMN OF DATA AS A PROSPECTIVE PRIMARY KEY AND THE SELECTED SECOND COLUMN OF DATA AS A PROSPECTIVE FOREIGN KEY TO FORM AN INCLUSION DEPENDENCY PAIR
103
RECEIVE MULTIPLE PREDETERMINED INCLUSION DEPENDENCY PAIRS COMPRISING PRIMARY KEY-FOREIGN KEY PAIRS CLASSIFIED AS POSITIVE TRAINING DATA AND POSITIVE VALIDATION DATA, AND NON-PRIMARY KEY-FOREIGN KEY PAIRS CLASSIFIED AS NEGATIVE TRAINING DATA AND NEGATIVE VALIDATION DATA, FROM A SOURCE DATABASE
104
SPLIT THE POSITIVE TRAINING DATA AND THE NEGATIVE TRAINING DATA INTO TRAINING DATA SETS
105
COMPUTE PRIMARY KEY-FOREIGN KEY FEATURES FOR THE INCLUSION DEPENDENCY PAIR OF THE PROSPECTIVE PRIMARY KEY AND THE PROSPECTIVE FOREIGN KEY, THE TRAINING DATA SETS, AND THE VALIDATION DATA SET
106
GENERATE TRAINED MACHINE LEARNING MODELS CORRESPONDING TO THE TRAINING DATA SETS BY TRAINING EACH MACHINE LEARNING CLASSIFICATION ALGORITHM USING THE TRAINING DATA SETS AND THE COMPUTED PRIMARY KEY-FOREIGN KEY FEATURES OF THE TRAINING DATA SETS
A

FIG. 1A

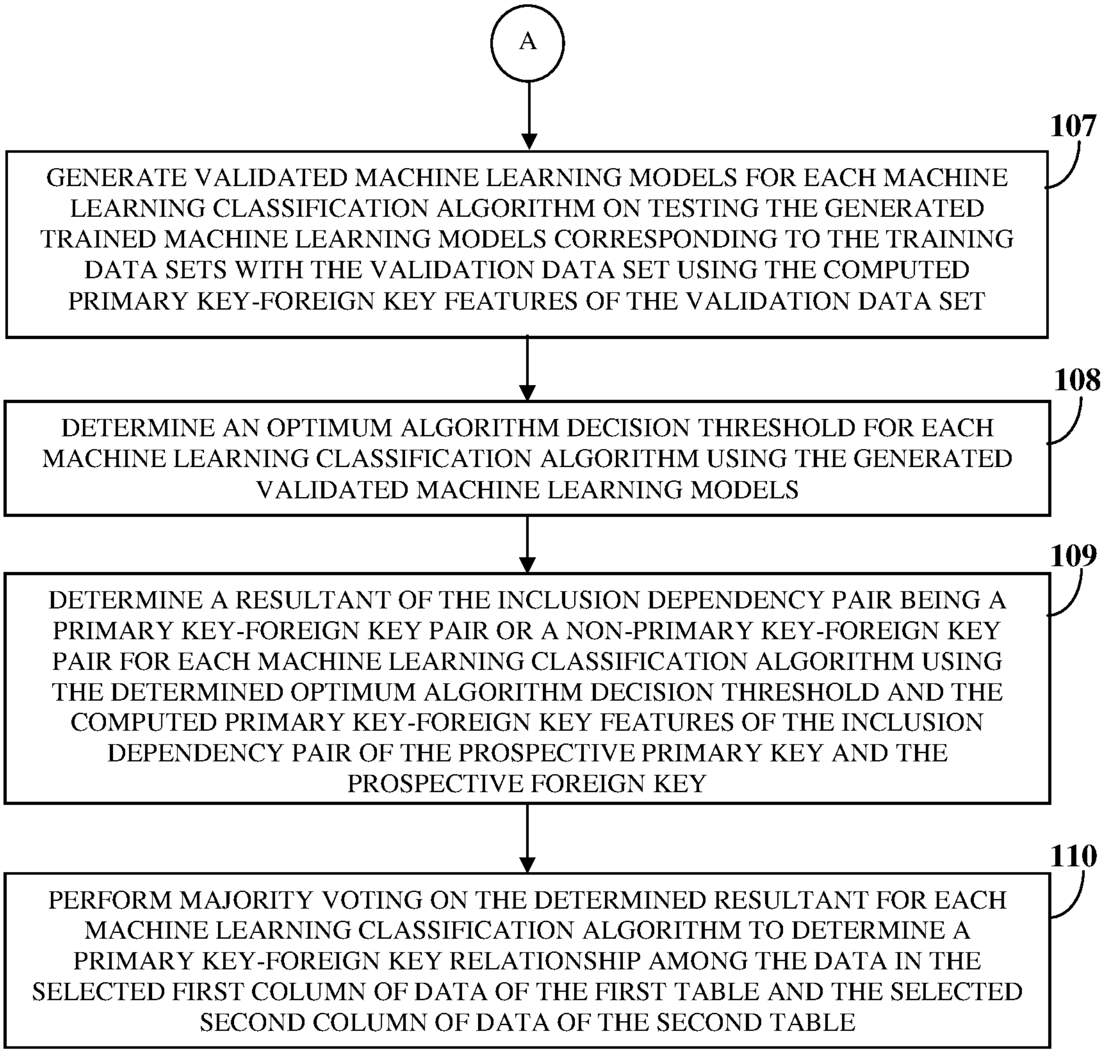

A
107
GENERATE VALIDATED MACHINE LEARNING MODELS FOR EACH MACHINE LEARNING CLASSIFICATION ALGORITHM ON TESTING THE GENERATED TRAINED MACHINE LEARNING MODELS CORRESPONDING TO THE TRAINING DATA SETS WITH THE VALIDATION DATA SET USING THE COMPUTED PRIMARY KEY-FOREIGN KEY FEATURES OF THE VALIDATION DATA SET
108
DETERMINE AN OPTIMUM ALGORITHM DECISION THRESHOLD FOR EACH MACHINE LEARNING CLASSIFICATION ALGORITHM USING THE GENERATED VALIDATED MACHINE LEARNING MODELS
109
DETERMINE A RESULTANT OF THE INCLUSION DEPENDENCY PAIR BEING A PRIMARY KEY-FOREIGN KEY PAIR OR A NON-PRIMARY KEY-FOREIGN KEY PAIR FOR EACH MACHINE LEARNING CLASSIFICATION ALGORITHM USING THE DETERMINED OPTIMUM ALGORITHM DECISION THRESHOLD AND THE COMPUTED PRIMARY KEY-FOREIGN KEY FEATURES OF THE INCLUSION DEPENDENCY PAIR OF THE PROSPECTIVE PRIMARY KEY AND THE PROSPECTIVE FOREIGN KEY
110
PERFORM MAJORITY VOTING ON THE DETERMINED RESULTANT FOR EACH MACHINE LEARNING CLASSIFICATION ALGORITHM TO DETERMINE A PRIMARY KEY-FOREIGN KEY RELATIONSHIP AMONG THE DATA IN THE SELECTED FIRST COLUMN OF DATA OF THE FIRST TABLE AND THE SELECTED SECOND COLUMN OF DATA OF THE SECOND TABLE

FIG. 1B

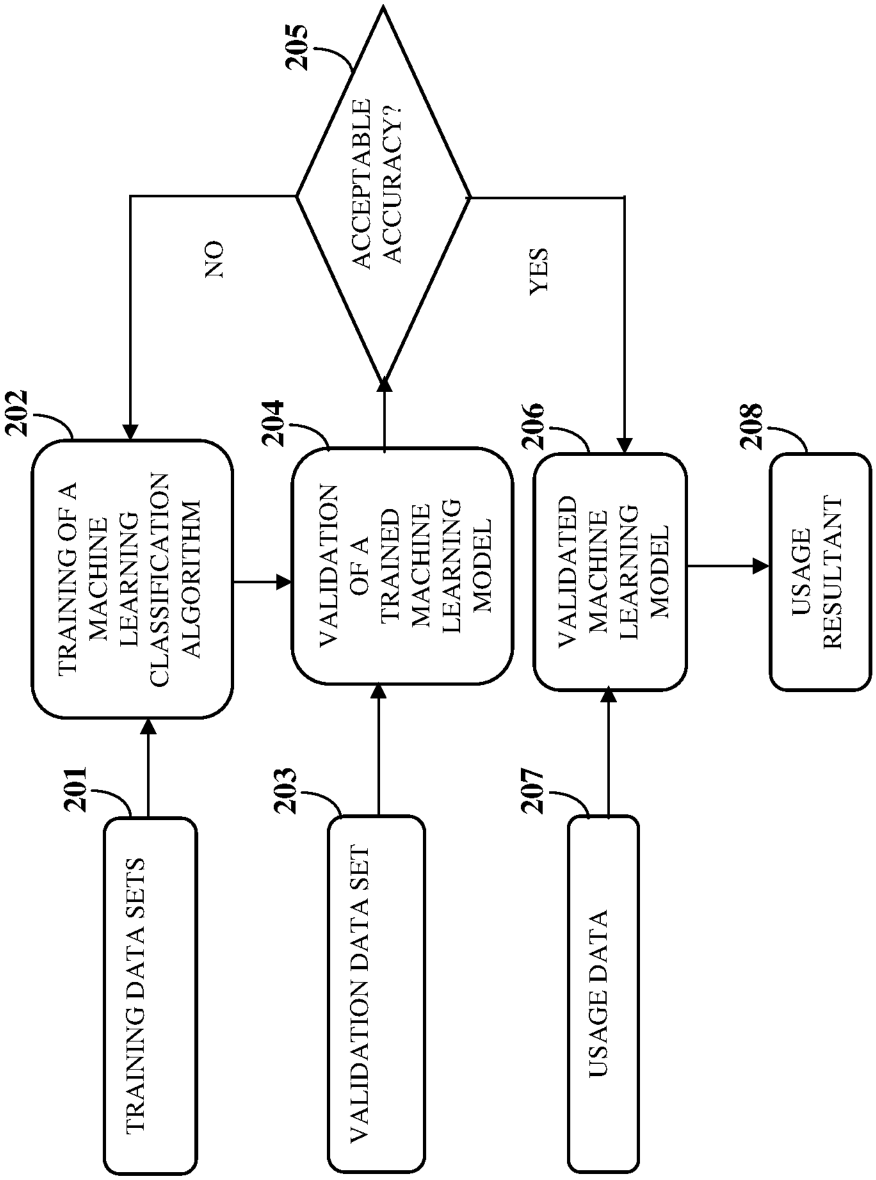
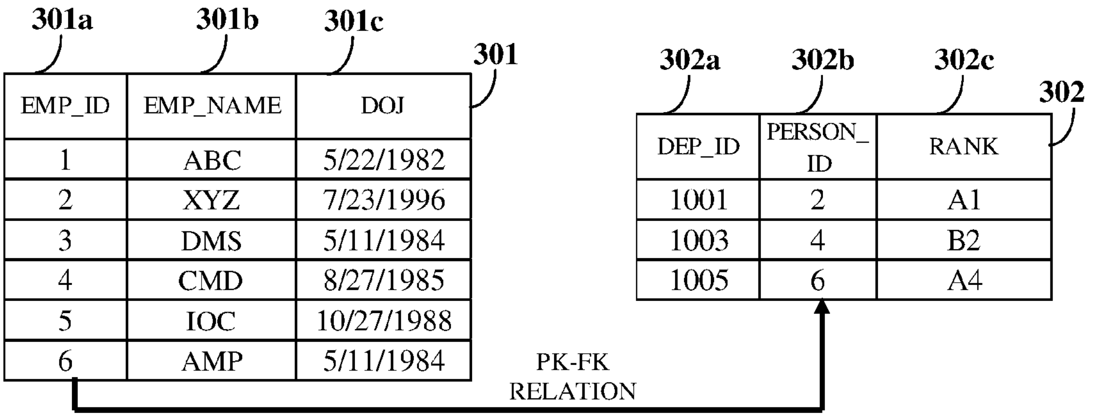

201
TRAINING DATA SETS
202
TRAINING OF A MACHINE LEARNING CLASSIFICATION ALGORITHM
203
VALIDATION DATA SET
204
VALIDATION OF A TRAINED MACHINE LEARNING MODEL
205
ACCEPTABLE ACCURACY?
NO
YES
206
VALIDATED MACHINE LEARNING MODEL
207
USAGE DATA
208
USAGE RESULTANT

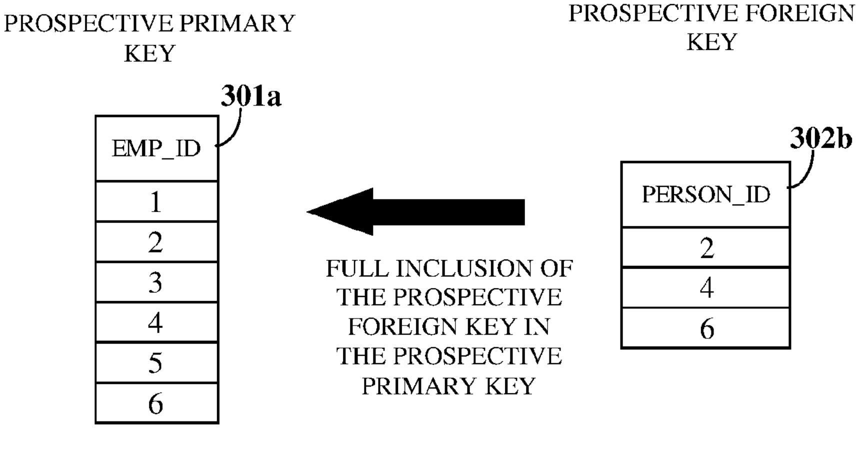
FIG. 2



EMP_ID	EMP_NAME	DOJ
1	ABC	5/22/1982
2	XYZ	7/23/1996
3	DMS	5/11/1984
4	CMD	8/27/1985
5	IOC	10/27/1988
6	AMP	5/11/1984

DEP_ID	PERSON_ ID	RANK
1001	2	A1
1003	4	B2
1005	6	A4

FIG. 3A


PROSPECTIVE PRIMARY KEY
PROSPECTIVE FOREIGN KEY
301a
302b
FULL INCLUSION OF THE PROSPECTIVE FOREIGN KEY IN THE PROSPECTIVE PRIMARY KEY

EMP_ID
1
2
3
4
5
6

PERSON_ID
2
4
6

FIG. 3B

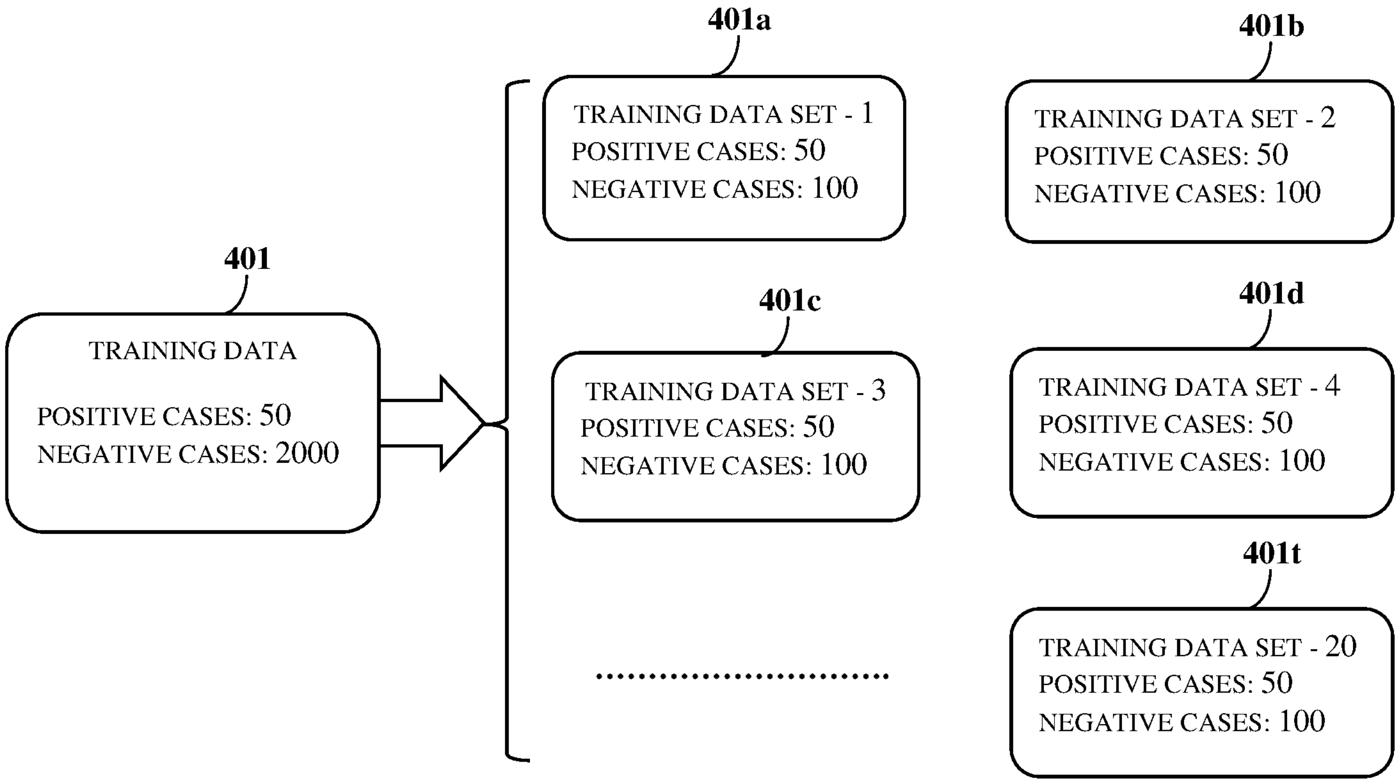

401
TRAINING DATA
POSITIVE CASES: 50
NEGATIVE CASES: 2000
401a
TRAINING DATA SET - 1
POSITIVE CASES: 50
NEGATIVE CASES: 100
401b
TRAINING DATA SET - 2
POSITIVE CASES: 50
NEGATIVE CASES: 100
401c
TRAINING DATA SET - 3
POSITIVE CASES: 50
NEGATIVE CASES: 100
401d
TRAINING DATA SET - 4
POSITIVE CASES: 50
NEGATIVE CASES: 100
401t
TRAINING DATA SET - 20
POSITIVE CASES: 50
NEGATIVE CASES: 100

FIG. 4

501

INSTANCE	ACTUAL RESULT	M-1	M-2	....	M-20	YES COUNT	%YES
1	Y	Y	Y	..	N	12	60
2	N	Y	Y	..	N	4	20
3	Y	Y	Y	..	N	5	25
..	Y	N	Y	..	Y	10	50
..	N	N	N	..	Y	2	10
1200	Y	Y	N	..	Y	14	70

FIG. 5

601

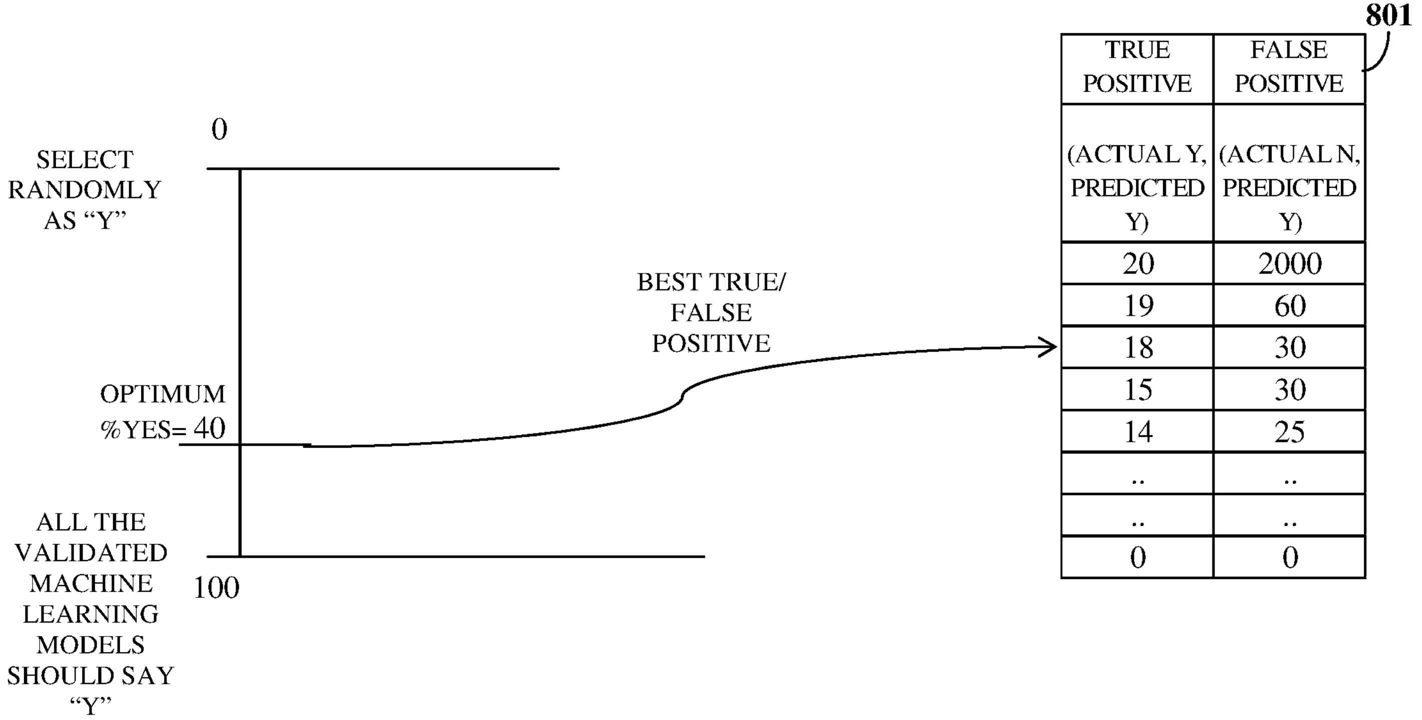
% YES	YES COUNT	COUNT ACTUAL "YES"	COUNT ACTUAL "NO"
100	5	4	1
99	0	0	0
98	0	0	0
.	0	0	0
.	0	0	0
50	220	70	150
.	0	0	0
.	0	0	0
.	0	0	0
2	0	0	0
1	0	0	0
0	1200	50	1150

FIG. 6

701

% YES	YES COUNT	COUNT ACTUAL "YES"	COUNT ACTUAL "NO"	CUMULATIVE "YES"	CUMULATIVE "NO"
100	5	4	1	4	1
99	0	0	0	4	1
98	0	0	0	4	1
.	0	0	0	4	1
.	0	0	0	4	1
50	220	70	150	74	151
.	0	0	0	74	151
.	0	0	0	74	151
.	0	0	0	74	151
2	0	0	0	74	151
1	0	0	0	74	151
0	1200	50	1150	124	1301

FIG. 7


0
SELECT RANDOMLY AS “Y”
OPTIMUM %YES= 40
ALL THE VALIDATED MACHINE LEARNING MODELS SHOULD SAY “Y”
100
BEST TRUE/ FALSE POSITIVE
801

TRUE POSITIVE	FALSE POSITIVE
(ACTUAL Y, PREDICTED Y)	(ACTUAL N, PREDICTED Y)
20	2000
19	60
18	30
15	30
14	25
..	..
..	..
0	0

FIG. 8

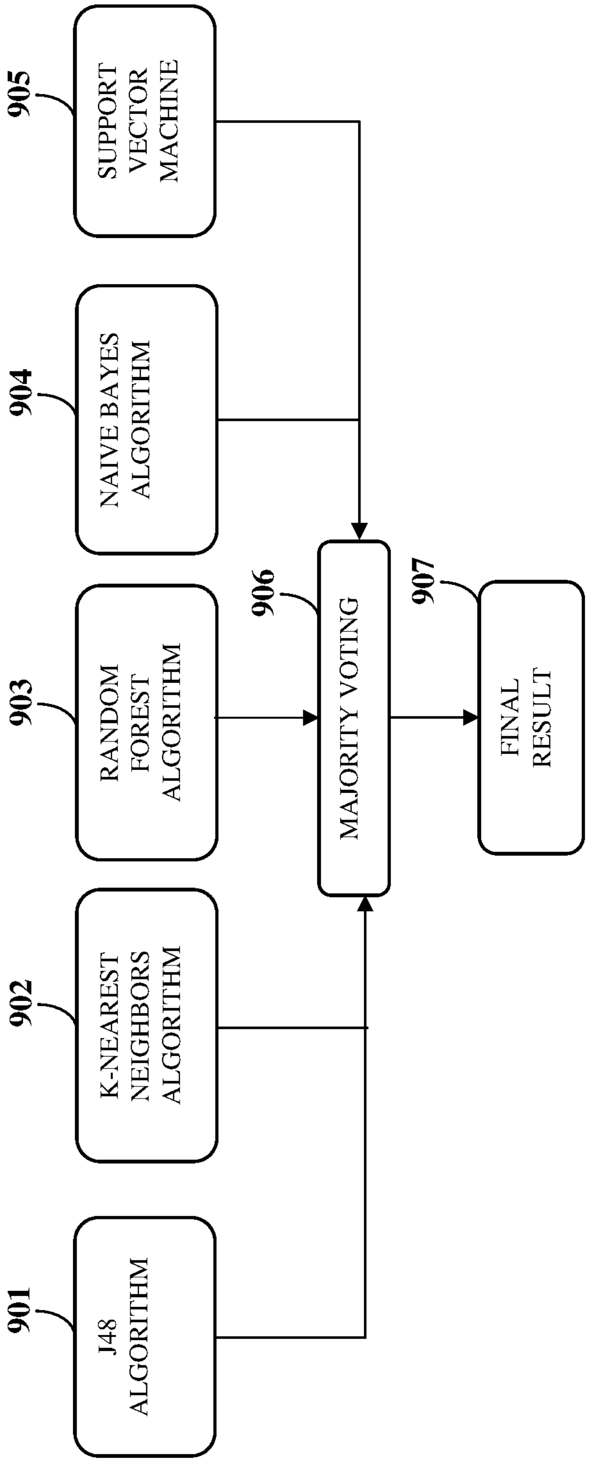

901
J48 ALGORITHM
902
K-NEAREST NEIGHBORS ALGORITHM
903
RANDOM FOREST ALGORITHM
904
NAIVE BAYES ALGORITHM
905
SUPPORT VECTOR MACHINE
906
MAJORITY VOTING
907
FINAL RESULT

FIG. 9

TABLE T1

1001a

EMP_ID	EMP_FIRST_NAME	SURNAME	DATE OF JOINING	YEARS OF EXP
1	ROBERT	JOSEPH	MAY 10, 2013	5
2	SUSANNE	LEE	MAY 12, 2013	7
3	GEORGE	WALTER	JUNE 10, 2013	12
4	TOM	CRATE	JUNE 15, 2013	7
5	JOHN	WELCH	JULY 04, 2013	8
6	LUCY	MARGARET	JULY 05, 2013	9
7	PETER	WARREN	JULY 20, 2013	15

FIG. 10A

TABLE T2

1001b

CHECKUP_ID	EMP_CODE	CHECKUP-DATE	NO. OF TESTS
12	2	AUG 12, 2013	6
13	3	AUG 12, 2013	5
14	5	AUG 13, 2013	7
15	6	AUG 13, 2013	8

FIG. 10B

1101

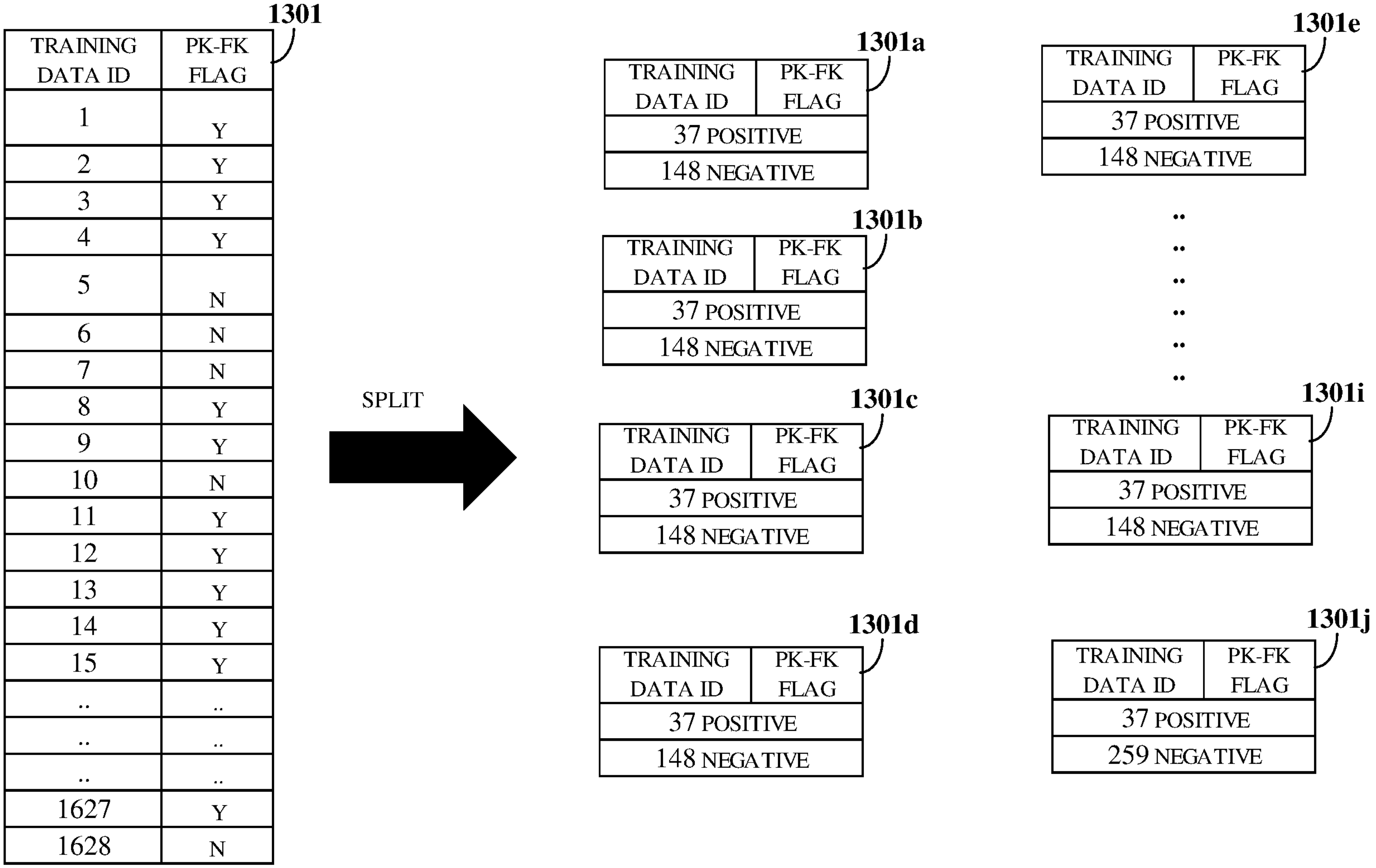
ID	TABLE_NAME_P	COLUMN_NAME_P	TABLE_NAME_D	COLUMN_NAME_D	PK-FK FLAG
1	CREDITCARD	CREDITCARDID	PERSONCREDITCARD	CREDITCARDID	Y
2	ADDRESS	ADDRESSID	BUSINESSENTITYADDRESS	ADDRESSID	Y
3	ADDRESS	ADDRESSID	SALESORDERHEADER	BILLTOADDRESSID	Y
4	ADDRESS	ADDRESSID	SALESORDERHEADER	SHIPTOADDRESSID	Y
5	BUSINESSENTITYCONTACT	ADDRESSID	WORKORDERROUTING	OPERATIONSEQUENCE	N
6	CONTACTTYPE	CONTACTTYPEID	ADDRESSTYPE	ADDRESSTYPEID	N
7	CONTACTTYPE	CONTACTTYPEID	BUSINESSENTITYADDRESS	ADDRESSTYPEID	N
8	BUSINESSENTITY	BUSINESSENTITYID	BUSINESSENTITYADDRESS	BUSINESSENTITYID	Y
9	BUSINESSENTITY	BUSINESSENTITYID	STORE	BUSINESSENTITYID	Y
10	CONTACTTYPE	CONTACTTYPEID	CREDITCARD	EXPMONTH	N
11	EMPLOYEE	BUSINESSENTITYID	EMPLOYEEDEPARTMENTHISTORY	BUSINESSENTITYID	Y
12	EMPLOYEE	BUSINESSENTITYID	EMPLOYEEPAYHISTORY	BUSINESSENTITYID	Y
13	LOCATION	LOCATIONID	PRODUCTINVENTORY	LOCATIONID	Y
14	LOCATION	LOCATIONID	WORKORDERROUTING	LOCATIONID	Y
15	PERSON	BUSINESSENTITYID	PASSWORD	BUSINESSENTITYID	Y
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
1627	SALESPERSON	BUSINESSENTITYID	STORE	SALESPERSONID	Y
1628	CONTACTTYPE	CONTACTTYPEID	PRODUCTSUBCATEGORY	PRODUCTCATEGORYID	N

FIG. 11

1201

ID	TABLE_NAME_P	COLUMN_NAME_P	TABLE_NAME_D	COLUMN_NAME_D	PK-FK FLAG
100001	H_CUSTOMER	C_CUSTKEY	H_LINEITEM	L_LINENUMBER	N
100002	H_CUSTOMER	C_CUSTKEY	H_LINEITEM	L_QUANTITY	N
100003	H_CUSTOMER	C_CUSTKEY	H_LINEITEM	L_SUPPKEY	N
100004	H_CUSTOMER	C_CUSTKEY	H_ORDER	O_CUSTKEY	Y
100005	H_CUSTOMER	C_CUSTKEY	H_PART	P_SIZE	N
100006	H_CUSTOMER	C_CUSTKEY	H_PARTSUPP	PS_SUPPKEY	N
100007	H_CUSTOMER	C_CUSTKEY	H_SUPPLIER	S_SUPPKEY	N
100008	H_CUSTOMER	C_CUSTKEY	H_PARTSUPP	PS_AVAILQTY	N
100009	H_NATION	N_NATIONKEY	H_CUSTOMER	C_NATIONKEY	Y
100010	H_NATION	N_NATIONKEY	H_LINEITEM	L_LINENUMBER	N
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
100579	CUSTOMERS	CUST_ID	TIMES	WEEK_ENDING_DAY_ID	N
100580	PERSON	BUSINESSENTITYID	PERSONPHONE	BUSINESSENTITYID	Y

FIG. 12



1301

TRAINING DATA ID	PK-FK FLAG
1	Y
2	Y
3	Y
4	Y
5	N
6	N
7	N
8	Y
9	Y
10	N
11	Y
12	Y
13	Y
14	Y
15	Y
..	..
..	..
..	..
1627	Y
1628	N

1301a

TRAINING DATA ID	PK-FK FLAG
37 POSITIVE	
148 NEGATIVE	

1301b

TRAINING DATA ID	PK-FK FLAG
37 POSITIVE	
148 NEGATIVE	

1301c

TRAINING DATA ID	PK-FK FLAG
37 POSITIVE	
148 NEGATIVE	

1301d

TRAINING DATA ID	PK-FK FLAG
37 POSITIVE	
148 NEGATIVE	

1301e

TRAINING DATA ID	PK-FK FLAG
37 POSITIVE	
148 NEGATIVE	

..
..
..
..
..
..

1301i

TRAINING DATA ID	PK-FK FLAG
37 POSITIVE	
148 NEGATIVE	

1301j

TRAINING DATA ID	PK-FK FLAG
37 POSITIVE	
259 NEGATIVE	

FIG. 13

1401

ID	TABLE_NAME_P	COLUMN_NAME_P	TABLE_NAME_D	COLUMN_NAME_D	FEATURE 1	FEATURE 2	FEATURE 3	FEATURE 4	FEATURE 5	FEATURE 6	FEATURE 7	PK-FK FLAG
1	CREDITCARD	CREDITCARDID	PERSONCREDITCARD	CREDITCARDID	0.6540	0.2982	0.3971	1	1.0000	0.987988	0.1940	Y
2	ADDRESS	ADDRESSID	BUSINESSENTITYADDRESS	ADDRESSID	0.9350	0.7645	0.5012	1	1.0000	0.550551	0.6570	Y
3	ADDRESS	ADDRESSID	SALESORDERHEADER	BILLTOADDRESSID	0.6790	0.0755	0.5287	1	0.6000	0.330330	0.5290	Y
4	ADDRESS	ADDRESSID	SALESORDERHEADER	SHIPTOADDRESSID	0.5800	0.3020	0.8051	1	0.6000	0.911912	0.4460	Y
5	BUSINESSENTITY	BUSINESSENTITYID	BUSINESSENTITYADDRESS	BUSINESSENTITYID	0.7910	0.9888	0.5378	1	1.0000	0.636637	0.2470	Y
6	BUSINESSENTITY	BUSINESSENTITYID	STORE	BUSINESSENTITYID	0.7710	0.9278	0.6050	1	1.0000	0.144144	0.2450	Y
7	EMPLOYEE	BUSINESSENTITYID	EMPLOYEEDEPARTMENTHISTORY	BUSINESSENTITYID	0.6000	0.9829	0.7630	1	1.0000	0.818819	0.4490	Y
8	EMPLOYEE	BUSINESSENTITYID	EMPLOYEEPAYHISTORY	BUSINESSENTITYID	0.9900	0.2831	0.7969	1	1.0000	0.417417	0.5630	Y

FIG. 14A

1401

ID	TABLE_NAME_P	COLUMN_NAME_P	TABLE_NAME_D	COLUMN_NAME_D	FEATURE 1	FEATURE 2	FEATURE 3	FEATURE 4	FEATURE 5	FEATURE 6	FEATURE 7	PK-FK FLAG
9	LOCATION	LOCATIONID	PRODUCTINVENTORY	LOCATIONID	0.9010	0.6981	0.8713	1	1.0000	0.821822	0.1350	Y
..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..
1626	PERSON	BUSINESS ENTITYID	SALESTERRITORY	STATEPROVINCEID	0.8530	0.8572	0.5580	1	0.1875	0.101101	0.5870	N
1627	PERSON	BUSINESS ENTITYID	SALESTERRITORYHISTORY	TERRITORYID	0.9580	0.7164	0.6881	1	0.3125	0.159159	0.4370	N
1628	PERSON	BUSINESS ENTITYID	SHIPMETHOD	SHIPMETHODID	0.8860	0.1402	0.9442	1	0.3125	0.827828	0.9410	N

FIG. 14B

1501

ID	TABLE_NAME_P	COLUMN_NAME_P	TABLE_NAME_D	COLUMN_NAME_D	FEATURE 1	FEATURE 2	FEATURE 3	FEATURE 4	FEATURE 5	FEATURE 6	FEATURE 7	PK-FK FLAG
100001	H_CUSTOMER	C_CUSTKEY	H_LINEITEM	L_LINENUMBER	0.6527	0.9678	0.6022	0	0.166667	0.332332	0.6950	N
100002	H_CUSTOMER	C_CUSTKEY	H_LINEITEM	L_QUANTITY	0.5810	0.8741	0.5958	0	0.4	0.291291	0.8550	N
100003	H_CUSTOMER	C_CUSTKEY	H_LINEITEM	L_SUPPKEY	0.9650	0.2106	0.2903	1	0.555556	0.835836	0.5580	N
100004	H_CUSTOMER	C_CUSTKEY	H_ORDER	O_CUSTKEY	0.6070	0.0287	0.0937	1	0.888889	0.647648	0.3450	Y
100005	H_CUSTOMER	C_CUSTKEY	H_PART	P_SIZE	0.7420	0.2240	0.3106	0	0.333333	0.495495	0.4100	N
100006	H_CUSTOMER	C_CUSTKEY	H_PARTSUPP	PS_SUPPKEY	0.7660	0.3911	0.0890	1	0.5	0.337337	0.5910	N
100007	H_CUSTOMER	C_CUSTKEY	H_SUPPLIER	S_SUPPKEY	0.9650	0.5833	0.2477	1	0.555556	0.362362	0.6870	N
100008	H_CUSTOMER	C_CUSTKEY	H_PARTSUPP	PS_AVAILQTY	0.8810	0.0361	0.0029	0	0.181818	0.976977	0.4560	N

FIG. 15A

1501

ID	TABLE_NAME_P	COLUMN_NAME_P	TABLE_NAME_D	COLUMN_NAME_D	FEATURE 1	FEATURE 2	FEATURE 3	FEATURE 4	FEATURE 5	FEATURE 6	FEATURE 7	PK-FK FLAG
100009	H_NATION	N_NATIONKEY	H_CUSTOMER	C_NATIONKEY	0.7260	0.2134	0.3601	1	0.909091	0.222222	0.3430	Y
100010	H_NATION	N_NATIONKEY	H_LINEITEM	L_LINENUMBER	0.6290	0.8268	0.5708	0	0.166667	0.359359	0.4570	N
100011	H_NATION	N_NATIONKEY	H_ORDER	O_SHIPPRIORITY	0.8040	0.1791	0.5491	0	0.285714	0.5655660	0.4520	N
100012	H_NATION	N_NATIONKEY	H_REGION	R_REGIONKEY	0.7390	0.7211	0.5492	1	0.636364	0.814815	0.6140	N
..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..
100579	TRANSACTIONHISTORYARCHIVE	TRANSACTIONID	WORKORDER	PRODUCTID	0.9300	0.4583	0.3616	1	0.384615	0.560561	0.7460	N
100580	WORKORDER	WORKORDERID	BUSINESSENTITYADDRESS	ADDRESSTYPEID	0.6530	0.6776	0.3851	1	0.230769	0.745746	0.5530	N

FIG. 15B

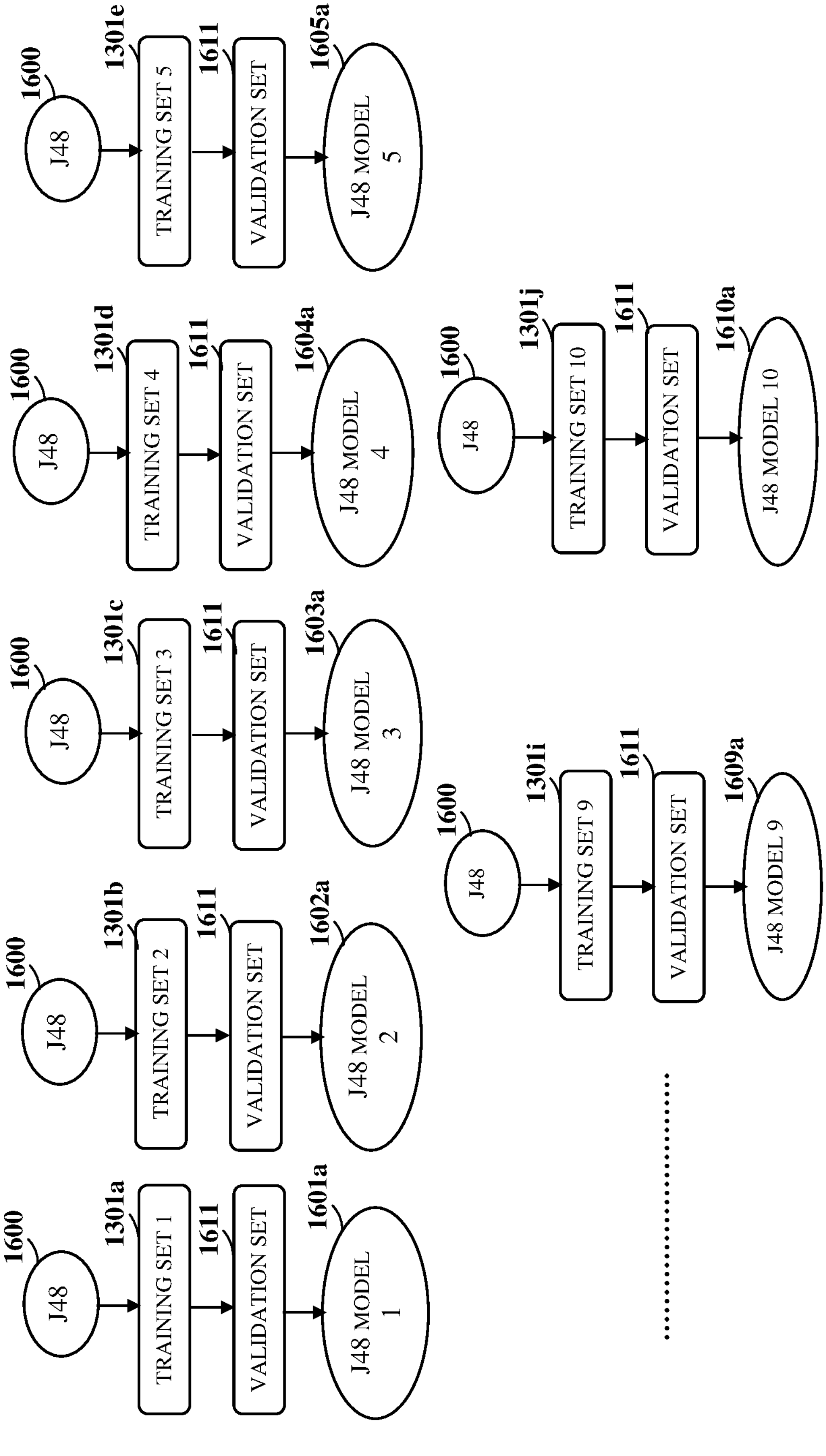

1600
J48
1301a
TRAINING SET 1
1611
VALIDATION SET
1601a
J48 MODEL 1
1600
J48
1301b
TRAINING SET 2
1611
VALIDATION SET
1602a
J48 MODEL 2
1600
J48
1301c
TRAINING SET 3
1611
VALIDATION SET
1603a
J48 MODEL 3
1600
J48
1301d
TRAINING SET 4
1611
VALIDATION SET
1604a
J48 MODEL 4
1600
J48
1301e
TRAINING SET 5
1611
VALIDATION SET
1605a
J48 MODEL 5
1600
J48
1301i
TRAINING SET 9
1611
VALIDATION SET
1609a
J48 MODEL 9
1600
J48
1301j
TRAINING SET 10
1611
VALIDATION SET
1610a
J48 MODEL 10

FIG. 16

1701

ID	ACTUAL PK-FK FLAG	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	YES COUNT	% YES
100001	N	N	N	Y	Y	N	N	N	Y	N	N	3	30
100002	N	Y	N	N	N	N	Y	N	N	N	N	2	20
100003	N	N	N	N	N	N	N	N	N	N	N	0	0
100004	Y	Y	Y	N	Y	Y	Y	Y	N	N	N	6	60
100005	N	N	Y	Y	Y	N	N	Y	N	N	N	4	40
100006	N	N	N	N	N	Y	N	N	Y	N	Y	3	30
100007	N	N	N	N	N	Y	N	N	N	Y	N	2	20
100008	N	Y	N	N	N	N	N	Y	N	N	N	2	20
100009	Y	N	Y	Y	N	Y	Y	Y	N	N	Y	6	60
100010	N	N	N	Y	Y	N	N	Y	N	N	N	3	30
100011	N	N	N	N	N	N	Y	N	N	N	N	1	10
100012	N	N	Y	Y	Y	N	Y	N	N	N	Y	5	50
..	..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..	..
100579	N	N	Y	N	Y	N	N	N	N	N	N	2	20
100580	N	N	N	Y	Y	N	Y	N	N	Y	Y	5	50

FIG. 17

1801

% YES	INSTANCE COUNT	ACTUAL Y	ACTUAL N	CUMULATIVE Y	CUMULATIVE N
100	1	1	0	1	0
99	0	0	0	1	0
98	0	0	0	1	0
97	0	0	0	1	0
96	0	0	0	1	0
95	0	0	0	1	0
94	0	0	0	1	0
93	0	0	0	1	0
92	0	0	0	1	0
91	0	0	0	1	0
90	5	4	1	5	1
89	0	0	0	5	1
88	0	0	0	5	1
87	0	0	0	5	1
86	0	0	0	5	1
85	0	0	0	5	1
84	0	0	0	5	1
83	0	0	0	5	1
82	0	0	0	5	1
81	0	0	0	5	1
80	3	2	1	7	2
79	0	0	0	7	2
78	0	0	0	7	2
77	0	0	0	7	2
76	0	0	0	7	2
75	0	0	0	7	2
74	0	0	0	7	2
73	0	0	0	7	2
72	0	0	0	7	2
71	0	0	0	7	2
70	4	2	2	9	4
69	0	0	0	9	4
68	0	0	0	9	4
67	0	0	0	9	4
66	0	0	0	9	4
65	0	0	0	9	4

FIG. 18A

1801

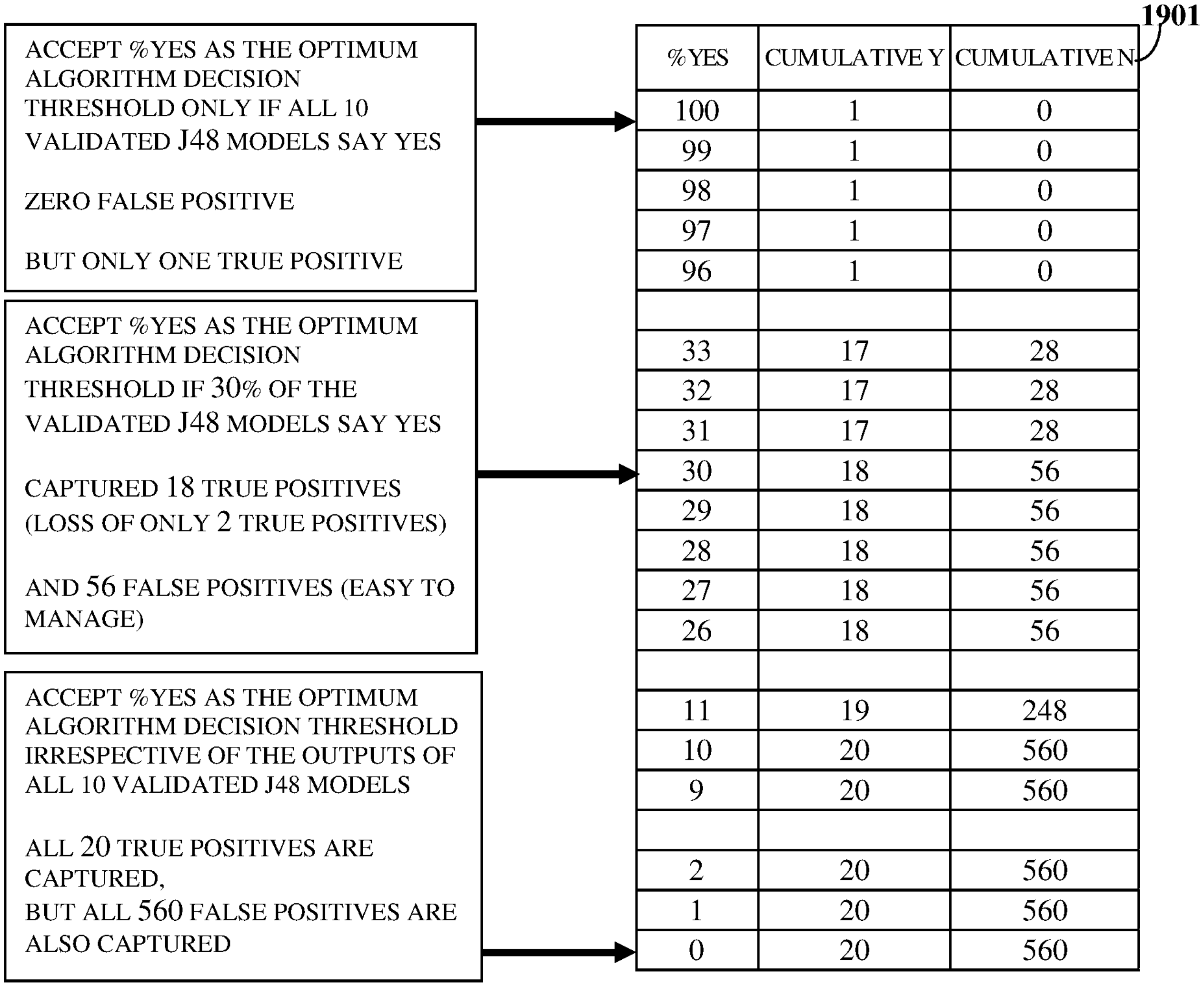
% YES	INSTANCE COUNT	ACTUAL Y	ACTUAL N	CUMULATIVE Y	CUMULATIVE N
64	0	0	0	9	4
63	0	0	0	9	4
62	0	0	0	9	4
61	0	0	0	9	4
60	4	2	2	11	6
59	0	0	0	11	6
58	0	0	0	11	6
57	0	0	0	11	6
56	0	0	0	11	6
55	0	0	0	11	6
54	0	0	0	11	6
53	0	0	0	11	6
52	0	0	0	11	6
51	0	0	0	11	6
50	13	1	12	12	18
49	0	0	0	12	18
48	0	0	0	12	18
47	0	0	0	12	18
46	0	0	0	12	18
45	0	0	0	12	18
44	0	0	0	12	18
43	0	0	0	12	18
42	0	0	0	12	18
41	0	0	0	12	18
40	15	5	10	17	28
39	0	0	0	17	28
38	0	0	0	17	28
37	0	0	0	17	28
36	0	0	0	17	28
35	0	0	0	17	28

FIG. 18B

1801

% YES	INSTANCE COUNT	ACTUAL Y	ACTUAL N	CUMULATIVE Y	CUMULATIVE N
34	0	0	0	17	28
33	0	0	0	17	28
32	0	0	0	17	28
31	0	0	0	17	28
30	29	1	28	18	56
29	0	0	0	18	56
28	0	0	0	18	56
27	0	0	0	18	56
26	0	0	0	18	56
25	0	0	0	18	56
24	0	0	0	18	56
23	0	0	0	18	56
22	0	0	0	18	56
21	0	0	0	18	56
20	193	1	192	19	248
19	0	0	0	19	248
18	0	0	0	19	248
17	0	0	0	19	248
16	0	0	0	19	248
15	0	0	0	19	248
14	0	0	0	19	248
13	0	0	0	19	248
12	0	0	0	19	248
11	0	0	0	19	248
10	313	1	312	20	560
9	0	0	0	20	560
8	0	0	0	20	560
7	0	0	0	20	560
6	0	0	0	20	560
5	0	0	0	20	560
4	0	0	0	20	560
3	0	0	0	20	560
2	0	0	0	20	560
1	0	0	0	20	560
0	0	0	0	20	560

FIG. 18C



ACCEPT %YES AS THE OPTIMUM ALGORITHM DECISION THRESHOLD ONLY IF ALL 10 VALIDATED J48 MODELS SAY YES

ZERO FALSE POSITIVE

BUT ONLY ONE TRUE POSITIVE

ACCEPT %YES AS THE OPTIMUM ALGORITHM DECISION THRESHOLD IF 30% OF THE VALIDATED J48 MODELS SAY YES

CAPTURED 18 TRUE POSITIVES (LOSS OF ONLY 2 TRUE POSITIVES)

AND 56 FALSE POSITIVES (EASY TO MANAGE)

ACCEPT %YES AS THE OPTIMUM ALGORITHM DECISION THRESHOLD IRRESPECTIVE OF THE OUTPUTS OF ALL 10 VALIDATED J48 MODELS

ALL 20 TRUE POSITIVES ARE CAPTURED,
BUT ALL 560 FALSE POSITIVES ARE ALSO CAPTURED

%YES	CUMULATIVE Y	CUMULATIVE N
100	1	0
99	1	0
98	1	0
97	1	0
96	1	0
33	17	28
32	17	28
31	17	28
30	18	56
29	18	56
28	18	56
27	18	56
26	18	56
11	19	248
10	20	560
9	20	560
2	20	560
1	20	560
0	20	560

FIG. 19

2001

ID	J48_M1	J48_M2	J48_M3	J48_M4	J48_M5	J48_M6	J48_M7	J48_M8	J48_M9	J48_M10	YES COUNT	J48_RESULT
1	Y	N	N	Y	N	N	N	Y	N	N	3	Y
2	N	N	N	N	Y	N	Y	N	N	N	2	N
3	Y	Y	Y	Y	N	Y	Y	N	Y	Y	8	Y
4	N	N	N	N	N	N	N	N	N	Y	1	N
5	Y	N	Y	N	Y	Y	Y	N	N	N	5	Y
6	Y	N	N	N	N	N	N	N	N	Y	2	N
7	N	Y	N	N	N	N	N	Y	N	N	2	N
8	N	N	N	N	N	N	N	N	N	N	0	N
9	N	N	N	N	N	N	N	Y	N	N	1	N
10	N	N	Y	N	Y	N	N	N	N	N	2	N
11	N	Y	N	N	N	N	N	N	N	N	1	N
12	Y	N	Y	Y	Y	Y	N	Y	N	Y	7	Y
13	Y	N	N	Y	N	N	Y	N	N	Y	4	Y
14	N	N	N	N	N	N	N	N	N	N	0	N
15	N	N	Y	N	N	N	N	N	N	N	1	N

FIG. 20

2101

ID	J48_RESULT	NAIVE BAYES_RESULT	k-NEAREST NEIGHBORS_RESULT	RANDOM FOREST_RESULT	SUPPORT VECTOR MACHINE MODEL_RESULT	Y VOTE	FINAL DECISION
1	Y	Y	Y	Y	Y	5	Y
2	N	N	Y	N	N	1	N
3	Y	N	N	N	N	1	N
4	N	Y	Y	N	N	2	N
5	Y	Y	N	Y	Y	4	Y
6	N	Y	N	Y	N	2	N
7	N	Y	N	Y	Y	3	Y
8	N	N	Y	N	N	1	N
9	N	Y	N	Y	Y	3	Y
10	N	N	N	N	N	0	N
11	N	Y	N	N	N	1	N
12	Y	N	N	N	N	1	N
13	Y	Y	Y	Y	Y	5	Y
14	N	Y	N	N	N	1	N
15	N	N	N	N	N	0	N

FIG. 21

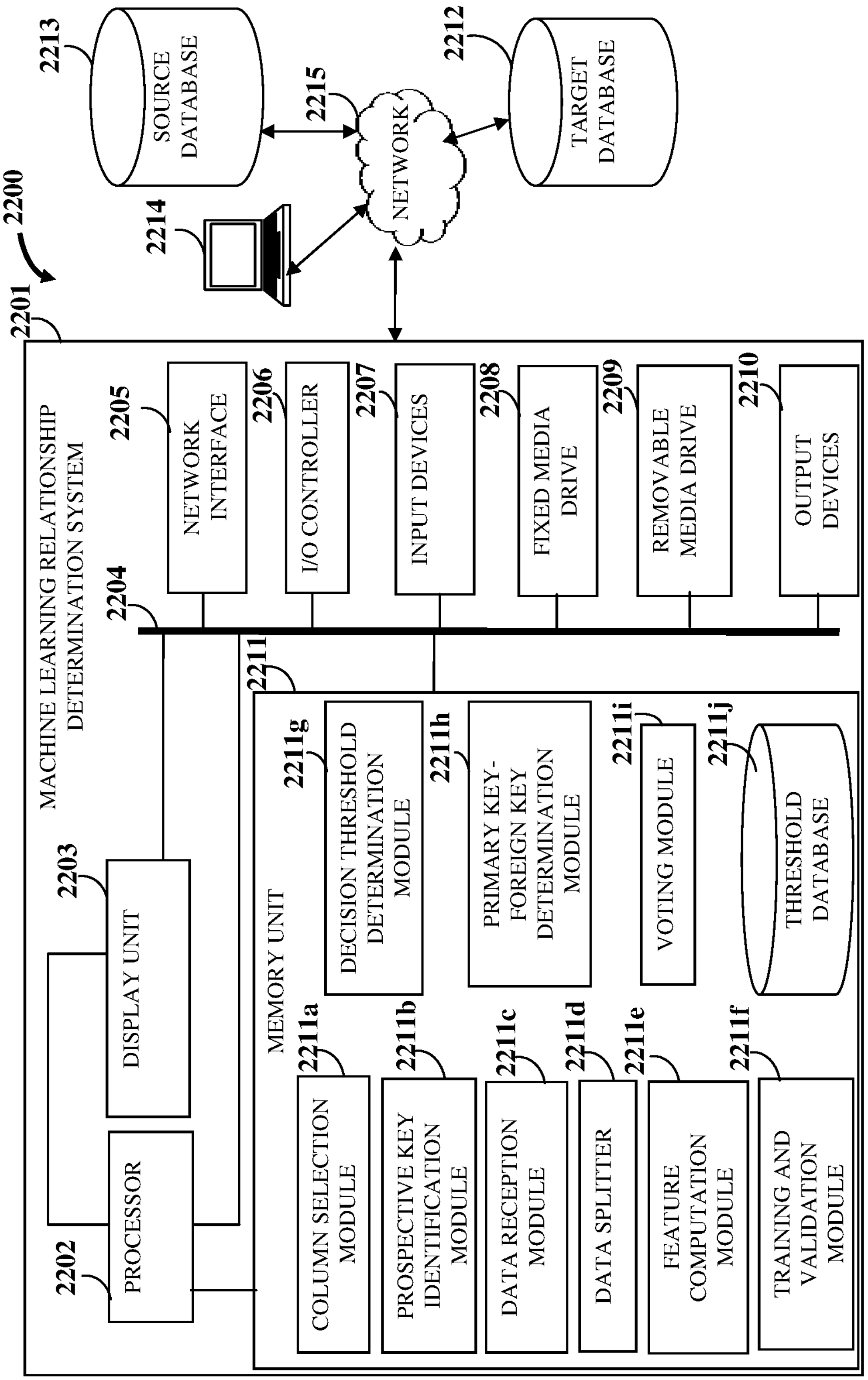

2200
2213
SOURCE DATABASE
2215
NETWORK
2212
TARGET DATABASE
2214
2201
MACHINE LEARNING RELATIONSHIP DETERMINATION SYSTEM
2205
NETWORK INTERFACE
2206
I/O CONTROLLER
2207
INPUT DEVICES
2208
FIXED MEDIA DRIVE
2209
REMOVABLE MEDIA DRIVE
2210
OUTPUT DEVICES
2204
2211
MEMORY UNIT
2203
DISPLAY UNIT
2202
PROCESSOR
2211g
DECISION THRESHOLD DETERMINATION MODULE
2211h
PRIMARY KEY-FOREIGN KEY DETERMINATION MODULE
2211i
VOTING MODULE
2211j
THRESHOLD DATABASE
2211a
COLUMN SELECTION MODULE
2211b
PROSPECTIVE KEY IDENTIFICATION MODULE
2211c
DATA RECEPTION MODULE
2211d
DATA SPLITTER
2211e
FEATURE COMPUTATION MODULE
2211f
TRAINING AND VALIDATION MODULE

FIG. 22

PRIMARY KEY-FORIEGN KEY RELATIONSHIP DETERMINATION THROUGH MACHINE LEARNING

BACKGROUND

[0001] For performing data integration in large enterprises, database structure and semantic relations between schema elements of a database have to be known and understood. Due to legacy data management in large enterprises, the semantic relations between schema elements, for example, columns of tables in a database are often lost or corrupted. Determining the semantic relations between the schema elements is a time consuming and costly process. When an explicit semantic relation is not available, it becomes time consuming to identify the semantic relation due to the vast size of the database and nature of data stored in the tables.

[0002] A significant class of semantic relations between schema elements is primary key-foreign key relationships. A primary key is a column in a table that uniquely identifies each record in the table. A foreign key is an attribute or a column in another table that maps to the primary key to form a relationship between the tables. The relationship between the primary key and the foreign key is referred to as a "primary key-foreign key relationship". The primary key-foreign key relationship helps in fetching records queried by a user of the database quickly without having to access numerous tables in an enterprise, thereby saving time and effort. The primary key-foreign key relationship allows determination of a data flow in a schema whenever any form of perturbation, insertion, or deletion occurs to any record in the database. However, determining primary key-foreign key relationships in databases of large enterprises is a time intensive, processor intensive, and computation intensive process. Consider an example where a primary key-foreign key relationship between 100 tables with 20 columns each has to be found. Around four million pairs of columns have to be explored to find a possible primary key-foreign key relationship. A brute force method cannot be used to find a possible primary key-foreign key relationship among four million pairs of columns. For a primary key-foreign key relationship to exist between the schema elements, a pre-condition of inclusion dependency needs to be satisfied. Inclusion dependency is a property of data which, when satisfied, requires every value of one column of a table to exist as a value of another column in a different or the same table. On determining inclusion dependency between the schema elements, the number of pairs of schema elements to be evaluated for primary key-foreign key relationships is significantly reduced, but is still significantly large for a manual determination of primary key-foreign key relationships. Therefore, there is a need for automating the process for determining primary key-foreign key relationships between the schema elements using computation intensive processors.

[0003] There are a few conventional methods for determining primary key-foreign key relationships. In one conventional method, metadata from the pairs of columns in tables is used to determine primary key-foreign key relationships. A single feature, for example, a column name is used to determine the primary key-foreign key relationships in this method. With the single feature, that is, the column name, the determination of the primary key-foreign key relationship may not be as accurate as the primary key identified may have repeated values and may not satisfy the property of a primary key. There is a need for a method for determining primary key-foreign key relationships between data in tables by using an intelligent combination of features of the data in the tables and by not relying on a single feature.

[0004] In another conventional method for determining primary key-foreign key relationships between data in tables, a pruning criterion and a ranking function are employed. The pruning criterion eliminates pairs of columns in the tables that are unlikely to have a primary key-foreign key relationship. The ranking function ranks the pairs of columns in the tables that satisfy the pruning criterion. The pruning criterion and the ranking function are limited by definition by a programmer. In other conventional methods, primary key-foreign key relationships are found using rule based approaches. One of the rule based approaches is to determine a cumulative probability distribution of the primary key and the foreign key in the pairs of columns in the tables and compute a score for each of the pairs of columns. However, the scope of determination of primary key-foreign key relationships using the rule based approaches is limited by the rules defined for the determination, which is typically not accurate. The rule based approaches also needs a human expert or a programmer to define the rules and execute an algorithm. The computation of a score is a processor intensive and time consuming process. There is a need for a method for determining primary key-foreign key relationships between data based on past observations more accurately while consuming less time. The machine learning based approach is one such approach for determining primary key-foreign key relationships accurately. The machine learning based approach learns inherent property of primary key-foreign key relationships from already classified data and hence is a robust approach for determining primary key-foreign key relationships.

[0005] In the machine learning approach, a machine learning classification algorithm learns from patterns of already classified data. The already classified data acts as training data for training the machine learning classification algorithm. If the machine learning classification algorithm is applied for a classification problem, the machine learning classification algorithm is trained on the already classified data that is classified into two categories: positive training data comprising primary key-foreign key pairs and negative training data comprising non-primary key-foreign key pairs. If the machine learning classification algorithm is trained on predominantly negative training data, a trained machine learning model generated from application of the machine learning classification algorithm will be biased towards the negative training data. When subjected to actual data whose primary key-foreign key relationship is to be determined, the trained machine learning model classifies the actual data spuriously. Furthermore, using a single machine learning classification algorithm for determining a primary key-foreign key relationship between schema elements may result in a spurious classification. A combination of multiple machine learning classification algorithms will result in a better determination of the primary key-foreign key relationship between the actual data.

[0006] Hence, there is a long felt need for a method and a system that determine primary key-foreign key relationships among schema elements, that is, data in multiple tables through machine learning using computation intensive processors. Moreover, there is a need for a method and a system that intelligently combine the features of data in a table for determining the primary key-foreign key relationship between the actual schema elements. Furthermore, there is a need for a method and a system that split the training data in a manner to avoid skewing of the training data towards negative training data to avoid an erroneous classification of the schema elements by a machine learning classification algorithm. Furthermore, there is a need for a method and a system that intelligently combines multiple machine learning classification algorithms for determining the primary key-foreign key relationship between the actual schema elements.

SUMMARY OF THE INVENTION

[0007] This summary is provided to introduce a selection of concepts in a simplified form that are further disclosed in the detailed description of the invention. This summary is not intended to determine the scope of the claimed subject matter.

[0008] The method and the system disclosed herein address the above mentioned need for determining primary key-foreign key relationships among schema elements, that is, data in multiple tables through machine learning using computation intensive processors. Moreover, the method and the system disclosed herein intelligently combine features of the data in each table for determining the primary key-foreign key relationship between actual schema elements. Furthermore, the method and the system disclosed herein split training data that trains machine learning classification algorithms in a manner to avoid skewing of the training data towards negative training data to avoid an erroneous classification of the schema elements by the machine learning classification algorithms. Furthermore, the method and the system disclosed herein intelligently combine multiple machine learning classification algorithms for determining the primary key-foreign key relationship between the actual schema elements.

[0009] The method disclosed herein employs a machine learning relationship determination system (MLRDS) comprising at least one processor configured to execute computer program instructions for determining primary key-foreign key relationships among data in multiple tables of a target database through machine learning. The MLRDS selects a first column of data from a first table among the tables and a second column of data from a second table among the tables for each of the tables in the target database. The first column of data comprises a first column name. The second column of data comprises a second column name different from the first column name. The MLRDS identifies the selected first column of data as a prospective primary key and the selected second column of data as a prospective foreign key to form an inclusion dependency pair on determining presence of data elements of the selected second column of data in the selected first column of data in their entirety. The MLRDS receives multiple predetermined inclusion dependency pairs comprising primary key-foreign key pairs classified as positive training data and positive validation data, and non-primary key-foreign key pairs classified as negative training data and negative validation data, from a source database. The positive validation data and the negative validation data form a validation data set. The MLRDS splits the positive training data and the negative training data into training data sets. The MLRDS computes multiple primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set. The MLRDS generates trained machine learning models corresponding to the training data sets by training each machine learning classification algorithm using the training data sets and the computed primary key-foreign key features of the training data sets.

[0010] The machine learning relationship determination system (MLRDS) generates validated machine learning models for each of the machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set. The MLRDS determines an optimum algorithm decision threshold for each of the machine learning classification algorithms using the generated validated machine learning models. The MLRDS then determines a resultant of the inclusion dependency pair being a primary key-foreign key pair or a non-primary key-foreign key pair for each of the machine learning classification algorithms using the determined optimum algorithm decision threshold and the computed primary key-foreign key features of the inclusion dependency pair of the prospective primary key and the prospective foreign key. The MLRDS performs majority voting on the determined resultant for each of the machine learning classification algorithms to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table.

[0011] In one or more embodiments, related systems comprise circuitry and/or programming for effecting the methods disclosed herein; the circuitry and/or programming can be any combination of hardware, software, and/or firmware configured to effect the methods disclosed herein depending upon the design choices of a system designer. Also, various structural elements can be employed depending on the design choices of the system designer.

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] The foregoing summary, as well as the following detailed description of the invention, is better understood when read in conjunction with the appended drawings. For the purpose of illustrating the invention, exemplary constructions of the invention are shown in the drawings. However, the invention is not limited to the specific methods and components disclosed herein. The description of a method step or a component referenced by a numeral in a drawing is applicable to the description of that method step or component shown by that same numeral in any subsequent drawing herein.

[0013] FIGS. **1A-1B** illustrate a method for determining primary key-foreign key relationships among data in multiple tables of a target database through machine learning.

[0014] FIG. **2** exemplarily illustrates a flowchart comprising the steps performed by a machine learning relationship determination system for training and validating a machine learning classification algorithm and for determining primary key-foreign key relationships between data in multiple tables of a target database.

[0015] FIGS. **3A-3B** exemplarily illustrate two tables of a target database with respective columns whose primary key-foreign key relationship is to be determined.

[0016] FIG. **4** exemplarily illustrates a schematic representation showing splitting of positive training data and negative training data into multiple training data sets.

[0017] FIG. **5** exemplarily illustrates a table containing test outputs of the trained machine learning models obtained by the machine learning relationship determination system on testing the trained machine learning models against a validation data set.

[0018] FIG. **6** exemplarily illustrates a table containing a number of instances of the validation data set that defines a primary key-foreign relationship between the instances of the validation data set for determining an optimum algorithm decision threshold using validated machine learning models.

[0019] FIG. **7** exemplarily illustrates a table containing a cumulative number of instances of the validation data set that defines a primary key-foreign relationship between the instances of the validation data set for determining an optimum algorithm decision threshold using the validated machine learning models.

[0020] FIG. **8** exemplarily illustrates a schematic representation for determining the optimum algorithm decision threshold using the validated machine learning models.

[0021] FIG. **9** exemplarily illustrates a flow diagram showing majority voting of a resultant of an identified inclusion dependency pair for each of multiple machine learning classification algorithms.

[0022] FIGS. **10**A-**10**B exemplarily illustrate two tables of a target database with respective columns whose primary key-foreign key relationship is to be determined.

[0023] FIG. **11** exemplarily illustrates a table from a source database containing training data.

[0024] FIG. **12** exemplarily illustrates a table from the source database containing a validation data set.

[0025] FIG. **13** exemplarily illustrates a schematic representation showing splitting of the training data into multiple training data sets.

[0026] FIGS. **14**A-**14**B exemplarily illustrate a table containing the training data with primary key-foreign key features computed for the training data by the machine learning relationship determination system.

[0027] FIGS. **15**A-**15**B exemplarily illustrate a table containing the validation data set with primary key-foreign key features computed for the validation data set by the machine learning relationship determination system.

[0028] FIG. **16** exemplarily illustrates flowchart comprising the steps performed by the machine learning relationship determination system for generating validated machine learning models for a machine learning classification algorithm.

[0029] FIG. **17** exemplarily illustrates a table containing outputs of the trained machine learning models obtained by the machine learning relationship determination system on validating the trained machine learning models against the validation data set.

[0030] FIGS. **18**A-**18**C exemplarily illustrate a table containing a cumulative number of instances of the validation data set that defines a primary key-foreign relationship between the instances of the validation data set for determining an optimum algorithm decision threshold using the validated machine learning models.

[0031] FIG. **19** exemplarily illustrates a schematic representation for determining an optimum algorithm decision threshold using the validated machine learning models.

[0032] FIG. **20** exemplarily illustrates a table showing resultants of the inclusion dependency pairs identified from the tables shown in FIGS. **10**A-**10**B, being primary key-foreign key pairs or non-primary key-foreign key pairs, generated by the machine learning relationship determination system using the optimum algorithm decision threshold.

[0033] FIG. **21** exemplarily illustrates a table containing final resultants of the inclusion dependency pairs identified from the tables shown in FIGS. **10**A-**10**B, being primary key-foreign key pairs or non-primary key-foreign key pairs, generated by the machine learning relationship determination system on performing majority voting on the resultants shown in FIG. **20**.

[0034] FIG. **22** exemplarily illustrates a system comprising the machine learning relationship determination system for determining primary key-foreign key relationships among data in multiple tables of a target database through machine learning.

DETAILED DESCRIPTION OF THE INVENTION

[0035] FIGS. **1**A-**1**B illustrate a method for determining primary key-foreign key relationships among data in multiple tables of a target database through machine learning. As used herein, a "target database" refers to a database that is targeted for determining primary key-foreign key relationships among a collection of data that is organized in multiple tables for access, management, and updation of the data. Each table of the target database comprises multiple rows and columns. In the target database, primary key-foreign key relationships between data in the columns of the tables are to be determined. As used herein, a "primary key-foreign key relationship" refers to a relationship between a primary key in a table and a foreign key in another table. The primary key in a table is a column in the table that uniquely identifies a row of the table. The table with the primary key is identified as a parent table. A foreign key is a column in another table, typically referred to as a child table, that maps to the primary key in the parent table to control the data to be stored in the child table. When a foreign key references or maps to a primary key, a link is created between the parent table and the child table, which defines the primary key-foreign key relationship between columns in the parent table and the child table. Machine learning refers to a type of artificial intelligence that provides processors with an ability to learn from and make predictions on data without being explicitly programmed. Machine learning focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data. An algorithm for machine learning is referred to as a "machine learning algorithm". A machine learning algorithm searches for a pattern in data used for training the machine learning algorithm and uses the pattern to detect patterns in new data and adjust program actions accordingly. The data used for training the machine learning algorithm is referred to as "training data". Machine learning algorithms are categorized as being supervised or unsupervised. Supervised machine learning algorithms infer from the training data and apply learning to new data. Unsupervised machine learning algorithms draw inferences from the training data.

[0036] The method disclosed herein employs a machine learning relationship determination system (MLRDS) comprising at least one processor configured to execute computer program instructions for determining primary key-foreign key relationships among data in multiple tables in a target database through machine learning. In an embodiment, the MLRDS is a computer system comprising at least one processor configured to execute computer program instructions for determining primary key-foreign key relationships among data in multiple tables in a target database through machine learning. In another embodiment, the MLRDS comprises a software application downloadable and usable on a user device. In another embodiment, the MLRDS is implemented as a web based platform, for example, a website hosted on a server or a network of servers accessible by a user device via a network, for example, the internet, a wireless network, a mobile telecommunication network, etc. In another embodiment, the MLRDS is implemented in a cloud computing environment and provides an open communication community service. As used herein, "cloud computing environment" refers to a processing environment comprising configurable computing physical and logical resources, for example, networks, servers, storage, applications, services, etc., and data distributed over a network, for example, the internet. The cloud computing environment provides on-demand network access to a shared pool of the configurable computing physical and logical resources. In another embodiment, the MLRDS is configured as a cloud computing based platform implemented as a service for determining primary key-foreign key relationships among data in multiple tables in a target database through machine learning.

[0037] The machine learning relationship determination system (MLRDS) selects **101** a first column of data from a first table among the multiple tables of the target database and a second column of data from a second table among the multiple tables of the target database for each of the multiple tables in the target database. As used herein, the "first table" refers to a prospective parent table with a prospective primary key and the "second table" refers to a prospective child table with a prospective foreign key. The MLRDS selects the first table and the second table from the multiple tables in the target database. Also, as used herein, the "first column" refers to a column of the prospective parent table and the "second column" refers to a column of the prospective child table. The first column of data comprises a first column name. The first column name forms metadata of the first column. The second column of data comprises a second column name. The second column name forms metadata of the second column and is different from the first column name. The MLRDS selects pairs of columns from different tables in the target database iteratively to determine primary key-foreign key relationships among data in the column pairs. Consider an example where the target database contains 5 tables with 100 columns each. The total number of columns in this target database is 500. The MLRDS selects a pair of columns from these 500 columns. The number of column pairs that can be selected from the 500 columns is $^{500}P_2$=500*499~250000. The MLRDS selects the possible number of about 250000 column pairs from the 5 tables in the target database to determine primary key-foreign key relationships between the 500 columns.

[0038] The machine learning relationship determination system (MLRDS) identifies **102** the selected first column of data as a prospective primary key and the selected second column of data as a prospective foreign key to form an inclusion dependency pair on determining presence of data elements of the selected second column of data in the selected first column of data in their entirety. As used herein, "inclusion dependency pair" refers to a pair of the selected first column and the selected second column where the data elements in the selected second column are a subset of the data elements in the selected first column. That is, all the data elements in the selected second column are present in the selected first column. Also, as used herein, "data elements" refers to data or values in the columns in the tables of the target database. The MLRDS determines the presence of all the data elements of the second column in the first column and identifies the first column and the second column to form an inclusion dependency pair. To identify inclusion dependency between the first column and the second column, the MLRDS sorts both the columns and for each data element in the second column, the MLRDS searches if that data element is present in the first column.

[0039] For a primary key-foreign key relationship to exist between the first column and the second column, a necessary condition is that the first column and the second column form an inclusion dependency pair. Merely determining that the first column and the second column form an inclusion dependency pair is insufficient for determining a primary key-foreign key relationship. While all primary key-foreign key relationships possess inclusion dependency, not all inclusion dependency pairs are primary key-foreign key pairs. On satisfying the condition for forming an inclusion dependency pair, the machine learning relationship determination system (MLRDS) identifies the selected first column as a prospective primary key and the selected second column as a prospective foreign key. Identifying inclusion dependency pairs of columns in the target database results in a significant reduction in the number of possible column pairs of columns in the multiple tables of the target database to be evaluated for determining the primary key-foreign key relationships among the multiple tables in the target database. Multiple preconditions, for example, same data type, NULL value, etc., are to be met by the column pairs to hold primary key-foreign key relationships. The precondition of the same data type is satisfied by the column pairs when data elements of the column pairs are of the same data type. The precondition of NULL value is satisfied when the column identified as a primary key or a foreign key does not contain a NULL value. The MLRDS eliminates the column pairs that do not satisfy the predetermined conditions. In this manner, the MLRDS eliminates a significant number of spurious pairs. Consider an example of a pair of columns, namely, EMP_ID that uniquely identifies an employee of an organization and DEP_KEY that uniquely identifies a department of the organization. Also, consider the data type of the data elements in the column EMP_ID is integer. For the column pair EMP_ID and DEP_KEY to hold a primary key-foreign key relationship, the data type of the data elements in the column DEP_KEY must be integer. If the data type of the data elements in the column DEP_KEY is not integer, the MLRDS eliminates the column pair EMP_ID and DEP_KEY as a spurious pair that cannot hold a primary key-foreign key relationship. If the data type of the data elements in the column DEP_KEY is an integer, the MLRDS evaluates the EMP_ID and DEP_KEY column pair for inclusion dependency. The column pairs that satisfy the condition for inclusion dependency are subjected to machine learning, and the remaining column pairs that do not satisfy the condition for inclusion dependency are eliminated.

[0040] The machine learning relationship determination system (MLRDS) receives **103** multiple predetermined inclusion dependency pairs comprising primary key-foreign key pairs and non-primary key-foreign key pairs from a source database. As used herein, "predetermined inclusion dependency pairs" refers to pairs of columns in the tables of a source database that are found to be inclusion dependency pairs. Also, as used herein, "primary key-foreign key pairs" refers to the inclusion dependency pairs that are confirmed to possess primary key-foreign key relationships. Also, as used herein, "non-primary key-foreign key pairs" refers to the inclusion dependency pairs that are confirmed not to have primary key-foreign key relationships, that is, the column pairs are not related by a primary key and a foreign key. Also, as used herein, a "source database" refers to an external database with tables separate from the target database. In the source database, the primary key-foreign key pairs and the non-primary key-foreign key pairs of the columns in the tables are already identified. Thus, the source database acts as a source for the predetermined inclusion dependency pairs comprising the primary key-foreign key pairs and the non-primary key-foreign key pairs. In the source database, the metadata of the columns in the tables is available and aids in identifying the primary key-foreign key relationships.

[0041] The primary key-foreign key pairs are classified into positive training data and positive validation data. The non-primary key-foreign key pairs are classified into negative training data and negative validation data. As used herein, "training data" refers to labeled data comprising pairs of input values and predetermined output values for training a machine learning classification algorithm. As used herein, "machine learning classification algorithm" refers to a machine learning algorithm that classifies columns in the tables of the target database into primary key-foreign key pairs and non-primary key-foreign key pairs. The machine learning classification algorithm learns from already classified data and applies its learning to unclassified inclusion dependency pairs. The training data used by the machine learning relationship determination system (MLRDS) comprises the predetermined inclusion dependency pairs of columns of the tables in the source database comprising predetermined primary key-foreign key pairs and predetermined non-primary key-foreign key pairs. The input values of the training data comprise, for example, the column names or the data in the predetermined inclusion dependency pairs of columns of the tables in the source database. The predetermined output values of the training data comprise, for example, primary key-foreign key flags indicating whether the predetermined inclusion dependency pairs hold a primary key-foreign key relationship or not. For example, if a predetermined inclusion dependency pair is a primary key-foreign key pair, the primary key-foreign key flag is "Y", and if the predetermined inclusion dependency pair is a non-primary key-foreign key pair, the primary key-foreign key flag is "N". "Y" indicates YES that denotes that the predetermined inclusion dependency pair is a primary key-foreign key pair, and "N" indicates NO that denotes that the predetermined inclusion dependency pair is a non-primary key-foreign key pair. The primary key-foreign key pairs from the predetermined inclusion dependency pairs form the "positive training data" and the non-primary key-foreign key pairs form the "negative training data" used by the MLRDS to train the machine learning classification algorithm. The positive training data comprises, for example, input values as column names of the pairs of columns in the source database that are primary key-foreign key pairs and the primary key-foreign key flag "Y" as the predetermined output value. The negative training data comprises, for example, input values as column names of the pairs of columns in the source database that are non-primary key-foreign key pairs and the primary key-foreign key flag "N" as the predetermined output value.

[0042] Also, as used herein, "validation data" refers to labeled data comprising pairs of input values and predetermined output values for testing a machine learning classification algorithm that is trained on the training data. The validation data used by the machine learning relationship determination system (MLRDS) comprises predetermined inclusion dependency pairs of columns of the tables in the source database comprising predetermined primary key-foreign key pairs and predetermined non-primary key-foreign key pairs. The input values of the validation data comprise, for example, the column names or the data in the predetermined inclusion dependency pairs of columns of the tables in the source database. The predetermined output values of the validation data comprise, for example, primary key-foreign key flags indicating whether the predetermined inclusion dependency pairs hold a primary key-foreign key relationship or not. For example, the primary key-foreign key pairs constitute the positive validation data and are indicated with a "Y" as the primary key-foreign key flag, and the non-primary key-foreign key pairs constitute the negative validation data and are indicated with an "N" as the primary key-foreign key flag. The MLRDS receives the predetermined inclusion dependency pairs pre-classified into positive training data, negative training data, positive validation data, and negative validation data from the source database. The positive validation data and the negative validation data form a validation data set. In an embodiment, the MLRDS receives only positive training data and negative training data. In this embodiment, the MLRDS uses a predetermined percentage of the received positive training data for training the machine learning classification algorithm, and the remaining percentage of the received positive training data as the positive validation data for validating the trained machine learning classification algorithm. Similarly, the MLRDS uses a predetermined percentage of the received negative training data for training the machine learning classification algorithm, and the remaining percentage of the received negative validation data for validating the trained machine learning classification algorithm. For example, if the MLRDS receives 100 samples of positive training data and 100 samples of negative training data, the MLRDS uses 30 samples of the positive training data as positive validation data, and 30 samples of the negative training data as negative validation data. The remaining 70 samples of the positive training data and the remaining 70 samples of the negative training data constitute the training data used by the MLRDS for training the machine learning classification algorithm.

[0043] The machine learning relationship determination system (MLRDS) uses the positive training data and the negative training data to train each of a combination of machine learning classification algorithms to determine primary key-foreign key relationships between data in the target database. The MLRDS uses the positive validation data and the negative validation data to test and validate the trained machine learning classification algorithm. The MLRDS then determines the primary key-foreign key relationship of the inclusion dependency pair to be a primary key-foreign key pair, or a non-primary key-foreign key pair using the validated machine learning classification algorithm. The machine learning relationship determination system (MLRDS) uses a combination of machine learning classification algorithms, for example, the J48 algorithm, the k-Nearest Neighbors algorithm, the Naive Bayes algorithm, the Random Forest algorithm, Bayes network model, a multilayer perceptron model, a support vector machine model, etc., for identifying primary key-foreign key pairs and non-primary key-foreign key pairs from the columns in the tables of the target database. A single machine learning classification algorithm may result in an output with a possible bias towards, for example, non-primary key-foreign key pairs because of training of the single machine learning classification algorithm using the non-primary key-foreign key pairs in the training data sets. On using the combination of machine learning classification algorithms, the MLRDS eliminates the bias in the outputs of a single machine learning classification algorithm as outputs of multiple machine learning classification algorithms are used by the MLRDS to determine an unbiased resultant. The MLRDS performs majority voting of the outputs of the multiple machine learning classification algorithms to obtain an unbiased resultant.

[0044] The machine learning relationship determination system (MLRDS) splits **104** the positive training data and the negative training data into training data sets. As used herein, “training data sets” refers to sets of the training data for training a machine learning classification algorithm. Only a fraction of the training data is positive, that is, only a fraction of the training data comprises primary key-foreign key pairs and the remaining training data comprises non-primary key-foreign key pairs. If the machine learning classification algorithm is trained using a majority of the negative training data, the machine learning classification algorithm will be biased towards the non-primary key-foreign key pairs and will result in a false classification of the prospective primary key-prospective foreign key pairs. Therefore, the MLRDS splits the training data into multiple training data sets to reduce a skew of the MLRDS towards a false determination of primary key-foreign key relationships in the identified inclusion dependency pairs. The MLRDS splits the negative training data into multiple training data sets and adds the positive training data to each training data set. Consider an example where the MLRDS receives 1000 non-primary key-foreign key pairs as negative training data and 20 primary key-foreign key pairs as positive training data. To split the negative training data and the positive training data into training data sets, the MLRDS determines a configurable ratio of 1:5 of the positive training data and the negative training data in each training data set. The MLRDS then splits the negative training data into 10 training data sets with 100 non-primary key-foreign key pairs and adds 20 primary key-foreign key pairs to each training data set. The MLRDS then trains the machine learning classification algorithm with 10 training data sets, each with 20 primary key-foreign key pairs and **100** non-primary key-foreign key pairs.

[0045] The machine learning relationship determination system (MLRDS) computes **105** multiple primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set. As used herein, “primary key-foreign key features” refer to characteristics of an inclusion dependency pair that enable the MLRDS to provide an indication on whether the inclusion dependency pair is a primary key-foreign key pair or a non-primary key-foreign key pair. The selection of the primary key-foreign key features has an influence on the performance of the machine learning classification algorithm. The MLRDS computes the primary key-foreign key features, for example, based on coverage since almost all primary keys are covered by foreign keys, names of the columns being similar, name patterns such as column names containing “_ID”, statistical distribution of the primary key and foreign key being the same, etc. The MLRDS computes the primary key-foreign key features comprising, for example, a normalized rank sum, a unique foreign key ratio, a unique foreign share, a name similarity index, a name pattern acceptance, a distribution displacement, and an element count ratio, for determining whether an inclusion dependency pair is a primary key-foreign key pair or a non-primary key-foreign key pair. To compute the primary key-foreign key features, the MLRDS uses combinations of items identified from the tables of the source database and the target database. The MLRDS computes the primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key using one of multiple items comprising, for example, data elements of the prospective primary key identified by the selected first column of data, the data elements of the prospective foreign key identified by the selected second column of data, a number of unique data elements of the prospective foreign key, Levenshtein distance between names of the prospective primary key and the prospective foreign key, a prefix matching score obtained from the names of the prospective primary key and the prospective foreign key, sound codes obtained by applying a Metaphone algorithm on the names of the prospective primary key and the prospective foreign key, patterns of the names of the prospective primary key and the prospective foreign key, statistical measures, and any combination thereof, from the target database. The Levenshtein distance is a string metric for measuring the difference between two strings. The Metaphone algorithm is a phonetic algorithm that indexes words by their English pronunciation.

[0046] The machine learning relationship determination system (MLRDS) further computes the primary key-foreign key features for the training data sets and the validation data set using one of multiple items comprising, for example, data elements of the predetermined inclusion dependency pairs, a number of unique data elements of foreign keys in the predetermined inclusion dependency pairs, Levenshtein distance between names of primary keys and the foreign keys in the predetermined inclusion dependency pairs, a prefix matching score obtained from the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, sound codes obtained by applying a Metaphone algorithm on the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, patterns such as suffixes of the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, statistical measures, and any combination thereof, from the source database.

[0047] Consider an example of an inclusion dependency pair (F, P), where F is a prospective foreign key and P is a prospective primary key referenced by the prospective foreign key F. The machine learning relationship determination system (MLRDS) computes the primary key-foreign key feature, namely, normalized rank sum of two columns represented by the prospective foreign key F and the prospective primary key P by arranging the data elements in F and P in ascending order and inserting all the elements of F in P. In this example, the data elements of P are represented as {AB, CD, EF, GH, IJ, KL} and the data elements of F are represented as {AB, EF, IJ}. On inserting all the data elements of F in P, P union F (P U F) is represented as {AB, AB, CD, EF, EF, GH, IJ, IJ, KL}. The MLRDS computes a rank for each data element in P U F as follows: The rank for AB is (1+2)/2=1.5. Similarly, the ranks for CD, EF, GH, IJ, and KL are 3, 4.5, 6, 7.5, and 9 respectively. The MLRDS computes the normalized rank sum as a total sum of ranks divided by a product of the total number of data elements and the number of data elements in the prospective foreign key F. That is, the MLRDS computes the normalized rank sum as 31.5/6*3=1.75. The MLRDS computes the primary key-foreign key feature, namely, the unique foreign key ratio as a ratio of the number of unique data elements in the prospective foreign key F and the total data elements in the prospective foreign key F. The MLRDS computes the primary key-foreign key feature, namely, the unique foreign share as the total number of unique data elements in the prospective foreign key F divided by the number of data elements in the prospective primary key P.

[0048] The machine learning relationship determination system (MLRDS) computes the primary key-foreign key feature, namely, the name similarity index using the Levenshtein distance between the names of the prospective primary key P and the prospective foreign key F, a prefix matching score obtained from the names of the prospective primary key and the prospective foreign key, and a sound code score obtained from the names of prospective primary key P and the prospective foreign key F. Consider an example where the names of the prospective primary key P and the prospective foreign key F are given as Np and Nf respectively. The Levenshtein distance between Np and Nf is denoted as Ld. The Levenshtein distance measures the similarity between the two names, for example, Np and Nf. The Levenshtein distance between the two names, Np and Nf, is the minimum number of single character edits, that is, insertions, deletions, or substitutions required to change one name Np into the other name Nf. The MLRDS computes the prefix matching score Pr as number of initial matching characters in Np and Nf divided by length of the longer name between Np and Nf. The MLRDS computes a sound code by applying the Metaphone algorithm on the name strings Np and Nf. The sound codes of Np and Nf are denoted as Sp and Sf respectively. The sound code score Sc is a prefix score of Sp and Sf and is given as a prefix score (Sp, Sf), that is, the number of matching characters in prefixes of Sp and Sf divided by length of the longer sound code between Sp and Sf. The MLRDS computes the Levenshtein distance Ld and computes a Levenshtein distance score Ls between Sp and Sf as Ls=1−(Ld) divided by length of the longer name between Np and Nf. The MLRDS then computes the name similarity index as a maximum of Ls, Pr, and Sc.

[0049] The machine learning relationship determination system (MLRDS) computes the primary key-foreign key feature, namely, the name pattern acceptance of the prospective primary key P and the prospective foreign key F by checking whether the name of the prospective primary key P or the name of the prospective foreign key F ends with a predetermined pattern, for example, "KEY" or "ID". If Np or Nf ends with "KEY" or "ID", the MLRDS assigns the name pattern acceptance value as 1. If Np or Nf does not end with "KEY" or "ID", the MLRDS assigns the name pattern acceptance value as **0**. The MLRDS computes the primary key-foreign key feature, namely, distribution displacement of the inclusion dependency pair of P and F by calculating an earth mover's distance between P and F. The earth mover's distance is a measure of the distance between probability distributions of P and F over a region D. The MLRDS also computes the primary key-foreign key feature, namely, the element count ratio of P and F as a ratio of the number of data elements in F and the number of data elements in P. A generic computer using a generic program cannot compute the primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set in accordance with the method steps disclosed above. The computed primary key-foreign key features do not decide deterministically whether or not the given inclusion dependency pair is a primary key-foreign key pair. The MLRDS presents the computed primary key-foreign key features to the machine learning classification algorithm to generate a machine learning model that determines whether or not the given inclusion dependency pair is a primary key-foreign key pair.

[0050] The machine learning relationship determination system (MLRDS) generates 106 trained machine learning models corresponding to the training data sets by training each machine learning classification algorithm using the training data sets and the computed primary key-foreign key features of the training data sets. As used herein, "trained machine learning models" refer to models generated by the machine learning classification algorithms trained on the training data sets using the computed primary key-foreign key features. For each machine learning classification algorithm, the MLRDS generates a trained machine learning model corresponding to each training data set using the computed primary key-foreign key features of the training data set. The trained machine learning models are obtained when the machine learning classification algorithm is trained on the computed primary key-foreign key features of the training data sets and the corresponding predetermined output values, that is, the corresponding primary key-foreign key flags of the training data set. Consider an example where the MLRDS splits the training data into 20 training data sets. The MLRDS trains a machine learning classification algorithm on the 20 training data sets and generates 20 trained machine learning models. A generic computer using a generic program cannot generate trained machine learning models corresponding to the training data sets by training each machine learning classification algorithm using the training data sets and the computed primary key-foreign key features for the training data sets in accordance with the method steps disclosed above.

[0051] The machine learning relationship determination system (MLRDS) generates **107** validated machine learning models for each of the machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set. As used herein, "validated machine learning models" refers to the trained machine learning models that are tested against the positive validation data and the negative validation data of the validation data set. Consider an example where the MLRDS generates 20 trained machine learning models using the 20 training data sets, and the number of predetermined inclusion dependency pairs in a validation data set is 60. The 20 trained machine learning models are tested against 60 predetermined inclusion dependency pairs in the validation data set. The test outputs of the 20 trained machine learning models to the validation data set are tabulated with expected outputs, that is, the predetermined output values of the validation data set.

[0052] On comparison of the test outputs of the 20 trained machine learning models to the 60 predetermined inclusion dependency pairs in the validation data set with the expected outputs of the 60 predetermined inclusion dependency pairs in the validation data set, the machine learning relationship determination system (MLRDS) computes parameters, for example, a YES COUNT and a % YES for every predetermined inclusion dependency pair in the validation data set. The parameter YES COUNT refers to the number of trained machine learning models that predict a predetermined inclusion dependency pair in the validation data set to be a primary key-foreign key pair. That is, the trained machine learning model predicts the predetermined inclusion dependency pair in the validation data set to be a primary key-foreign key pair and indicates the primary key-foreign key flag of the predetermined inclusion dependency pair with a "Y". The % YES refers to a percentage of trained machine learning models that output a "Y" primary key-foreign key flag to the predetermined inclusion dependency pair in the validation data set. The % YES is given by (YES COUNT*100) divided by the total number of trained machine learning models.

[0053] Four combinations of test outputs and expected outputs of the trained machine learning model for a predetermined inclusion dependency pair in the validation data set can be obtained as follows: If the expected output for the predetermined inclusion dependency pair is a YES and the test output for the predetermined inclusion dependency pair is a YES, the test output of the trained machine learning model is a true positive. If the expected output for the predetermined inclusion dependency pair is a YES and the test output for the predetermined inclusion dependency pair is a NO, the test output of the trained machine learning model is a false negative. If the expected output for the predetermined inclusion dependency pair is a NO and the test output for the predetermined inclusion dependency pair is a NO, the test output of the trained machine learning model is a true negative. If the expected output for the predetermined inclusion dependency pair is a NO and the test output for the predetermined inclusion dependency pair is a YES, the output of the trained machine learning model is a false positive. The possible test outputs of the trained machine learning models to the validation data set are true positive, false positive, true negative, and false negative.

[0054] The machine learning relationship determination system (MLRDS) generates validated machine learning models for each of the machine learning classification algorithms on testing the generated trained machine learning models with the predetermined inclusion dependency pairs in the validation data set. Each predetermined inclusion dependency pair in the validation data set has a corresponding YES COUNT and % YES parameters computed using the test outputs of the generated trained machine learning models. A generic computer using a generic program cannot generate validated machine learning models for each of the machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set in accordance with the method steps disclosed above.

[0055] The machine learning relationship determination system (MLRDS) further determines **108** an optimum algorithm decision threshold for each of the machine learning classification algorithms using the generated validated machine learning models. As used herein, an "optimum algorithm decision threshold" refers to an optimum value of a decision threshold. Also, as used herein, a "decision threshold" refers to a number of validated machine learning models whose output for a predetermined inclusion dependency pair in the validation data set needs to be "Y" to confirm that the inclusion dependency pair is a primary key-foreign key pair. The inclusion dependency pair that is a non-primary key-foreign key pair is indicated by "N". The optimum algorithm decision threshold is a value of the decision threshold where the number of false positive outputs of the validated machine learning models is substantially less and the number of true positive outputs of the validated machine learning models is substantially high. The % YES parameter along with the number of predetermined inclusion dependency pairs of the validation data set with expected outputs as YES and expected outputs as NO are tabulated in a descending order ranging from 100 to 0. The % YES parameter is the decision threshold.

[0056] The machine learning relationship determination system (MLRDS) also tabulates cumulative YES COUNT and cumulative NO COUNT in the validation data set. The cumulative YES COUNT represents the number of instances of the validation data set with true positive outputs and the cumulative NO COUNT represents the number of instances of the validation data set with false positive outputs. As used herein, "instances of the validation data set" refer to the predetermined inclusion dependency pairs of the validation data set. A 100% YES extreme condition corresponds to a decision threshold that confirms an inclusion dependency pair to be a primary key-foreign key pair only if all the validated machine learning models output that the inclusion dependency pair is a primary key-foreign key pair. A 0% YES extreme condition corresponds to a decision threshold that confirms an inclusion dependency pair to be a primary key-foreign key pair irrespective of the output of the validated machine learning models. The MLRDS facilitates selection of the optimum algorithm decision threshold between the two extreme conditions such that the number of false positive outputs is minimized and the number of true positive outputs is maximized. The MLRDS stores the selected optimum algorithm decision threshold for each machine learning classification algorithm in a threshold database. A generic computer using a generic program cannot determine an optimum algorithm decision threshold for each of the machine learning classification algorithms using the generated validated machine learning models in accordance with the method steps disclosed above.

[0057] Using the optimum algorithm decision threshold, the machine learning relationship determination system (MLRDS) determines **109** a resultant of the inclusion dependency pair of the prospective primary key and the prospective foreign key being a primary key-foreign key pair or a non-primary key-foreign key pair for each of the machine learning classification algorithms. The MLRDS subjects the inclusion dependency pair of the prospective primary key and the prospective foreign key to the validated machine learning models using the computed primary key-foreign key features of the inclusion dependency pair of the prospective primary key and the prospective foreign key. The MLRDS receives the outputs of the validated machine learning models and based on the optimum algorithm decision threshold, the MLRDS determines whether the inclusion dependency pair of the prospective primary key and the prospective foreign key is a primary key-foreign key pair or a non-primary key-foreign key pair. The MLRDS iterates the process of determining whether the inclusion dependency pair of the prospective primary key and the prospective foreign key is a primary key-foreign key pair or a non-primary key-foreign key pair for each machine learning classification algorithm. A generic computer using a generic program cannot determine a resultant of the inclusion dependency pair of the prospective primary key and the prospective foreign key being a primary key-foreign key pair or a non-primary key-foreign key pair for each of the machine learning classification algorithms in accordance with the method steps disclosed above.

[0058] The machine learning relationship determination system (MLRDS) then performs **110** majority voting on the determined resultant for each of the machine learning classification algorithms to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table, that is, to confirm that a primary key-foreign key relationship between the prospective primary key and the prospective foreign key exists. A generic computer using a generic program cannot perform majority voting on the determined resultant of each of the machine learning classification algorithms to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table in accordance with the method steps disclosed above.

[0059] The number of machine learning classification algorithms and the combination of the machine learning classification algorithms is configurable. In an embodiment, the machine learning relationship determination system (MLRDS) selects an odd number of machine learning classification algorithms for determining primary key-foreign key relationships among data in the selected first column and the selected second column. On performing majority voting on the determined resultants for the odd number of machine learning classification algorithms, the MLRDS obtains a clear majority of the resultants which enables the MLRDS to quickly determine the final resultant of the odd number of machine learning classification algorithms. The MLRDS obtains a clear majority of the resultants of the odd number of machine learning classification algorithms when the number of machine learning classification algorithms with the same resultant is greater than 50% of the odd number of machine learning classification algorithms. In another embodiment, the MLRDS selects an even number of machine learning classification algorithms for determining primary key-foreign key relationships among data in the selected first column and the selected second column. On performing majority voting on the determined resultants for the even number of machine learning classification algorithms, the MLRDS will not obtain a clear majority of resultants. In this embodiment, the MLRDS receives a selection of a minimum limit of 50% of the even number of machine learning classification algorithms to define a majority from the user device. That is, the resultants of 50% or more of the even number of machine learning classification algorithms define the majority.

[0060] On implementing the method disclosed herein, the end result generated by the machine learning relationship determination system (MLRDS) is a tangible determination of primary key-foreign key relationships among data in the tables of the target database. Determination of primary key-foreign key relationships maintains referential integrity of the tables in the target database. With the referential integrity, the quality of data stored in the tables of the target database is boosted. With the referential integrity maintained, writing custom programming codes for the tables individually is eliminated and chances of bugs in the programming code is reduced. There will also be consistency in data references across application programs that access the tables in the target database, thereby reducing the time for development of the application programs.

[0061] In the method disclosed herein, the machine learning relationship determination system (MLRDS) determines primary key-foreign key relationships between data in tables whose metadata is not updated or maintained. The MLRDS utilizes a combination of machine learning classification algorithms for determining the primary key-foreign key relationships. The machine learning classification algorithms recognize hidden patterns in the computed primary key-foreign key features of the training data and apply the hidden patterns on the data of the tables for determining the primary key-foreign key relationships. The primary key-foreign key features of the training data are selected in such a way that the machine learning classification algorithms are trained on all possible combinations and patterns of the training data. The primary key-foreign key features are also interdependent.

[0062] The method disclosed herein provides an improvement in computer related technology related to machine learning as follows: On implementing the method disclosed herein by the machine learning relationship determination system (MLRDS), the primary key-foreign key relationships between data in the tables are determined where data flow between the tables in the target database is affected due to any kind of perturbation, for example, deletion, insertion, etc., which results in the metadata of the tables not being updated. The MLRDS facilitates the search for the primary key and foreign key of the tables by eliminating column pairs in tables that do not satisfy the condition of inclusion dependency. On eliminating the non-inclusion dependency pairs, there may still be a large number of column pairs with inclusion dependency. For the identified inclusion dependency pairs, the MLRDS uses a combination of machine learning classification algorithms to classify a large number of inclusion dependency pairs in a short duration, thereby reducing human intervention and achieving the classification of the inclusion dependency pairs into primary key-foreign key pairs and non-primary key-foreign key pairs with computation intensive processors. The combination of machine learning classification algorithms recognize hidden characteristics of already known primary key-foreign key pairs and apply the hidden characteristics to identify new inclusion dependency pairs that have primary key-foreign key relationships. To identify the inclusion dependency pairs from the tables of the target database, compute the primary key-foreign key features, generate trained and validated machine learning models using the training data sets and the validation data set, determine an optimum algorithm threshold for each of the machine learning classification algorithms, determine a resultant of the inclusion dependency pair being a primary key-foreign key pair or a non-primary key-foreign key pair, and perform majority voting on the determined resultant for each of the machine learning classification algorithms requires six or more separate computer programs, the execution of which cannot be performed by a person using a generic computer.

[0063] The data inputted to the machine learning relationship determination system (MLRDS), for example, the training data for training the machine learning classification algorithms, the validation data set for validating the trained machine learning models, the identified inclusion dependency pairs, the optimum decision threshold, and an acceptable accuracy for a trained machine learning model is transformed, processed, and executed by an algorithm in the MLRDS. In splitting the training data into multiple training data sets, the MLRDS transforms the training data for training the machine learning classification algorithms to ensure an adequate combination of the positive training data and the negative training data in each training data set. In computing the primary key-foreign key features, for example, a name similarity index of the training data, the validation data set, and the identified inclusion dependency pairs, the MLRDS transforms the training data, the validation data set, and the identified inclusion dependency pairs, for example, into respective sound codes using the Metaphone algorithm. The MLRDS transforms the optimum algorithm decision threshold to a whole number of validated machine learning models whose output to a predetermined inclusion dependency pair in the validation data set is “Y” to confirm that the predetermined inclusion dependency pair is a primary key-foreign key pair. The MLRDS uses the whole number of the validated machine learning models to determine a resultant of the identified inclusion dependency pairs from the tables of the target database being primary key-foreign key pairs or non-primary key-foreign key pairs. The MLRDS transforms the acceptable accuracy of the trained machine learning models from a percentage value to a whole number to compare the output of the trained machine learning models to the expected output in the validation data set, on validating with the trained machine learning models against the validation data set. The determined primary key-foreign key relationships control any transformation of the data in the target database.

[0064] To obtain a complete insight of the data in the target database, it is important to know the relationship between the data in various columns in a schema. One of the relationships is a primary key-foreign key relationship. Determining the primary key-foreign key relationship among the columns in a large target database schema is challenging if explicit information about the schema is not available. The precondition of inclusion dependency solves the problem of evaluating each pair of columns of the target database for determining a primary key-foreign key relationship to some extent but the problem is still significant for a manual determination of a primary key-foreign key relationship. Machine learning classification algorithms recognize the hidden characteristics of already known primary key-foreign key pairs and apply the same characteristics to determine the primary key-foreign key relationship among the identified inclusion dependency pairs. On implementing a combination of machine learning classification algorithms, the machine learning relationship determination system (MLRDS) improves the prediction accuracy and computation time of determining primary key-foreign key relationships among the data in the target database. This is because some machine learning classification algorithms are optimally suited for a particular type of data than others and allow identification and learning from certain patterns in the data. The method disclosed herein provides a specialized way to utilize appropriate primary key-foreign key features and a combination of appropriate machine learning classification algorithms to determine the primary key-foreign key relationships between the data in the target database. By determining the primary key-foreign key relationships between the data in the target database, the MLRDS addresses the problems of detection of flow of the data in the target database or other data analytics, for example, determining a source of information in an executive report in a short duration with an improved accuracy.

[0065] FIG. **2** exemplarily illustrates a flowchart comprising the steps performed by the machine learning relationship determination system (MLRDS) for training and validating a machine learning classification algorithm and for determining primary key-foreign key relationships between data in multiple tables of the target database. The MLRDS receives training data and splits the training data into multiple training data sets **201**. The MLRDS also receives a validation data set **203** from a source database. The MLRDS uses the training data sets **201** as input for training **202** a machine learning classification algorithm. On training **202** the machine learning classification algorithm, the MLRDS generates trained machine learning models as disclosed in detailed description of FIGS. **1A-1B**. The MLRDS validates **204** the generated trained machine learning models against the validation data set **203** using predetermined inclusion dependency pairs in the validation data set **203**.

[0066] The machine learning relationship determination system (MLRDS) determines **205** whether the trained machine learning model has an acceptable accuracy. The accuracy of the trained machine learning model refers to the number of times the trained machine learning model makes a correct prediction of a primary key-foreign key relationship for an inclusion dependency pair in the validation data set **203** when compared with the expected output for the inclusion dependency pair in the validation data set **203**. In an embodiment, a user of the MLRDS configures the acceptable accuracy for a trained machine learning model. If the trained machine learning model exhibits the acceptable accuracy against the validation data set **203**, the MLRDS generates a validated machine learning model **206** from the trained machine learning model. If the trained machine learning model does not exhibit the acceptable accuracy against the validation data set **203**, the MLRDS re-trains the trained machine learning model until the acceptable accuracy **205** is met. That is, the MLRDS generates the validated machine learning model **206** for each of the machine learning classification algorithms **202** when the generated trained machine learning model corresponding to the training data sets **201** meets a predetermined criterion, that is, the acceptable accuracy, on testing the generated trained machine learning model against the validation data set **203**. The MLRDS retrains the generated trained machine learning model on the training data sets **201** until the generated trained machine learning model meets the predetermined criterion, that is, the acceptable accuracy, for the generation of the validated machine learning model **206** for each of the machine learning classification algorithms **202**. The MLRDS inputs the usage data **207**, that is, the data in the tables of the target database to the validated machine learning model **206**. The validated machine learning model **206** outputs a usage resultant **208**, that is, the determined primary key-foreign key relationships among the usage data **207** in the tables of the target database. The validated machine learning model **206** determines whether the usage data **207** is a primary key-foreign key pair or a non-primary key-foreign key pair.

[0067] FIGS. **3A-9** exemplarily illustrate an example for determining primary key-foreign key relationships among data in tables **301** and **302** of a target database by the machine learning relationship determination system (MLRDS) through machine learning.

[0068] FIGS. **3A-3B** exemplarily illustrate two tables **301** and **302** of a target database with respective columns **301***a,* **301***b,* **301***c,* **302***a,* **302***b,* and **302***c* whose primary key-foreign key relationship is to be determined. For a primary key-foreign key relationship to exist between the tables **301** and **302**, a condition of inclusion dependency has to be satisfied by the columns **301***a,* **301***b,* **301***c,* **302***a,* **302***b,* and **302***c* of the tables **301** and **302** as disclosed in the detailed description of FIGS. **1A-1B**. The machine learning relationship determination system (MLRDS) selects the column **301***a* from the table **301** and the column **302***a* from the table **302**. The MLRDS determines whether all the data elements in the column **302***a* are present in the column **301***a.* Since all the data elements in the column **302***a* are not a subset of the data elements in the column **301***a,* the column **302***a* has no inclusion dependency with the column **301***a.* The MLRDS selects the column **301***a* and the column **302***b* from the tables **301** and **302** respectively. The data elements in the column **302***b* are a subset of the data elements in the column **301***a.* The column **301***a* and the column **302***b* therefore satisfy the condition of inclusion dependency even though the names of the column **301***a* and the column **302***b* are different. Therefore, the MLRDS identifies the column **301***a* as a prospective primary key and the column **302***b* as a prospective foreign key and the tables **301** and **302** are a prospective parent table and a prospective child table respectively.

[0069] The machine learning relationship determination system (MLRDS) receives multiple predetermined inclusion dependency pairs comprising primary key-foreign key pairs and non-primary key-foreign key pairs from a source database. The primary key-foreign key pairs are classified into positive training data and positive validation data. The non-primary key-foreign key pairs are classified into negative training data and negative validation data. The positive training data and the negative training data are used to train each of the selected machine learning classification algorithms and the positive validation data and the negative validation data are used to validate each of the selected machine learning classification algorithms. Consider an example where the MLRDS receives 2050 predetermined inclusion dependency pairs comprising positive training data and negative training data as training data to train a machine learning classification algorithm. Out of the 2050 predetermined inclusion dependency pairs, 50 predetermined inclusion dependency pairs constitute the positive training data and 2000 predetermined inclusion dependency pairs constitute the negative training data. The MLRDS splits the positive training data and the negative training data into multiple training data sets.

[0070] FIG. **4** exemplarily illustrates a schematic representation showing splitting of the positive training data and the negative training data into multiple training data sets **401***a,* **401***b,* **401***c,* **401***d,* . . . , and **401***t.* The machine learning relationship determination system (MLRDS) determines a ratio of the positive training data to the negative training data as **1**:**2** in each of the training data sets **401***a,* **401***b,* **401***c,* **401***d,* . . . , and **401***t.* The MLRDS splits the training data **401** into (2000)/(50*2)=20 training data sets **401***a,* **401***b,* **401***c,* **401***d,* . . . , and **401***t.* Each of the training data sets **401***a,* **401***b,* **401***c,* **401***d,* . . . , and **401***t,* has 50 primary key-foreign key pairs and 100 non-primary key-foreign key pairs. The MLRDS also receives validation data as a validation data set comprising 1200 predetermined inclusion dependency pairs as exemplarily illustrated in FIG. **5**. The 1200 predetermined inclusion dependency pairs are classified into 50 primary key-foreign key pairs and 1150 non-primary key-foreign key pairs. The 50 primary key-foreign key pairs constitute the positive validation data and the 1150 non-primary key-foreign key pairs constitute the negative validation data.

[0071] The machine learning relationship determination system (MLRDS) computes multiple primary key-foreign key features for the inclusion dependency pairs of the prospective primary key and the prospective foreign key identified from the tables **301** and **302** in FIG. **3**A. The MLRDS also computes primary key-foreign key features for the predetermined inclusion dependency pairs in the training data sets and the validation data set. The MLRDS uses a combination of machine learning classification algorithms, for example, the J48 algorithm, the k-Nearest Neighbors algorithm, the Random Forest algorithm, the Naive B ayes algorithm, a support vector machine model, etc., for identifying primary key-foreign key pairs and non-primary key-foreign key pairs from the inclusion dependency pairs of the prospective primary key and the prospective foreign key identified from the tables **301** and **302**. The MLRDS trains each of the machine learning classification algorithms on the computed primary key-foreign key features of the training data sets. The machine learning classification algorithm learns from the patterns in the computed primary key-foreign key features of the training data sets. For each of the training data sets **401***a,* **401***b,* **401***c,* **401***d,* . . . , and **401***t* exemplarily illustrate in FIG. **4**, on which the machine learning classification algorithm, for example, the Random Forest algorithm, is trained, the MLRDS generates a trained machine learning model. Thus, the MLRDS generates 20 trained Random Forest models. The MLRDS tests the 20 trained Random Forest models against the validation data set.

[0072] FIG. **5** exemplarily illustrates a table **501** containing test outputs of the trained machine learning models, that is, the 20 trained Random Forest models, obtained by the machine learning relationship determination system (MLRDS) on testing the 20 trained Random Forest models against the validation data set. In the table **501**, column INSTANCE refers to instance identifier (ID) and column ACTUAL RESULT indicates whether an instance is an actual primary key-foreign key pair or not. For each instance of the validation data set, the MLRDS tabulates the test outputs of the 20 trained Random Forest models obtained based on the computed primary key-foreign key features of the validation data set against an expected output. The MLRDS computes parameters YES COUNT and % YES for each instance of the validation data set. A YES output of the trained Random Forest model is indicated by a primary key-foreign key flag "Y" and a NO output of the trained Random Forest model is indicated by a primary key-foreign key flag "N" in the table **501**.

[0073] Consider instance **2** of the validation data set exemplarily illustrated in FIG. **5**. The number of trained Random Forest models that output "Y" is **4** as indicated in the YES COUNT column of the table **501**. The machine learning relationship determination system (MLRDS) computes the % YES parameter as (YES COUNT*100) divided by the total number of trained Random Forest models=4*100/20=20% as indicated in the % YES column of the table **501**. In a similar manner, MLRDS computes the parameters YES COUNT and % YES for all the 1200 predetermined inclusion dependency pairs in the validation data set. The MLRDS retrains the Random Forest models until the trained Random Forest models exhibit an acceptable accuracy on testing the Random Forest models with the validation data set. Using the acceptable accuracy, the MLRDS generates validated Random Forest models. Using the validated Random Forest models, the MLRDS determines an optimum algorithm decision threshold for determining whether the inclusion dependency pairs identified from the tables **301** and **302** exemplarily illustrated in FIG. **3**A, are primary key-foreign key pairs or non-primary key-foreign key pairs.

[0074] FIG. **6** exemplarily illustrates a table **601** containing a number of instances of the validation data set that defines a primary key-foreign key relationship between the instances of the validation data set for determining the optimum algorithm decision threshold using validated machine learning models, that is, the 20 validated Random Forest models disclosed in the detailed description of FIG. **5**. The machine learning relationship determination system (MLRDS) tabulates the number of instances of the validation data set with true positive outputs of the validated Random Forest models under the column COUNT ACTUAL "YES" for each % YES value in the table **601**. The MLRDS also tabulates the number of instances of the validation data set with false positive outputs of the validated Random Forest models under the column COUNT ACTUAL "NO" for each % YES value in the table **601**. For a 100% YES value in the table **601**, the total number of instances where the test output of all the 20 trained Random Forest models is "Y", is 5 as indicated in the column COUNT in the table **601**. Out of the 5 instances, the number of instances where the expected output is also "Y" is 4 as indicated in the column COUNT ACTUAL "YES" in the table **601**. In 1 remaining instance, the expected output is "N", while the test output of the 20 trained Random Forest models is "Y" as indicated in the column COUNT ACTUAL "NO" in the table **601**. The 20 trained Random Forest models inaccurately predicted the primary key-foreign key relationship for the 1 remaining instance of the validation data set. Similarly, the MLRDS tabulates the COUNT ACTUAL "YES" and the COUNT ACTUAL "NO" parameters for all values under the % YES column exemplarily illustrated in the table **501** in FIG. **5**, ranging from 0 to 100 in descending order. The MLRDS also computes a cumulative number of the values in the column COUNT ACTUAL "YES" and a cumulative number of the values in the column COUNT ACTUAL "NO" for each % YES parameter from 100% to 0%.

[0075] FIG. **7** exemplarily illustrates a table **701** containing a cumulative number of instances of the validation data set that defines a primary key-foreign relationship between the instances of the validation data set for determining the optimum algorithm decision threshold using the validated Random Forest models. For a value of % YES, the cumulative number of instances of the validation data set for which the test output of the trained Random Forest models is a true positive is indicated in the column CUMULATIVE "YES" in the table **701**. For a value of % YES, the cumulative value for the number of instances of the validation data set for which the test output of the trained Random Forest models is a false positive is indicated in the column CUMULATIVE "NO" in the table **701**. For a % YES value 100, the value in the column CUMULATIVE "YES" is 4 as the value in the column COUNT ACTUAL "YES" is 4, and the value in the column CUMULATIVE "NO" is 1 as the value in the column COUNT ACTUAL "NO" is 1 as disclosed in the detailed description of FIG. **6**. For a YES % 50, the COUNT is 220, the value in the column COUNT ACTUAL "YES" is 70, and the value in the column COUNT ACTUAL "NO" is 150. The value in the column CUMULATIVE "YES" is 4+70=74, and the value in the column CUMULATIVE "NO" is 1+150=151. Using the cumulative number of instances of the validation data set, the machine learning relationship determination system (MLRDS) determines the optimum value of % YES where the number of true positive outputs of the validated machine learning models is more while reducing the number of false positive outputs of the validated machine learning models. The % YES is the decision threshold and the optimum value of % YES is the optimum algorithm decision threshold.

[0076] FIG. **8** exemplarily illustrates a schematic representation for determining the optimum algorithm decision threshold using the validated Random Forest models. The machine learning relationship determination system (MLRDS) facilitates selection of an optimum value of % YES between extreme conditions of 0 and 100. As exemplarily illustrated in FIG. **8**, the number of true positive outputs and the number of false positive outputs reduce as % YES reduces from 100% to 0%. The optimum algorithm decision threshold is selected in such a way that the loss of the number of true positive outputs is as minimum as possible and the number of false positive outputs is reduced as much as possible. For reducing the number of false positive outputs, the value of % YES is decreased but there is also a decrease in the number of true positive outputs which is to be avoided. Hence, the optimum algorithm decision threshold is selected as the level of % YES where a slight jump towards the next value of % YES will result in either a substantial loss of the number of true positive outputs or a minimal gain towards reducing the number of false positive outputs. For a value of % YES more than 40, the number of true positive outputs is more while the number of false positive outputs also increases. For value of % YES less than 40, the number of true positive outputs is reduced along with a reduction in the number of false positive outputs. However, for the value of % YES less than 40, 3 true positive outputs are lost at the cost of no reduction in the number of false positive outputs. Thus, the value of % YES as 40 is the optimum value of % YES where at the cost of 2 true positive outputs, 1970 false positive outputs are eliminated. The % YES as 40 is the optimum algorithm decision threshold. That is, if at least 40*20/100=8 validated Random Forest models predict an inclusion dependency pair **301***a* and **302***b* exemplarily illustrated in FIG. **3**B, identified from the tables **301** and **302** exemplarily illustrated in FIG. **3**A, as a primary key-foreign key pair, the resultant of the Random Forest algorithm for the inclusion dependency pair **301***a* and **302***b* is "Y".

[0077] The machine learning relationship determination system (MLRDS) inputs the identified inclusion dependency pair **301***a* and **302***b* exemplarily illustrated in FIG. **3**B, with the computed primary key-foreign key features to the validated machine learning models of the machine learning classification algorithms. Using the optimum algorithm decision threshold, the validated machine learning models for each of the machine learning classification algorithms determine a resultant for the identified inclusion dependency pair **301***a* and **302***b*. The MLRDS performs majority voting on the resultant of the identified inclusion dependency pair **301***a* and **302***b* for each of the machine learning classification algorithms.

[0078] FIG. **9** exemplarily illustrates a flow diagram showing majority voting of the resultant of the identified inclusion dependency pair **301***a* and **302***b* for each of the machine learning classification algorithms. The machine learning relationship determination system (MLRDS) subjects the resultants of the J48 algorithm **901**, the k-Nearest Neighbors algorithm **902**, the Random Forest algorithm **903**, the Naive Bayes algorithm **904**, and the support vector machine model **905** to majority voting **906** for determining a primary key-foreign key relationship among the data in the column **301***a* of the table **301** and the column **302***b* of the table **302** exemplarily illustrated in FIGS. **3**A-**3**B. The majority of the resultants of the machine learning classification algorithms **901**, **902**, **903**, **904**, and **905** provides a final result **907** indicated by a primary key-foreign key flag "Y" or "N" for the primary key-foreign key relationship between the identified inclusion dependency pair **301***a* and **302***b* exemplarily illustrated in FIG. **3**B.

[0079] FIGS. **10**A-**21** exemplarily illustrate another example for determining primary key-foreign key relationships among data in tables **1001***a* and **1001***b* of a target database by the machine learning relationship determination system (MLRDS) through machine learning.

[0080] FIGS. **10**A-**10**B exemplarily illustrate two tables T**1** **1001***a* and T**2** **1001***b* of a target database with respective columns whose primary key-foreign key relationship is to be determined. The machine learning relationship determination system (MLRDS) employs at least one processor configured to execute computer program instructions for determining primary key-foreign key relationships among data in the tables T**1** **1001***a* and T**2** **1001***b*. Table T**1** **1001***a* is an employee information table with five columns, for example, EMP_ID, EMP_FIRST_NAME, SURNAME, DATE OF JOINING, and YEARS OF EXP. Table T**2** **1001***b* is a medical checkup information table with four columns, for example, CHECKUP_ID, EMP_CODE, CHECKUP_DATE, and NO. OF TESTS. The MLRDS selects pairs of columns from the tables T**1** **1001***a* and T**2** **1001***b* to check for the condition of inclusion dependency between the tables T**1** **1001***a* and T**2** **1001***b*. The MLRDS selects a first column, for example, EMP_ID from the table T**1** **1001***a* and a second column, for example, EMP_CODE from the table T**2** **1001***b*. Since all the data elements in the column EMP_CODE are a subset of the data elements in the column EMP_ID, the column pair (T**1**.EMP_ID, T**2**.EMP_CODE) satisfies the condition of inclusion dependency pair and hence may possess a primary key-foreign key relationship. The MLRDS identifies the column EMP_ID as the prospective primary key and the column EMP_CODE as the prospective foreign key. The MLRDS then selects the column EMP_ID from the table T**1** **1001***a* and the column NO. OF TESTS from the table T**2** **1001***b*. The MLRDS determines whether the column pair (T**1**.EMP_ID, T**2**. NO. OF TESTS) form an inclusion dependency pair. Since all the data elements in the column NO. OF TESTS are not a subset of the data elements in the column EMP_ID, the column pair (T**1**.EMP_ID, T**2**. NO. OF TEST) does not form an inclusion dependency pair and hence cannot be a primary key-foreign key pair. Similarly, the MLRDS identifies all the inclusion dependency pairs from the tables T**1** **1001***a* and T**2** **1001***b*. The MLRDS receives multiple predetermined inclusion dependency pairs comprising primary key-foreign key pairs classified as positive training data and positive validation data and non-primary key-foreign key pairs classified as negative training data and negative validation data from a source database.

[0081] FIG. **11** exemplarily illustrates a table **1101** from the source database containing training data. The machine learning relationship determination system (MLRDS) receives the training data comprising column pairs satisfying the condition of inclusion dependency and identified as primary key-foreign key pairs and non-primary key-foreign key pairs from the source database. As exemplarily illustrated in FIG. **11**, the table **1101** contains six columns, for example, ID of the training data, TABLE_NAME_P, COLUMN_NAME_P, TABLE_NAME_D, COLUMN_NAME_D, and PK-FK FLAG. The column TABLE_NAME_P is an attribute of the table containing the primary key COLUMN_NAME_P. The column TABLE_NAME_D is an attribute of the table containing the foreign key COLUMN_NAME_D. The data elements in the columns TABLE_NAME_P and TABLE_NAME_D are names of the parent table and the child table respectively. The data elements in the columns COLUMN_NAME_P and COLUMN_NAME_D are the names of the primary key and the foreign key contained in the parent table and the child table respectively. The PK-FK flag is a primary key-foreign key flag identifying the predetermined inclusion dependency pair given by (TABLE_NAME_P. COLUMN_NAME_P, TABLE_NAME_D. COLUMN_NAME_D) as a primary key-foreign key pair or a non-primary key-foreign key pair. The primary key-foreign pair is indicated by "Y" and the non-primary key-foreign pair is indicated by "N". The column ID identifies an instance, that is, a predetermined inclusion dependency pair in the training data. In the table **1101**, **1628** instances are available for training multiple machine learning classification algorithms. The number of primary key-foreign key pairs, that is, the positive training data is **37** identified by the primary key-foreign key flag as "Y". The remaining **1591** instances are non-primary key-foreign key pairs, that is, the negative training data, indicated by the primary key-foreign key flag as "N". The MLRDS splits the positive training data and the negative training data in the table **1101** into multiple training data sets as disclosed in the detailed description FIG. **13**. The MLRDS also receives a validation data set comprising primary key-foreign key pairs and non-primary key-foreign key pairs from the source database.

[0082] FIG. **12** exemplarily illustrates a table **1201** from the source database containing the validation data set. The validation data set contains predetermined inclusion dependency pairs classified into positive validation data and negative validation data. The positive validation data is identified by "Y" as the primary key-foreign key flag in the column named PK-FK flag, and the negative validation data is identified by "N" as the primary key-foreign key flag in the column named PK-FK flag. The total number of predetermined inclusion dependency pairs in the validation data set in the table **1201** is 580. The number of primary key-foreign key pairs out of the 580 predetermined inclusion dependency pairs is 20. The remaining 560 predetermined inclusion dependency pairs are non-primary key-foreign key pairs.

[0083] FIG. **13** exemplarily illustrates a schematic representation showing splitting of the training data indicated in a table **1301** into multiple training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j.* Since the number of primary key-foreign key pairs constituting the positive training data is **37** and the number of non-primary key-foreign key pairs constituting the negative training data is **1591** from the training data exemplarily illustrated in FIG. **11**, the machine learning relationship determination system (MLRDS) splits the negative training data into multiple training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j* and adds the positive training data to each of the training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j.* The ratio of the positive training data to the negative training data in a training data set is predetermined, for example, 1:4. Thus, the training data is split into 1591/(37*4)=10.75 training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j.* Rounding off to the closest whole number, the MLRDS splits the training data in the table **1101** exemplarily illustrated in FIG. **11**, into 9 training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i* with each having 148 non-primary key-foreign key pairs constituting the negative training data and **37** primary key-foreign key pairs constituting the positive training data. The last training data set **1301***j* has 259 non-primary key-foreign key pairs constituting the negative training data and 37 primary key-foreign key pairs constituting the positive training data since the MLRDS adds the remaining 111 non-primary key-foreign key pairs to the 148 non-primary key-foreign key pairs in the last training data set **1301***j.* The MLRDS computes multiple primary key-foreign key features for the training data in the table **1101**, for the validation data set in the table **1201**, and for the inclusion dependency pair of the prospective primary key and the prospective foreign key identified from the tables T**1** **1001***a* and T**2** **1001***b* exemplarily illustrated in FIGS. **10**A-**10**B, as disclosed in the detailed description of FIGS. **1**A-**1**B.

[0084] FIGS. **14**A-**14**B exemplarily illustrate a table **1401** containing the training data of the table **1101** exemplarily illustrated in FIG. **11**, with primary key-foreign key features computed for the training data by the machine learning relationship determination system (MLRDS). The MLRDS computes the primary key-foreign key features comprising, for example, a normalized rank sum, a unique foreign key ratio, a unique foreign share, a name pattern acceptance, a name similarity index, an element count ratio, and a distribution displacement for the instances, that is, the predetermined inclusion dependency pairs in the training data in the table **1101**, as disclosed in detailed description of FIGS. **1**A-**1**B.

[0085] FIGS. **15**A-**15**B exemplarily illustrate a table **1501** containing the validation data set of the table **1201** exemplarily illustrated in FIG. **12**, with primary key-foreign key features computed for the validation data set by the machine learning relationship determination system (MLRDS). The MLRDS computes the primary key-foreign key features for all the instances, that is, the predetermined inclusion dependency pairs in the validation data set in the table **1201** and generates the table **1501**. The MLRDS uses a combination of machine learning classification algorithms, for example, the J48 algorithm, the k-Nearest Neighbors algorithm, the Naive Bayes algorithm, the Random Forest algorithm, the Bayes network model, the multilayer perceptron model, the support vector machine model, etc., for identifying primary key-foreign key pairs and non-primary key-foreign key pairs from the inclusion dependency pairs of the prospective primary keys and the prospective foreign keys identified from the tables T**1** **1001***a* and T**2** **1001***b* exemplarily illustrated in FIGS. **10**A-**10**B.

[0086] FIG. **16** exemplarily illustrates a flowchart comprising the steps performed by the machine learning relationship determination system (MLRDS) for generating validated machine learning models, for example, **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a* for a machine learning classification algorithm, for example, the J48 algorithm **1600**. The MLRDS generates trained machine learning models corresponding to the training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j* exemplarily illustrated in FIG. **13**, by training each of the machine learning classification algorithms using the training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j* and the computed primary key-foreign key features of the training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j.* For example, the MLRDS trains the J48 algorithm **1600** on trends and patterns in the computed primary key-foreign key features of the 10 training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j* for predetermined output values of primary key-foreign key flags in the table **1401** exemplarily illustrated in FIGS. **14**A-**14**B, and generates 10 trained J48 models. Once training is completed, the MLRDS validates the 10 trained J48 models against the validation data set **1611**.

[0087] The machine learning relationship determination system (MLRDS) generates validated machine learning models for each of the machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets **1301***a,* **1301***b,* **1301***c,* **1301***d,* **1301***e,* . . . , **1301***i,* and **1301***j* with the validation data set **1611** and the computed primary key-foreign key features of the validation data set **1611**. As exemplarily illustrated in FIG. **16**, the validation data set **1611** in the table **1501** exemplarily illustrated in FIGS. **15**A-**15**B is input to the 10 trained J48 models. Based on the training of the J48 algorithm **1600** on the training data in the table **1401**, the 10 trained J48 models predict the primary key-foreign key relationships of the instances of the validation data set **1611** in the table **1501**. If the test outputs of the 10 trained J48 models meet an acceptable accuracy, the MLRDS stores the 10 trained J48 models as validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a.* The MLRDS validates the test outputs of the 10 trained J48 models for the validation data set **1611** in the table **1501** against the expected output for the validation data set **1611** in the table **1501**. For example, the MLRDS validates all the trained J48 models against the same validation data set **1611** and the trained J48 models that exhibit a configurable accuracy of more than 50% on validation are stored as the validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a.* The MLRDS repeats the training and the validation for another 4 machine learning classification algorithms and obtains 50 validated machine learning models, that is, 10 validated machine learning models for each machine learning classification algorithm. The MLRDS then determines an optimum algorithm decision threshold for each of the machine learning classification algorithms using the generated validated machine learning models.

[0088] FIG. **17** exemplarily illustrates a table **1701** containing outputs of the trained machine learning models, that is, the validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a* obtained by the machine learning relationship determination system (MLRDS) on validating the trained machine learning models against the validation data set **1611** exemplarily illustrated in FIG. **16**. The MLRDS generates the table **1701** on testing the 10 trained J48 models independently on the instances of the validation data set **1611** from the table **1501** exemplarily illustrated in FIGS. **15**A-**15**B, and collecting the test outputs of the 10 trained J48 models. The table **1701** contains the test outputs of the 10 trained J48 models to the validation data set **1611** along with the expected output of the 10 trained J48 models given by the primary key-foreign key flag in the table **1401** exemplarily illustrated in FIGS. **14**A-**14**B. The MLRDS also tabulates the YES COUNT parameter for every instance of the validation data set **1611** along with the % YES parameter given by (YES COUNT)***100**/total number of the 10 trained J48 models.

[0089] Consider the first instance in the table **1701** identified with an ID **10001**. The 10 trained J48 models are identified as M**1**, M**2**, M**3**, M**4**, M**5**, M**6**, M**7**, M**8**, M**9**, and M**10** in the table **1701**. The expected output of the 10 trained J48 models for the instance is given by the column ACTUAL PK-FK FLAG in the table **1701**. For the ID **100001**, the ACTUAL PK-FK FLAG is "N". The trained J48 models M**1**, M**2**, M**3**, M**4**, M**5**, M**6**, M**7**, M**8**, M**9**, and M**10** predict the primary key-foreign key relationship for the first instance ID **10001** in the validation data set **1611** in the table **1701** as "N", "N", "Y", "Y", "N", "N", "N", "Y", "N", and "N" respectively. The machine learning relationship determination system (MLRDS) computes the YES COUNT parameter for the instance ID **100001** as 3 since the number of "Y" in the test outputs of the trained J48 models is 3. The MLRDS calculates the % YES parameter as 3*100/10=30%. The trained J48 model M**1** outputs "N" and since the expected output is also "N" in the instance ID **100001**, the test output of the trained J48 model M**1** is a true negative. The trained J48 model M**3** outputs "Y" and since the expected output is "N" in the instance ID **100001**, the test output of the trained J48 model M**3** is a false positive. Consider the instance with ID **100004** where the expected output is "Y". The trained J48 model M**1** outputs "Y". The output of the trained J48 model M**1** is a true positive since the test output and the expected output are both "Y". For the instance ID **100004**, the trained J48 model M**3** outputs "N" and since the expected output is "Y", the test output of the trained J48 model M**3** is a false negative. The MLRDS tabulates the number of instances of the validation data set **1611** with true positive outputs and false positive outputs of the validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a* exemplarily illustrated in FIG. **16**. The MLRDS also computes and tabulates a cumulative number of true positive outputs and false positive outputs of the validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a* for each % YES parameter ranging from 100% to 0% as exemplarily illustrated in FIGS. **18**A-**18**C.

[0090] FIGS. **18**A-**18**C exemplarily illustrate a table **1801** containing a cumulative number of instances of the validation data set **1611** exemplarily illustrated in FIG. **16**, that defines a primary key-foreign relationship between the instances of the validation data set **1611** for determining the optimum algorithm decision threshold using the validated machine learning models, that is, the validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a* exemplarily illustrated in FIG. **16**. As exemplarily illustrated in FIG. **18**A, the number of instances with % YES as 100 is 1. Therefore, the value in the column INSTANCE COUNT of the table **1801** for % YES as 100 is 1. The number of instances of the validation data set **1611** where the test output of the 10 validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a* is a true positive is 1 and is indicated in the column ACTUAL Y of the table **1801**. The number of instances of the validation data set **1611** where the test output of the 10 validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a* is a false positive is 0 and is indicated in the column ACTUAL N of the table **1801**. CUMULATIVE Y is a summation of values in the column ACTUAL Y in the table **1801**. CUMULATIVE N is a summation of values in the column ACTUAL N in the table **1801**. CUMULATIVE Y indicates the number of true positive outputs of the validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a.* CUMULATIVE N indicates the number of false positive outputs of the validated J48 models **1601***a,* **1602***a,* **1603***a,* **1604***a,* **1605***a,* . . . , **1609***a,* and **1610***a.* The machine learning relationship determination system (MLRDS) uses the CUMULATIVE Y values and the CUMULATIVE N values to determine the optimum algorithm decision threshold. The maximum possible value of CUMULATIVE Y is 20 since the number of instances with an expected output "Y" in the validation data set **1611** in the table **1201** is 20 as disclosed in the description of FIG. **12**. The maximum possible value of CUMULATIVE N is 560 since the number of instances with an expected output "N" in the validation data set **1611** in the table **1201** is 560. The MLRDS generates the table **1801** for the validated machine learning models generated for each of the machine learning classification algorithms.

[0091] FIG. 19 exemplarily illustrates a schematic representation for determining an optimum algorithm decision threshold using the validated machine learning models, that is, the validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a exemplarily illustrated in FIG. 16. In the table 1901, the values of CUMULATIVE Y and CUMULATIVE N are 1 and 0 respectively for % YES as 100. The number of true positive outputs for % YES as 0% is 20 and the number of false positive outputs is 560. Consider % YES as 30% with 18 true positive outputs and 56 false positive outputs. The % YES as 30% is a decision threshold that confirms an inclusion dependency pair of the prospective primary key and prospective foreign key identified from the tables T1 1001a and T2 1001b exemplarily illustrated in FIGS. 10A-10B, to be a primary key-foreign key pair only if 30% of the number of validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a output that the inclusion dependency pair is a primary key-foreign key pair. Since the number of validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a is 10, the decision threshold is 3 or more than 3 of the validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a must output that the inclusion dependency pair is a primary key-foreign key pair to confirm that the inclusion dependency pair is a primary key-foreign key pair.

[0092] With % YES as 0%, the machine learning relationship determination system (MLRDS) captures 20 true positive outputs and 560 false positive outputs. Filtering of the 560 false positive outputs is a tedious task as the false positive outputs indicate an inaccurate prediction of the primary key-foreign key pairs as non-primary key-foreign key pairs and vice versa. For % YES as 10%, that is, if at least one validated J48 model 1601c outputs a "Y", the MLRDS captures all the 580 instances of the validation data set 1611 exemplarily illustrated in FIG. 16, as "Y" with 20 true positive outputs and 560 false positive outputs. There are again spurious predictions whose filtration is a tedious task. For % YES as 30%, the number of true positive outputs is 18 and the number of false positive outputs is 56. Out of the 20 true positive instances in the validation data set 1611, 2 instances are lost, while 56 false positive outputs are manageable. For % YES as 31%, there are 28 false positive outputs and 3 true positive outputs are lost. On comparing % YES as 31% with % YES as 30%, the machine learning relationship determination system (MLRDS) allows a user to manually select 30% as the optimum % YES since losing a true positive output is less desirable than reducing the false positive outputs. That is, a correct prediction of a primary key-foreign key relationship is lost while trying to avoid the false prediction of the primary key-foreign key relationship. On comparing the number of true positive outputs and the number of false positive outputs for different % YES values, the optimum algorithm decision threshold is selected as 30%. When a new instance is to be classified by 10 validated machine learning models, for example, 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a, the MLRDS outputs "Y" only if a minimum 30% that is 3 out of the 10 validated machine learning models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a say "Y" to the instance. The predictions of at least 3 of the validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a is considered correct and the MLRDS confirms the predicted primary key-foreign relationship as the primary key-foreign key relationship for the inclusion dependency pairs identified from the tables T1 1001a and T2 1001b exemplarily illustrated in FIGS. 10A-10B. The MLRDS determines the optimum algorithm decision threshold for each of the machine learning classification algorithms and stores the determined optimum algorithm decision thresholds in the threshold database.

[0093] The validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a and the optimum algorithm decision threshold of 3 are available for determining primary key-foreign key relationships between the inclusion dependency pairs identified from the tables T1 1001a and T2 1001b. The machine learning relationship determination system (MLRDS) determines a resultant of each inclusion dependency pair being a primary key-foreign key pair or a non-primary key-foreign key pair for each of the machine learning classification algorithms using the determined optimum algorithm decision threshold and the computed primary key-foreign key features of each inclusion dependency pair of the prospective primary key and the prospective foreign key identified from the tables T1 1001a and T2 1001b. The MLRDS inputs the computed primary key-foreign key features of the inclusion dependency pairs identified from the tables T1 1001a and T2 1001b into the 10 validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a. The 10 validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a output a prediction of the primary key-foreign key relationship as "Y" and "N" and the MLRDS tabulates the predictions.

[0094] FIG. 20 exemplarily illustrates a table 2001 showing resultants of the inclusion dependency pairs identified from the tables T1 1001a and T2 1001b shown in FIGS. 10A-10B, being primary key-foreign key pairs or non-primary key-foreign key pairs, generated by the machine learning relationship determination system (MLRDS) using the optimum algorithm decision threshold. Consider an example where 15 inclusion dependency pairs are identified from the tables Ti 1001a and T2 1001b. For each inclusion dependency pair, the MLRDS tabulates the outputs of the validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a exemplarily illustrated in FIG. 16. The MLRDS computes the YES COUNT for each inclusion dependency pair. For instance ID 1, the validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a output "Y", "N", "N", "Y", "N", "N", "N", "Y", "N", and "N". The YES COUNT is 3. Since the optimum algorithm decision threshold is 3, the MLRDS confirms the YES output of the validated J48 models 1601a, 1602a, 1603a, 1604a, 1605a, . . . , 1609a, and 1610a indicated with a "Y" primary key-foreign key flag and generates a resultant "Y" confirming that the inclusion dependency pair with ID 1 is a primary key-foreign key pair. For the instance ID 4, the YES COUNT is 1 Since the YES COUNT is less than the optimum algorithm decision threshold, the MLRDS generates a resultant "N" confirming that the inclusion dependency pair with ID 4 is a non-primary key-foreign key pair. For the instance ID 3, the YES COUNT is 8. Since the YES COUNT is greater than the optimum algorithm decision threshold, the MLRDS generates a resultant "Y" confirming that the inclusion dependency pair with ID 3 is a primary key-foreign key pair. The MLRDS generates a similar table for the validated machine learning models generated for each of the other machine learning classification algorithms, for example, the Random Forest algorithm, the Naive Bayes algorithm, the k-Nearest Neighbors algorithm, and the support vector machine model. The MLRDS tabulates the resultants of the five machine learning classification algorithms for each of the inclusion dependency pairs identified from the tables T**1** **1001**a and T**2** **1001**b.

[0095] FIG. **21** exemplarily illustrates a table **2101** containing final resultants of the inclusion dependency pairs identified from the tables T**1** **1001**a and T**2** **1001**b shown in FIGS. **10**A-**10**B, being primary key-foreign key pairs or non-primary key-foreign key pairs, generated by the machine learning relationship determination system (MLRDS) on performing majority voting on the resultants shown in FIG. **20**. The MLRDS performs majority voting on the resultants of the machine learning classification algorithms and tabulates voting results in a column Y VOTE in the table **2101**. For instance ID **4**, the resultants of the J-48 algorithm, the Naive Bayesian algorithm, the k-Nearest Neighbors algorithm, the Random Forest algorithm, and the support vector machine model are "N", "Y", "Y", "N", and "N" respectively. On performing majority voting, the MLRDS determines that the number of machine learning classification algorithms with output as "Y" is 2, which is less than the number of machine learning classification algorithms with an output as "N". Since the majority is the number of machine learning classification algorithms with the output as "N", the MLRDS confirms that the inclusion dependency pair with ID **4** is a non-primary key-foreign key pair. For instance ID **5**, the resultants of the J-48 algorithm, the Naive Bayes algorithm, the k-Nearest Neighbors algorithm, the Random Forest algorithm, and the support vector machine are "Y", "Y", "N", "Y", and "Y" respectively. On performing majority voting, the MLRDS determines that the number of machine learning classification algorithms with the output as "Y" is 4, which is greater than the number of machine learning classification algorithms with the output as "N". Since the majority is the number of machine learning classification algorithms with the output as "Y", the MLRDS confirms that the inclusion dependency pair with ID **5** is a primary key-foreign key pair. Similarly, the primary key-foreign key relationships are determined for all the 15 inclusion dependency pairs identified from the tables T**1** **1001**a and T**2** **1001**b.

[0096] FIG. **22** exemplarily illustrates a system **2200** comprising the machine learning relationship determination system (MLRDS) **2201** for determining primary key-foreign key relationships among data in multiple tables of a target database **2212** through machine learning. The MLRDS **2201** is a computer system that is programmable using a high level computer programming language. In an embodiment, the MLRDS **2201** uses programmed and purposeful hardware. The MLRDS **2201** is implemented on a computing device, for example, a personal computer, a tablet computing device, a mobile computer, a portable computing device, a laptop, a touch centric device, a workstation, a server, a portable electronic device, a network enabled computing device, an interactive network enabled communication device, any other suitable computing equipment, combinations of multiple pieces of computing equipment, etc. The MLRDS **2201** communicates with a user device **2214** via a network **2215**, for example, a short range network or a long range network. The user device **2214** is an electronic device, for example, a personal computer, a tablet computing device, a mobile computer, a mobile phone, a smartphone, a portable computing device, a personal digital assistant, a laptop, a wearable computing device such as the Google Glass® of Google Inc., the Apple Watch® of Apple Inc., etc., a touch centric device, a client device, a portable electronic device, a network enabled computing device, an interactive network enabled communication device, any other suitable computing equipment, combinations of multiple pieces of computing equipment, etc. In an embodiment, the user device **2214** is a hybrid computing device that combines the functionality of multiple devices. Examples of a hybrid computing device comprise a cellular telephone that includes a media player functionality, a gaming device that includes a wireless communications capability, a cellular telephone that includes a document reader and multimedia functions, and a portable device that has network browsing, document rendering, and network communication capabilities.

[0097] The network **2215** is, for example, the internet, an intranet, a wired network, a wireless network, a communication network that implements Bluetooth® of Bluetooth Sig, Inc., a network that implements Wi-Fi® of Wi-Fi Alliance Corporation, an ultra-wideband communication network (UWB), a wireless universal serial bus (USB) communication network, a communication network that implements ZigBee® of ZigBee Alliance Corporation, a general packet radio service (GPRS) network, a mobile telecommunication network such as a global system for mobile (GSM) communications network, a code division multiple access (CDMA) network, a third generation (3G) mobile communication network, a fourth generation (4G) mobile communication network, a fifth generation (5G) mobile communication network, a long-term evolution (LTE) mobile communication network, a public telephone network, etc., a local area network, a wide area network, an internet connection network, an infrared communication network, etc., or a network formed from any combination of these networks. In an embodiment, the machine learning relationship determination system (MLRDS) **2201** is accessible to a user, for example, through a broad spectrum of technologies and devices such as cellular phones, tablet computing devices, etc., with access to the internet.

[0098] As exemplarily illustrated in FIG. **22**, the machine learning relationship determination system (MLRDS) **2201** comprises a non-transitory computer readable storage medium, for example, a memory unit **2211** for storing programs and data, and at least one processor **2202** communicatively coupled to the non-transitory computer readable storage medium. As used herein, "non-transitory computer readable storage medium" refers to all computer readable media, for example, non-volatile media such as optical discs or magnetic disks, volatile media such as a register memory, a processor cache, etc., and transmission media such as wires that constitute a system bus coupled to the processor **2202**, except for a transitory, propagating signal. Non-volatile media comprise, for example, solid state drives, optical discs or magnetic disks, and other persistent memory volatile media including a dynamic random access memory (DRAM), which typically constitutes a main memory. Volatile media comprise, for example, a register memory, a processor cache, a random access memory (RAM), etc. Transmission media comprise, for example, coaxial cables, copper wire, fiber optic cables, modems, etc., including wires that constitute a system bus coupled to the processor **2202**, etc. The non-transitory computer readable storage medium is configured to store computer program instructions defined by modules, for example, **2211***a*, **2211***b*, **2211***c*, **2211***d*, **2211***e*, **2211***f*, **2211***g*, **2211***h*, **2211***i*, etc., of the MLRDS **2201**. The modules, for example, **2211***a*, **2211***b*, **2211***c*, **2211***d*, **2211***e*, **2211***f*, **2211***g*, **2211***h*, **2211***i*, **2211***j*, etc., of the MLRDS **2201** are installed and stored in the memory unit **2211** of the MLRDS **2201**. The memory unit **2211** is used for storing program instructions, applications, and data. The memory unit **2211** is, for example, a random access memory (RAM) or another type of dynamic storage device that stores information and instructions for execution by the processor **2202**. The memory unit **2211** also stores temporary variables and other intermediate information used during execution of the instructions by the processor **2202**. The MLRDS **2201** further comprises a read only memory (ROM) or another type of static storage device that stores static information and instructions for the processor **2202**.

[0099] The processor **2202** is configured to execute the computer program instructions defined by the machine learning relationship determination system (MLRDS) **2201**. The processor **2202** refers to any of one or more microprocessors, central processing unit (CPU) devices, finite state machines, computers, microcontrollers, digital signal processors, logic, a logic device, an user circuit, an application specific integrated circuit (ASIC), a field-programmable gate array (FPGA), a chip, etc., or any combination thereof, capable of executing computer programs or a series of commands, instructions, or state transitions. In an embodiment, the processor **2202** is implemented as a processor set comprising, for example, a programmed microprocessor and a math or graphics co-processor. The processor **2202** is selected, for example, from the Intel® processors such as the Itanium® microprocessor or the Pentium® processors, Advanced Micro Devices (AMD®) processors such as the Athlon® processor, UltraSPARC® processors, microSPARC® processors, hp® processors, International Business Machines (IBM®) processors such as the PowerPC® microprocessor, the MIPS® reduced instruction set computer (RISC) processor of MIPS Technologies, Inc., RISC based computer processors of ARM Holdings, Motorola® processors, Qualcomm® processors, etc. The MLRDS **2201** disclosed herein is not limited to employing a processor **2202**. In an embodiment, the MLRDS **2201** employs a controller or a microcontroller. The processor **2202** executes the modules, for example, **2211***a*, **2211***b*, **2211***c*, **2211***d*, **2211***e*, **2211***f*, **2211***g*, **2211***h*, **2211***i*, etc., of the MLRDS **2201**.

[0100] As exemplarily illustrated in FIG. **22**, the machine learning relationship determination system (MLRDS) **2201** further comprises a data bus **2204**, a network interface **2205**, an input/output (I/O) controller **2206**, input devices **2207**, a fixed media drive **2208** such as a hard drive, a removable media drive **2209** for receiving removable media, output devices **2210**, etc. The data bus **2204** permits communications between the modules, for example, **2202**, **2203**, **2204**, **2205**, **2206**, **2207**, **2208**, **2209**, **2210**, **2211**, etc., of the MLRDS **2201**. The network interface **2205** enables connection of the MLRDS **2201** to the network **2215**. In an embodiment, the network interface **2205** is provided as an interface card also referred to as a "line card". The network interface **2205** comprises, for example, one or more of an infrared (IR) interface, an interface implementing Wi-Fi® of Wi-Fi Alliance Corporation, a universal serial bus (USB) interface, a FireWire® interface of Apple Inc., an Ethernet interface, a frame relay interface, a cable interface, a digital subscriber line (DSL) interface, a token ring interface, a peripheral controller interconnect (PCI) interface, a local area network (LAN) interface, a wide area network (WAN) interface, interfaces using serial protocols, interfaces using parallel protocols, Ethernet communication interfaces, asynchronous transfer mode (ATM) interfaces, a high speed serial interface (HSSI), a fiber distributed data interface (FDDI), interfaces based on transmission control protocol (TCP)/internet protocol (IP), interfaces based on wireless communications technology such as satellite technology, radio frequency (RF) technology, near field communication, etc. The I/O controller **2206** controls input actions and output actions performed by the MLRDS **2201**.

[0101] The display unit **2203** comprises, for example, a video display, a liquid crystal display, a plasma display, an organic light emitting diode (OLED) based display, etc. The display screen **2203** displays a graphical user interface. The input devices **2207** are used for routine maintenance of the MLRDS **2201**. The input devices **2207** are, for example, a keyboard such as an alphanumeric keyboard, a microphone, a joystick, a pointing device such as a computer mouse, a touch pad, a light pen, a physical button, a touch sensitive display device, a track ball, a pointing stick, any device capable of sensing a tactile input, etc.

[0102] The modules of the machine learning relationship determination system (MLRDS) **2201** comprise a column selection module **2211***a*, a prospective key identification module **2211***b*, a data reception module **2211***c*, a data splitter **2211***d*, a feature computation module **2211***e*, a training and validation module **2211***f*, a decision threshold determination module **2211***g*, a primary key-foreign key determination module **2211***h*, and a voting module **2211***i* stored in the memory unit **2211** of the MLRDS **2201**. The column selection module **2211***a* selects a first column of data from a first table among the multiple tables and a second column of data from a second table among the multiple tables for each of the multiple tables in the target database **2212** as disclosed in the detailed description of FIGS. **1A-1B**. The prospective key identification module **2211***b* identifies the selected first column of data as a prospective primary key and the selected second column of data as a prospective foreign key to form an inclusion dependency pair on determining presence of data elements of the selected second column of data in the selected first column of data in their entirety as disclosed in the detailed description of FIGS. **1A-1B**. The data reception module **2211***c* receives multiple predetermined inclusion dependency pairs comprising primary key-foreign key pairs classified as positive training data and positive validation data, and non-primary key-foreign key pairs classified as negative training data and negative validation data from a source database **2213**. The positive validation data and the negative validation data form a validation data set. The data splitter **2211***d* splits the positive training data and the negative training data into training data sets. The feature computation module **2211***e* computes primary key-foreign key features comprising, for example, a normalized rank sum, a unique foreign key ratio, a unique foreign share, a name similarity index, a name pattern acceptance, a distribution displacement, and an element count ratio for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set as disclosed in the detailed description of FIGS. **1A-1B**.

[0103] The training and validation module **2211***f* generates trained machine learning models corresponding to the training data sets by training each of the machine learning classification algorithms using the training data sets and the computed primary key-foreign key features of the training data sets as disclosed in the detailed description of FIGS. **1A-1B**. The training and validation module **2211***f* also generates validated machine learning models for each of the machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set as disclosed in the detailed description of FIGS. **1A-1B**. The training and validation module **2211***f* generates the validated machine learning models for each of the machine learning classification algorithms when the generated trained machine learning models corresponding to the training data sets meet a predetermined criterion, that is, an acceptable accuracy on testing the generated trained machine learning models with the validation data set. The training and validation module **2211***f* retrains the generated trained machine learning models on the training data sets until the generated trained machine learning models meet the acceptable accuracy for the generation of the validated machine learning models for each of the machine learning classification algorithms as disclosed in the detailed description of FIG. **2**.

[0104] The decision threshold determination module **2211***g* determines an optimum algorithm decision threshold for each of the machine learning classification algorithms using the generated validated machine learning models as disclosed in the detailed description of FIGS. **1A-1B**. The primary key-foreign key determination module **2211***h* determines a resultant of the inclusion dependency pair of the prospective primary key and the prospective foreign key being a primary key-foreign key pair or a non-primary key-foreign key pair for each of the machine learning classification algorithms using the determined optimum algorithm decision threshold and the computed primary key-foreign key features of the inclusion dependency pair of the prospective primary key and the prospective foreign key as disclosed in the detailed description of FIGS. **1A-1B**. The decision threshold determination module **2211g** stores the determined optimum algorithm decision threshold for each of the machine learning classification algorithms in a threshold database **2211***j*. The voting module **2211***i* performs majority voting on the determined resultant for each of the machine learning classification algorithms to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table as disclosed in the detailed description of FIGS. **1A-1B**.

[0105] The machine learning relationship determination system (MLRDS) **2201** receives a selection of a combination of machine learning classification algorithms from the user device **2214** via the network **2215**. A user can select any number of machine learning classification algorithms from a predefined set of machine learning classification algorithms. The MLRDS **2201** also receives user input from the user device **2214** via the network **2215** for configuring the predetermined criterion, that is, the acceptable accuracy to be met by the trained machine learning models when the trained machine learning models are tested against the validation data set to qualify as validated machine learning models. The MLRDS **2201** also receives a user selection of the optimum algorithm decision threshold between 0% and 100% extreme conditions of % YES from the user device **2214** via the network **2215**.

[0106] The threshold database **2211***j* of the machine learning relationship determination system (MLRDS) **2201** can be any storage area or medium that can be used for storing data and files. In an embodiment, the threshold database **2211***j* is an external database apart from the target database **2212** and the source database **2213**, for example, a structured query language (SQL) data store or a not only SQL (NoSQL) data store such as the Microsoft® SQL Server® , the Oracle® servers, the MySQL® database of MySQL AB Company, the mongoDB® of MongoDB, Inc., the Neo4j graph database of Neo Technology Corporation, the Cassandra database of the Apache Software Foundation, the HBase™ database of the Apache Software Foundation, etc. In an embodiment, the threshold database **2211***j* can also be a location on a file system. In another embodiment, the threshold database **2211***j* can be remotely accessed by the MLRDS **2201** via the network **2215** along with the target database **2212** and the source database **2213**. In another embodiment, the threshold database **2211***j*, the source database **2213**, and the target database **2212** are configured as a cloud based database implemented in a cloud computing environment, where computing resources are delivered as a service over the network **2215**.

[0107] Computer applications and programs are used for operating the machine learning relationship determination system (MLRDS) **2201**. The programs are loaded onto the fixed media drive **2208** and into the memory unit **2211** of the MLRDS **2201** via the removable media drive **2209**. In an embodiment, the computer applications and programs may be loaded directly on the MLRDS **2201** via the network **2215**. The processor **2202** executes an operating system, for example, the Linux® operating system, the Unix® operating system, any version of the Microsoft® Windows® operating system, the Mac OS of Apple Inc., the IBM® OS/2, VxWorks® of Wind River Systems, Inc., QNX Neutrino® developed by QNX Software Systems Ltd., the Palm OS®, the Solaris operating system developed by Sun Microsystems, Inc., etc. The MLRDS **2201** employs the operating system for performing multiple tasks. The operating system is responsible for management and coordination of activities and sharing of resources of the MLRDS **2201**. The operating system further manages security of the MLRDS **2201**, peripheral devices connected to the MLRDS **2201**, and network connections. The operating system employed on the MLRDS **2201** recognizes, for example, inputs provided by a user of the MLRDS **2201** using one of the input devices **2207**, the output devices **2210**, files, and directories stored locally on the fixed media drive **2208**. The operating system on the MLRDS **2201** executes different programs using the processor **2202**. The processor **2202** and the operating system together define a computer platform for which application programs in high level programming languages are written.

[0108] The processor **2202** retrieves instructions defined by the column selection module **2211***a*, the prospective key identification module **2211***b*, the data reception module **2211***c*, the data splitter **2211***d*, the feature computation module **2211***e,* the training and validation module **2211***f,* the decision threshold determination module **2211***g,* the primary key-foreign key determination module **2211***h,* and the voting module **2211***i* stored in the memory unit **2211** of the machine learning relationship determination system (MLRDS) **2201**, for performing respective functions disclosed above. The processor **2202** retrieves instructions for executing the modules, for example, **2211***a,* **2211***b,* **2211***c,* **2211***d,* **2211***e,* **2211***f,* **2211***g,* **2211***h,* **2211***i,* etc., of the MLRDS **2201** from the memory unit **2211**. A program counter determines the location of the instructions in the memory unit **2211**. The program counter stores a number that identifies the current position in the program of each of the modules, for example, **2211***a,* **2211***b,* **2211***c,* **2211***d,* **2211***e,* **2211***f,* **2211***g,* **2211***h,* **2211***i,* etc., of the MLRDS **2201**. The instructions fetched by the processor **2202** from the memory unit **2211** after being processed are decoded. The instructions are stored in an instruction register in the processor **2202**. After processing and decoding, the processor **2202** executes the instructions, thereby performing one or more processes defined by those instructions.

[0109] At the time of execution, the instructions stored in the instruction register are examined to determine the operations to be performed. The processor **2202** then performs the specified operations. The operations comprise arithmetic operations and logic operations. The operating system performs multiple routines for performing a number of tasks required to assign the input devices **2207**, the output devices **2210**, and the memory unit **2211** for execution of the modules, for example, **2211***a,* **2211***b,* **2211***c,* **2211***d,* **2211***e,* **2211***f,* **2211***g,* **2211***h,* **2211***i,* etc., of the machine learning relationship determination system (MLRDS) **2201**. The tasks performed by the operating system comprise, for example, assigning memory to the modules, for example, **2211***a,* **2211***b,* **2211***c,* **2211***d,* **2211***e,* **2211***f,* **2211***g,* **2211***h,* **2211***i,* etc., of the MLRDS **2201** and to data used by the MLRDS **2201**, moving data between the memory unit **2211** and disk units, and handling input/output operations. The operating system performs the tasks on request by the operations and after performing the tasks, the operating system transfers the execution control back to the processor **2202**. The processor **2202** continues the execution to obtain one or more outputs. The outputs of the execution of the modules, for example, **2211***a,* **2211***b,* **2211***c,* **2211***d,* **2211***e,* **2211***f,* **2211***g,* **2211***h,* **2211***i,* etc., of the MLRDS **2201** are displayed to a user of the MLRDS **2201** on the output device **2210**.

[0110] The non-transitory computer readable storage medium disclosed herein stores computer program codes comprising instructions executable by at least one processor **2202** for determining primary key-foreign key relationships among data in tables of the target database **2212** through machine learning. The computer program codes comprise a first computer program code for selecting a first column of data from a first table among the tables and a second column of data from a second table among the tables for each of the tables in the target database **2212**; a second computer program code for identifying the selected first column of data as a prospective primary key and the selected second column of data as a prospective foreign key to form an inclusion dependency pair on determining presence of data elements of the selected second column in the selected first column in their entirety; a third computer program code for receiving predetermined inclusion dependency pairs comprising primary key-foreign key pairs classified as positive training data and positive validation data and non-primary key-foreign key pairs classified as negative training data and negative validation data from the source database **2213**; a fourth computer program code for splitting the positive training data and the negative training data into training data sets; a fifth computer program code for computing primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set; a sixth computer program code for generating trained machine learning models corresponding to the training data sets by training each of the machine learning classification algorithms using the training data sets and the computed primary key-foreign key features of the training data sets; a seventh computer program code for generating validated machine learning models for each of the machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set; an eighth computer program code for determining an optimum algorithm decision threshold for each of the machine learning classification algorithms using the generated validated machine learning models; a ninth computer program code for determining a resultant of the inclusion dependency pair being a primary key-foreign key pair or a non-primary key-foreign key pair for each of the machine learning classification algorithms using the determined optimum algorithm decision threshold and the computed primary key-foreign key features of the inclusion dependency pair of the prospective primary key and the prospective foreign key; and a tenth computer program code for performing majority voting on the determined resultant for each of the machine learning classification algorithms to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table.

[0111] In an embodiment, the seventh computer program code comprises an eleventh computer program code for generating the validated machine learning models for each of the machine learning classification algorithms when the generated trained machine learning models corresponding to the training data sets meet a predetermined criterion on testing the generated trained machine learning models with the validation data set. In this embodiment, the sixth computer program code comprises a twelfth computer program code for retraining the generated trained machine learning models on the training data sets until the generated trained machine learning models meet the predetermined criterion for the generation of the validated machine learning models for each of the machine learning classification algorithms.

[0112] The computer program codes further comprise one or more additional computer program codes for performing additional steps that may be required and contemplated for determining primary key-foreign key relationships among data in the tables of the target database **2212**. In an embodiment, a single piece of computer program code comprising computer executable instructions performs one or more steps of the method disclosed herein for determining primary key-foreign key relationships among data in the tables of the target database **2212**. The computer program codes comprising computer executable instructions are embodied on the non-transitory computer readable storage medium.

The processor **2202** of the machine learning relationship determination system (MLRDS) **2201** retrieves these computer executable instructions and executes them. When the computer executable instructions are executed by the processor **2202**, the computer executable instructions cause the processor **2202** to perform the steps of the method for determining primary key-foreign key relationships among data in the tables of the target database **2212**.

[0113] It will be readily apparent in different embodiments that the various methods, algorithms, and computer programs disclosed herein are implemented on non-transitory computer readable storage media appropriately programmed for computing devices. The non-transitory computer readable storage media participates in providing data, for example, instructions that are read by a computer, a processor or a similar device. In different embodiments, the "non-transitory computer readable storage media" further refers to a single medium or multiple media, for example, a centralized database, a distributed database, and/or associated caches and servers that store one or more sets of instructions that are read by a computer, a processor or a similar device. The "non-transitory computer readable storage media" further refers to any medium capable of storing or encoding a set of instructions for execution by a computer, a processor or a similar device and that causes a computer, a processor or a similar device to perform any one or more of the methods disclosed herein. Common forms of non-transitory computer readable storage media comprise, for example, a floppy disk, a flexible disk, a hard disk, magnetic tape, a laser disc, a Blu-ray Disc® of the Blu-ray Disc Association, any magnetic medium, a compact disc-read only memory (CD-ROM), a digital versatile disc (DVD), any optical medium, a flash memory card, punch cards, paper tape, any other physical medium with patterns of holes, a random access memory (RAM), a programmable read only memory (PROM), an erasable programmable read only memory (EPROM), an electrically erasable programmable read only memory (EEPROM), a flash memory, any other memory chip or cartridge, or any other medium from which a computer can read.

[0114] In an embodiment, the computer programs that implement the methods and algorithms disclosed herein are stored and transmitted using a variety of media, for example, the computer readable media in a number of manners. In an embodiment, hard-wired circuitry or custom hardware is used in place of, or in combination with, software instructions for implementing the processes of various embodiments. Therefore, the embodiments are not limited to any specific combination of hardware and software. The computer program codes comprising computer executable instructions can be implemented in any programming language. Examples of programming languages that can be used comprise C, C++, C#, Java®, JavaScript®, Fortran, Ruby, Perl®, Python®, Visual Basic®, hypertext preprocessor (PHP), Microsoft® .NET, Objective-C®, etc. Other object-oriented, functional, scripting, and/or logical programming languages can also be used. In an embodiment, the computer program codes or software programs are stored on or in one or more mediums as object code. In another embodiment, various aspects of the method and the machine learning relationship determination system (MLRDS) **2201** disclosed herein are implemented in a non-programmed environment comprising documents created, for example, in a hypertext markup language (HTML), an extensible markup language (XML), or other format that render aspects of a graphical user interface (GUI) or perform other functions, when viewed in a visual area or a window of a browser program. In another embodiment, various aspects of the method and the MLRDS **2201** disclosed herein are implemented as programmed elements, or non-programmed elements, or any suitable combination thereof.

[0115] Where databases are described such as the threshold database **2211***j*, the target database **2212**, and the source database **2213**, it will be understood by one of ordinary skill in the art that (i) alternative database structures to those described may be employed, and (ii) other memory structures besides databases may be employed. Any illustrations or descriptions of any sample databases disclosed herein are illustrative arrangements for stored representations of information. In an embodiment, any number of other arrangements are employed besides those suggested by tables illustrated in the drawings or elsewhere. Similarly, any illustrated entries of the databases represent exemplary information only; one of ordinary skill in the art will understand that the number and content of the entries can be different from those disclosed herein. In another embodiment, despite any depiction of the databases as tables, other formats including relational databases, object-based models, and/or distributed databases are used to store and manipulate the data types disclosed herein. Object methods or behaviors of a database can be used to implement various processes such as those disclosed herein. In another embodiment, the databases are, in a known manner, stored locally or remotely from a device that accesses data in such a database. In embodiments where there are multiple databases in the machine learning relationship determination system (MLRDS) **2201**, the databases are integrated to communicate with each other for enabling simultaneous updates of data linked across the databases, when there are any updates to the data in one of the databases.

[0116] The method and the machine learning relationship determination system (MLRDS) **2201** disclosed herein can be configured to work in a network environment comprising one or more computers that are in communication with one or more devices via the network **2215**. In an embodiment, the computers communicate with the devices directly or indirectly, via a wired medium or a wireless medium such as the Internet, a local area network (LAN), a wide area network (WAN) or the Ethernet, a token ring, or via any appropriate communications mediums or combination of communications mediums. Each of the devices comprises processors, examples of which are disclosed above, that are adapted to communicate with the computers. In an embodiment, each of the computers is equipped with a network communication device, for example, a network interface card, a modem, or other network connection device suitable for connecting to the network **2215**. Each of the computers and the devices executes an operating system, examples of which are disclosed above. While the operating system may differ depending on the type of computer, the operating system provides the appropriate communications protocols to establish communication links with the network **2215**. Any number and type of machines may be in communication with the computers.

[0117] The method and the machine learning relationship determination system (MLRDS) **2201** disclosed herein are not limited to a particular computer system platform, processor, operating system, or network. In an embodiment, one or more aspects of the method and the MLRDS **2201** disclosed herein are distributed among one or more computer systems, for example, servers configured to provide one or more services to one or more client computers, or to perform a complete task in a distributed system. For example, one or more aspects of the method and the MLRDS **2201** disclosed herein are performed on a client-server system that comprises components distributed among one or more server systems that perform multiple functions according to various embodiments. These components comprise, for example, executable, intermediate, or interpreted code, which communicate over the network **2215** using a communication protocol. The method and the machine learning relationship determination system (MLRDS) **2201** disclosed herein are not limited to be executable on any particular system or group of systems, and are not limited to any particular distributed architecture, network, or communication protocol.

[0118] The foregoing examples have been provided merely for the purpose of explanation and are in no way to be construed as limiting of the method and the machine learning relationship determination system (MLRDS) **2201** disclosed herein. While the method and the MLRDS **2201** have been described with reference to various embodiments, it is understood that the words, which have been used herein, are words of description and illustration, rather than words of limitation. Further, although the method and the MLRDS **2201** have been described herein with reference to particular means, materials, and embodiments, the method and the MLRDS **2201** are not intended to be limited to the particulars disclosed herein; rather, the method and the MLRDS **2201** extend to all functionally equivalent structures, methods and uses, such as are within the scope of the appended claims. Those skilled in the art, having the benefit of the teachings of this specification, may effect numerous modifications thereto and changes may be made without departing from the scope and spirit of the method and the MLRDS **2201** disclosed herein in their aspects.

We claim:

1. A method for determining primary key-foreign key relationships among data in a plurality of tables of a target database through machine learning, the method employing a machine learning relationship determination system comprising at least one processor configured to execute computer program instructions for performing the method comprising:

selecting a first column of data from a first table among the tables and a second column of data from a second table among the tables for each of the tables in the target database by the machine learning relationship determination system, wherein the first column of data comprises a first column name and the second column of data comprises a second column name different from the first column name;

identifying the selected first column of data as a prospective primary key and the selected second column of data as a prospective foreign key to form an inclusion dependency pair by the machine learning relationship determination system on determining presence of data elements of the selected second column of data in the selected first column of data in entirety;

receiving a plurality of predetermined inclusion dependency pairs comprising primary key-foreign key pairs classified as positive training data and positive validation data, and non-primary key-foreign key pairs classified as negative training data and negative validation data, by the machine learning relationship determination system from a source database, wherein the positive validation data and the negative validation data form a validation data set;

splitting the positive training data and the negative training data into training data sets by the machine learning relationship determination system;

computing a plurality of primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set by the machine learning relationship determination system;

generating trained machine learning models corresponding to the training data sets by the machine learning relationship determination system by training each of one or more machine learning classification algorithms using the training data sets and the computed primary key-foreign key features of the training data sets;

generating validated machine learning models for the each of the one or more machine learning classification algorithms by the machine learning relationship determination system on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set;

determining an optimum algorithm decision threshold for the each of the one or more machine learning classification algorithms by the machine learning relationship determination system using the generated validated machine learning models;

determining a resultant of the inclusion dependency pair being one of a primary key-foreign key pair and a non-primary key-foreign key pair by the machine learning relationship determination system for the each of the one or more machine learning classification algorithms using the determined optimum algorithm decision threshold and the computed primary key-foreign key features of the inclusion dependency pair of the prospective primary key and the prospective foreign key; and

performing majority voting on the determined resultant for the each of the one or more machine learning classification algorithms by the machine learning relationship determination system to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table.

2. The method of claim **1**, wherein the validated machine learning models for the each of the one or more machine learning classification algorithms are generated by the machine learning relationship determination system when the generated trained machine learning models corresponding to the training data sets meet a predetermined criterion on testing the generated trained machine learning models with the validation data set.

3. The method of claim **2**, further comprising retraining the generated trained machine learning models on the training data sets until the generated trained machine learning models meet the predetermined criterion for the generation of the validated machine learning models for the each of the one or more machine learning classification algorithms.

4. The method of claim **1**, wherein the determined optimum algorithm decision threshold for the each of the one or more machine learning classification algorithms is stored in a threshold database by the machine learning relationship determination system.

5. The method of claim **1**, wherein the primary key-foreign key features comprise a normalized rank sum, a unique foreign key ratio, a unique foreign share, a name similarity index, a name pattern acceptance, a distribution displacement, and an element count ratio.

6. The method of claim **1**, wherein the primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key are computed by the machine learning relationship determination system using one of a plurality of items selected from the group consisting of data elements of the prospective primary key identified by the selected first column of data, the data elements of the prospective foreign key identified by the selected second column of data, a number of unique data elements of the prospective foreign key, Levenshtein distance between names of the prospective primary key and the prospective foreign key, a prefix matching score obtained from the names of the prospective primary key and the prospective foreign key, sound codes obtained by applying a Metaphone algorithm on the names of the prospective primary key and the prospective foreign key, patterns of the names of the prospective primary key and the prospective foreign key, statistical measures, and any combination thereof.

7. The method of claim **1**, wherein the primary key-foreign key features for the training data sets and the validation data set are computed by the machine learning relationship determination system using one of a plurality of items selected from the group consisting of data elements of the predetermined inclusion dependency pairs, a number of unique data elements of foreign keys in the predetermined inclusion dependency pairs, Levenshtein distance between names of primary keys and the foreign keys in the predetermined inclusion dependency pairs, a prefix matching score obtained from the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, sound codes obtained by applying a Metaphone algorithm on the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, patterns of the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, statistical measures, and any combination thereof.

8. The method of claim **1**, wherein the one or more machine learning classification algorithms comprise J48 algorithm, k-Nearest Neighbors algorithm, Naive Bayes algorithm, Random Forest algorithm, Bayes network model, a multilayer perceptron model, and a support vector machine model.

9. A machine learning relationship determination system for determining primary key-foreign key relationships among data in a plurality of tables of a target database through machine learning, the machine learning relationship determination system comprising:

a non-transitory computer readable storage medium configured to store computer program instructions defined by modules of the machine learning relationship determination system; and

at least one processor communicatively coupled to the non-transitory computer readable storage medium, the at least one processor configured to execute the computer program instructions defined by the modules of the machine learning relationship determination system, the modules comprising:

a column selection module configured to select a first column of data from a first table among the tables and a second column of data from a second table among the tables for each of the tables in the target database, wherein the first column of data comprises a first column name and the second column of data comprises a second column name different from the first column name;

a prospective key identification module configured to identify the selected first column of data as a prospective primary key and the selected second column of data as a prospective foreign key to form an inclusion dependency pair on determining presence of data elements of the selected second column of data in the selected first column of data in entirety;

a data reception module configured to receive a plurality of predetermined inclusion dependency pairs comprising primary key-foreign key pairs classified as positive training data and positive validation data, and non-primary key-foreign key pairs classified as negative training data and negative validation data, from a source database, wherein the positive validation data and the negative validation data form a validation data set;

a data splitter configured to split the positive training data and the negative training data into training data sets;

a feature computation module configured to compute a plurality of primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set;

a training and validation module configured to generate trained machine learning models corresponding to the training data sets by training each of one or more machine learning classification algorithms using the training data sets and the computed primary key-foreign key features of the training data sets;

the training and validation module further configured to generate validated machine learning models for the each of the one or more machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set;

a decision threshold determination module configured to determine an optimum algorithm decision threshold for the each of the one or more machine learning classification algorithms using the generated validated machine learning models;

a primary key-foreign key determination module configured to determine a resultant of the inclusion dependency pair being one of a primary key-foreign key pair and a non-primary key-foreign key pair for the each of the one or more machine learning classification algorithms using the determined optimum algorithm decision threshold and the computed primary key-foreign key features of the inclusion dependency pair of the prospective primary key and the prospective foreign key; and

a voting module configured to perform majority voting on the determined resultant for the each of the one or more machine learning classification algorithms to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table.

10. The machine learning relationship determination system of claim **9**, wherein the training and validation module is configured to generate the validated machine learning models for the each of the one or more machine learning classification algorithms when the generated trained machine learning models corresponding to the training data sets meet a predetermined criterion on testing the generated trained machine learning models with the validation data set.

11. The machine learning relationship determination system of claim **10**, wherein the training and validation module is further configured to retrain the generated trained machine learning models on the training data sets until the generated trained machine learning models meet the predetermined criterion for the generation of the validated machine learning models for the each of the one or more machine learning classification algorithms.

12. The machine learning relationship determination system of claim **9**, wherein the decision threshold determination module is further configured to store the determined optimum algorithm decision threshold for the each of the one or more machine learning classification algorithms in a threshold database.

13. The machine learning relationship determination system of claim **9**, wherein the primary key-foreign key features comprise a normalized rank sum, a unique foreign key ratio, a unique foreign share, a name similarity index, a name pattern acceptance, a distribution displacement, and an element count ratio.

14. The machine learning relationship determination system of claim **9**, wherein the feature computation module is configured to compute the primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key using one of a plurality of items selected from the group consisting of data elements of the prospective primary key identified by the selected first column of data, the data elements of the prospective foreign key identified by the selected second column of data, a number of unique data elements of the prospective foreign key, Levenshtein distance between names of the prospective primary key and the prospective foreign key, a prefix matching score obtained from the names of the prospective primary key and the prospective foreign key, sound codes obtained by applying a Metaphone algorithm on the names of the prospective primary key and the prospective foreign key, patterns of the names of the prospective primary key and the prospective foreign key, statistical measures, and any combination thereof.

15. The machine learning relationship determination system of claim **9**, wherein the feature computation module is configured to compute the primary key-foreign key features for the training data sets and the validation data set using one of a plurality of items selected from the group consisting of data elements of the predetermined inclusion dependency pairs, a number of unique data elements of foreign keys in the predetermined inclusion dependency pairs, Levenshtein distance between names of primary keys and the foreign keys in the predetermined inclusion dependency pairs, a prefix matching score obtained from the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, sound codes obtained by applying a Metaphone algorithm on the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, patterns of the names of the primary keys and the foreign keys in the predetermined inclusion dependency pairs, statistical measures, and any combination thereof.

16. The machine learning relationship determination system of claim **9**, wherein the one or more machine learning classification algorithms comprise J48 algorithm, k-Nearest Neighbors algorithm, Naive Bayes algorithm, Random Forest algorithm, Bayes network model, a multilayer perceptron model, and a support vector machine model.

17. A non-transitory computer readable storage medium having embodied thereon, computer program codes comprising instructions executable by at least one processor for determining primary key-foreign key relationships among data in a plurality of tables of a target database through machine learning, the computer program codes comprising:

a first computer program code for selecting a first column of data from a first table among the tables and a second column of data from a second table among the tables for each of the tables in the target database, wherein the first column of data comprises a first column name and the second column of data comprises a second column name different from the first column name;

a second computer program code for identifying the selected first column of data as a prospective primary key and the selected second column of data as a prospective foreign key to form an inclusion dependency pair on determining presence of data elements of the selected second column of data in the selected first column of data in entirety;

a third computer program code for receiving a plurality of predetermined inclusion dependency pairs comprising primary key-foreign key pairs classified as positive training data and positive validation data, and non-primary key-foreign key pairs classified as negative training data and negative validation data, from a source database, wherein the positive validation data and the negative validation data form a validation data set;

a fourth computer program code for splitting the positive training data and the negative training data into training data sets;

a fifth computer program code for computing a plurality of primary key-foreign key features for the inclusion dependency pair of the prospective primary key and the prospective foreign key, the training data sets, and the validation data set;

a sixth computer program code for generating trained machine learning models corresponding to the training data sets by training each of one or more machine learning classification algorithms using the training data sets and the computed primary key-foreign key features of the training data sets;

a seventh computer program code for generating validated machine learning models for the each of the one or more machine learning classification algorithms on testing the generated trained machine learning models corresponding to the training data sets with the validation data set using the computed primary key-foreign key features of the validation data set;

an eighth computer program code for determining an optimum algorithm decision threshold for the each of the one or more machine learning classification algorithms using the generated validated machine learning models;

a ninth computer program code for determining a resultant of the inclusion dependency pair being one of a primary key-foreign key pair and a non-primary key-foreign key pair for the each of the one or more machine learning classification algorithms using the determined optimum algorithm decision threshold and the computed primary key-foreign key features of the inclusion dependency pair of the prospective primary key and the prospective foreign key; and

a tenth computer program code for performing majority voting on the determined resultant for the each of the one or more machine learning classification algorithms to determine a primary key-foreign key relationship among the data in the selected first column of data of the first table and the selected second column of data of the second table.

18. The non-transitory computer readable storage medium of claim **17**, wherein the seventh computer program code comprises an eleventh computer program code for generating the validated machine learning models for the each of the one or more machine learning classification algorithms when the generated trained machine learning models corresponding to the training data sets meet a predetermined criterion on testing the generated trained machine learning models with the validation data set.

19. The non-transitory computer readable storage medium of claim **18**, wherein the sixth computer program code comprises a twelfth computer program code for retraining the generated trained machine learning models on the training data sets until the generated trained machine learning models meet the predetermined criterion for the generation of the validated machine learning models for the each of the one or more machine learning classification algorithms.

20. The non-transitory computer readable storage medium of claim **17**, wherein the primary key-foreign key features comprise a normalized rank sum, a unique foreign key ratio, a unique foreign share, a name similarity index, a name pattern acceptance, a distribution displacement, and an element count ratio.

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