Record Linking

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Objectives

1) Problem definition → Identify
   - Informal problem definition
   - Formal problem statement
2) A somewhat general solution → Implementation
   - Logistic Regression Theory
   - Mechanics
3) Practical tips → Successful / Painless Implementation
   - Various complications and compromises

What is record linking?

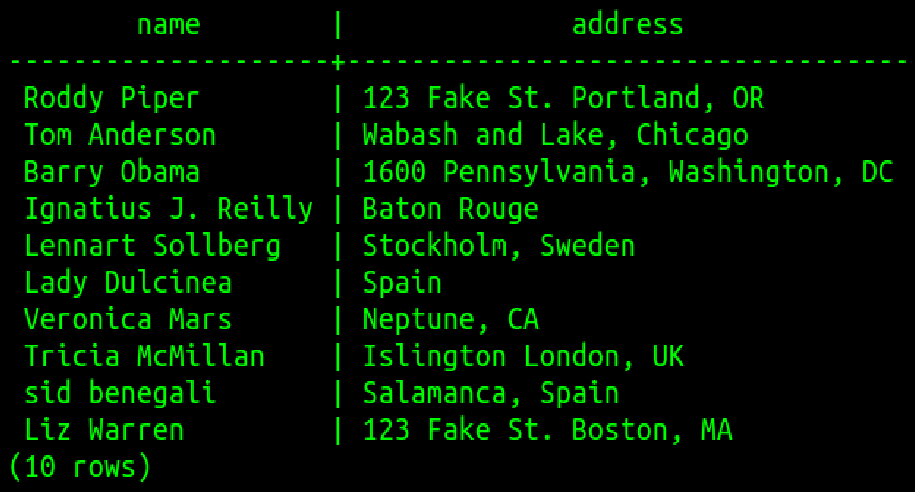
- Database Context
  - Two or more records, referencing the same entity, without a key.
- General Statement (Wikipedia)
  - “Record linkage refers to the task of finding records in a data set that refer to the same entity across different data sources. Record linkage is necessary when joining data sets based on entities that may or may not share a common identifier.”

https://en.wikipedia.org/wiki/Record_linkage

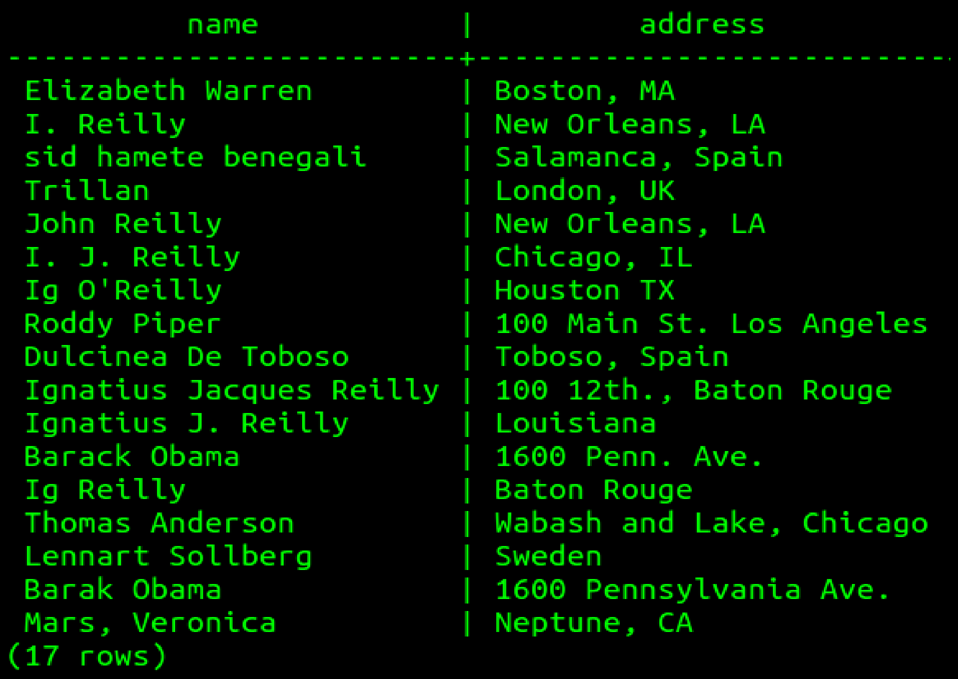
Common Experience

We'll draft requirements for joining tables without foreign keys,
.... and on data sets without natural keys.

Concrete Example: Two Tables



```
       name        |              address
-------------------+----------------------------------
 Roddy Piper       | 123 Fake St. Portland, OR
 Tom Anderson      | Wabash and Lake, Chicago
 Barry Obama       | 1600 Pennsylvania, Washington, DC
 Ignatius J. Reilly | Baton Rouge
 Lennart Sollberg  | Stockholm, Sweden
 Lady Dulcinea     | Spain
 Veronica Mars     | Neptune, CA
 Tricia McMillan   | Islington London, UK
 sid benegali      | Salamanca, Spain
 Liz Warren        | 123 Fake St. Boston, MA
(10 rows)
```



```
          name           |         address
-------------------------+--------------------------
 Elizabeth Warren        | Boston, MA
 I. Reilly               | New Orleans, LA
 sid hamete benegali     | Salamanca, Spain
 Trillan                 | London, UK
 John Reilly             | New Orleans, LA
 I. J. Reilly            | Chicago, IL
 Ig O'Reilly             | Houston TX
 Roddy Piper             | 100 Main St. Los Angeles
 Dulcinea De Toboso      | Toboso, Spain
 Ignatius Jacques Reilly | 100 12th., Baton Rouge
 Ignatius J. Reilly      | Louisiana
 Barack Obama            | 1600 Penn. Ave.
 Ig Reilly               | Baton Rouge
 Thomas Anderson         | Wabash and Lake, Chicago
 Lennart Sollberg        | Sweden
 Barak Obama             | 1600 Pennsylvania Ave.
 Mars, Veronica          | Neptune, CA
(17 rows)
```

One of the oldest problems facing civilization

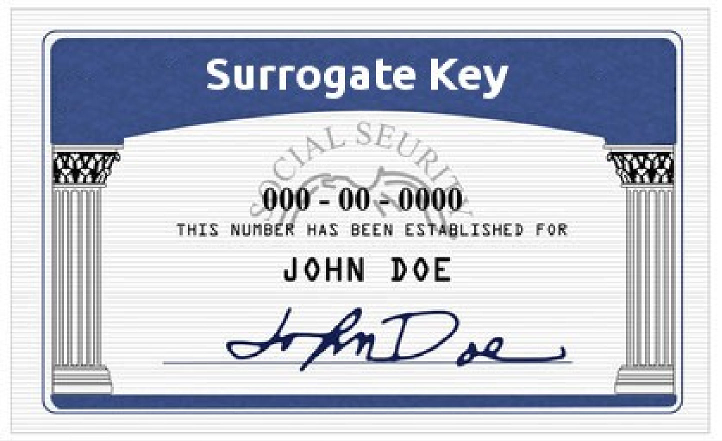
- 1946 article titled "Record Linkage" published in the American Journal of Public Health.
- Census as statecraft
  - Censuses in Egypt are said to have been taken during the early Pharaonic period in 3340 BCE and in 3056 BCE
  - US Census research

How Problem Emerges for Census

- Counting People
- Varied Data Sources:
  - Interviews
  - Mailed Surveys
  - Birth Certificates
  - Marriage Records
  - Death Records

The Many-faced Problem

- Typically Entities in data model
  - Companies
  - Buildings
  - People
  - Documents



- Typically arises from different data sources
  - User entries
  - Transcription errors
  - Divergent data sets (split brain)
  - Application Developers
- No natural Key
- Candidate keys include a set of possible values, including transcription and spelling errors
- Text

Duplicates Case

```
          name           |             address
-------------------------+-----------------------------------
 I. J. Reilly            | Chicago, IL
 Roddy Piper             | 100 Main St. Los Angeles
 John Reilly             | New Orleans, LA
 Tom Anderson            | Wabash and Lake, Chicago
 Lennart Sollberg        | Stockholm, Sweden
 Lennart Sollberg        | Sweden
 sid hamete benegali     | Salamanca, Spain
 Elizabeth Warren        | Boston, MA
 Dulcinea De Toboso      | Toboso, Spain
 Barak Obama             | 1600 Pennsylvania Ave.
 Thomas Anderson         | Wabash and Lake, Chicago
 Barack Obama            | 1600 Penn. Ave.
 Veronica Mars           | Neptune, CA
 Ignatius J. Reilly      | Louisiana
 Tricia McMillan         | Islington London, UK
 Ig Reilly               | Baton Rouge
 Ignatius Jacques Reilly | 100 12th., Baton Rouge
 Ignatius J. Reilly      | Baton Rouge
 sid benegali            | Salamanca, Spain
 Liz Warren              | 123 Fake St. Boston, MA
 Roddy Piper             | 123 Fake St. Portland, OR
 Trillan                 | London, UK
 Mars, Veronica          | Neptune, CA
 I. Reilly               | New Orleans, LA
 Lady Dulcinea           | Spain
 Barry Obama             | 1600 Pennsylvania, Washington, DC
 Ig O'Reilly             | Houston TX
```

Name & Conquer

Label the records in table1 as set **A**, and the records in table2 as set **B**.

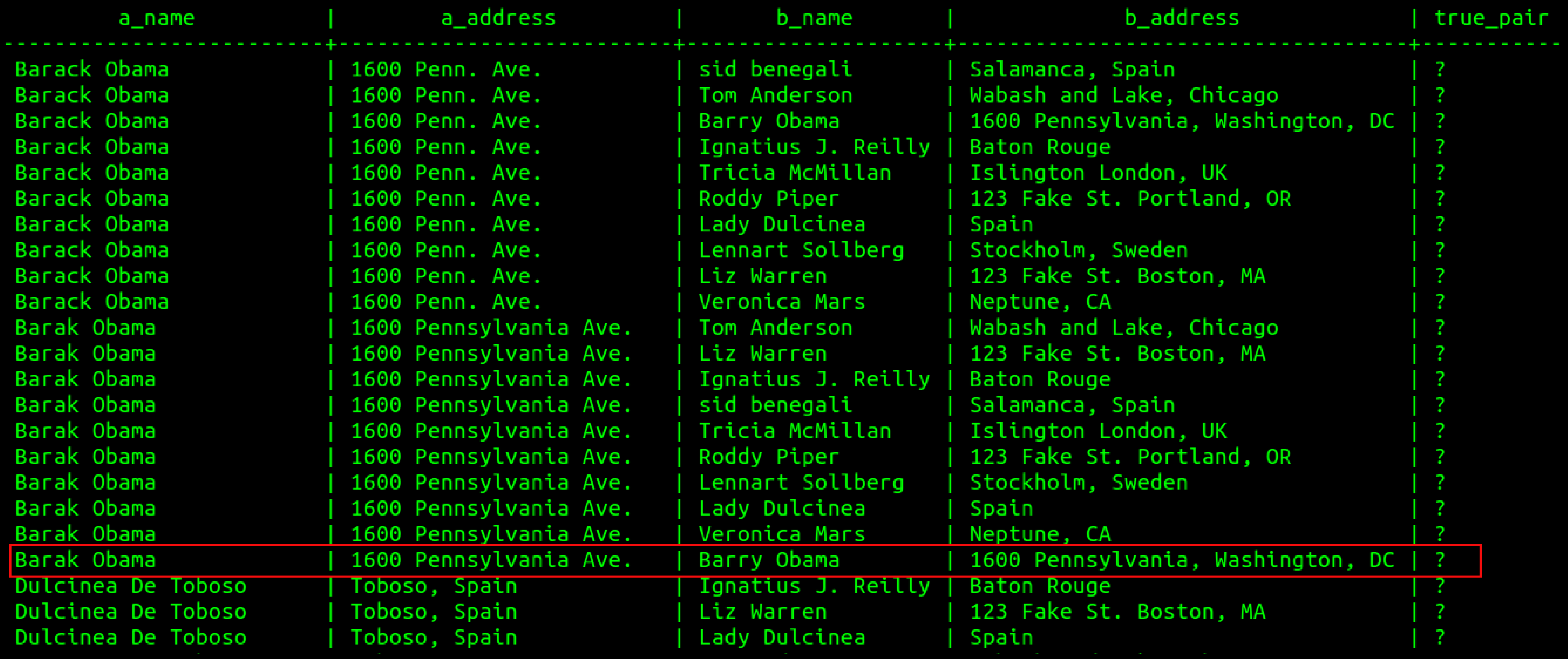
Define a set of possible matches as **A X B**, such that each pair (a∈A,b∈B) is a possible match or non-match.

The set of true pairs is labeled set **T** where (a=b), and the set of false pairs is labeled set **F** where (a≠b).

Solve the problem by distinguishing whether a given pair belongs to set **T** or set **F**.

T and **F** are a partition of **A X B**.

Concrete Pairs



```
         a_name          |         a_address         |       b_name       |             b_address             | true_pair
-------------------------+---------------------------+--------------------+-----------------------------------+-----------
 Barack Obama            | 1600 Penn. Ave.           | sid benegali       | Salamanca, Spain                  | ?
 Barack Obama            | 1600 Penn. Ave.           | Tom Anderson       | Wabash and Lake, Chicago          | ?
 Barack Obama            | 1600 Penn. Ave.           | Barry Obama        | 1600 Pennsylvania, Washington, DC | ?
 Barack Obama            | 1600 Penn. Ave.           | Ignatius J. Reilly | Baton Rouge                       | ?
 Barack Obama            | 1600 Penn. Ave.           | Tricia McMillan    | Islington London, UK              | ?
 Barack Obama            | 1600 Penn. Ave.           | Roddy Piper        | 123 Fake St. Portland, OR         | ?
 Barack Obama            | 1600 Penn. Ave.           | Lady Dulcinea      | Spain                             | ?
 Barack Obama            | 1600 Penn. Ave.           | Lennart Sollberg   | Stockholm, Sweden                 | ?
 Barack Obama            | 1600 Penn. Ave.           | Liz Warren         | 123 Fake St. Boston, MA           | ?
 Barack Obama            | 1600 Penn. Ave.           | Veronica Mars      | Neptune, CA                       | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Tom Anderson       | Wabash and Lake, Chicago          | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Liz Warren         | 123 Fake St. Boston, MA           | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Ignatius J. Reilly | Baton Rouge                       | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | sid benegali       | Salamanca, Spain                  | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Tricia McMillan    | Islington London, UK              | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Roddy Piper        | 123 Fake St. Portland, OR         | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Lennart Sollberg   | Stockholm, Sweden                 | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Lady Dulcinea      | Spain                             | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Veronica Mars      | Neptune, CA                       | ?
 Barak Obama             | 1600 Pennsylvania Ave.    | Barry Obama        | 1600 Pennsylvania, Washington, DC | ?
 Dulcinea De Toboso      | Toboso, Spain             | Ignatius J. Reilly | Baton Rouge                       | ?
 Dulcinea De Toboso      | Toboso, Spain             | Liz Warren         | 123 Fake St. Boston, MA           | ?
 Dulcinea De Toboso      | Toboso, Spain             | Lady Dulcinea      | Spain                             | ?
```

Binary Classification

- The problem is now stated as a binary classification problem which is well understood
- A solution can take the form of a function which returns a probability that a given pair is a true pair.

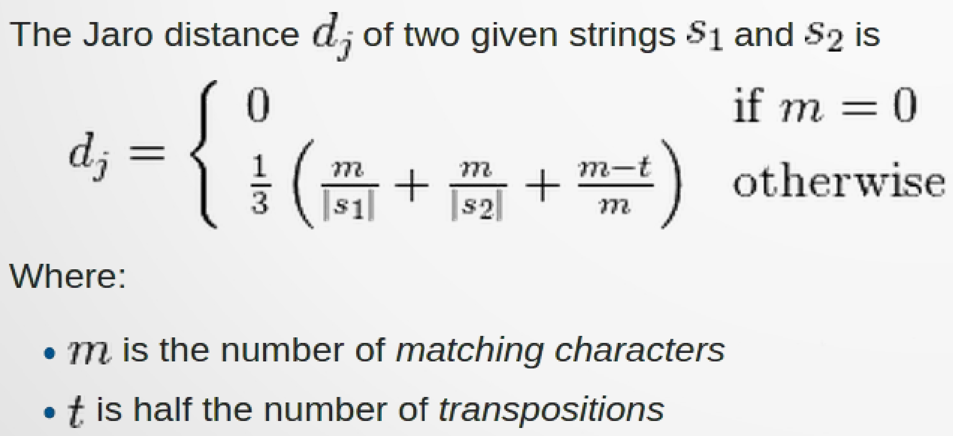
$$P(truepair) = f(a, b)$$

Need an Automated Solution

$$P(truepair) = f(a, b) \neq$$

Simple Solution: Discriminant Metric

- String distance metrics
  - Levenshtein (contrib/fuzzystrmatch)
  - Tri-gram (contrib/pg_trgm)
  - Jaro-Winkler
    - Returns value between 0 and 1
    - Developed for '95 Census

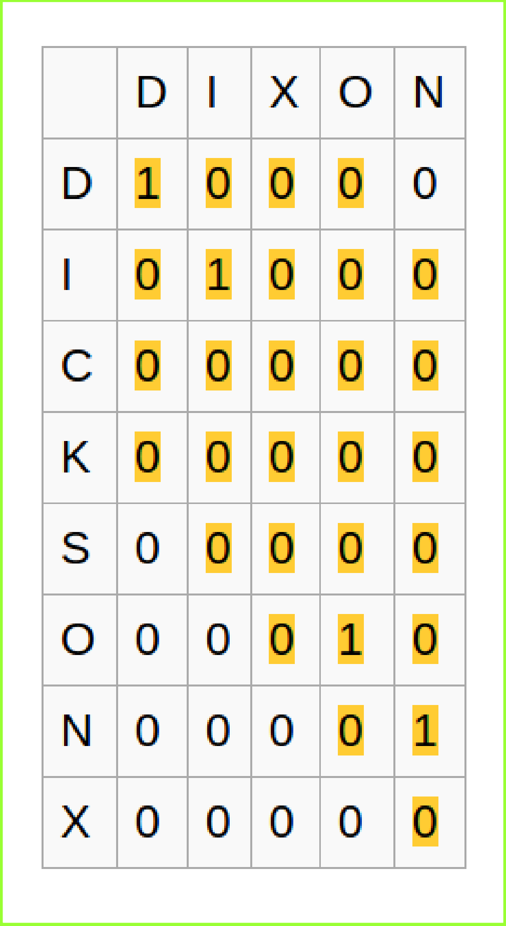


The Jaro distance d_j of two given strings s_1 and s_2 is

$$d_j = \begin{cases} 0 & \text{if } m = 0 \\ \frac{1}{3}\left(\frac{m}{|s_1|} + \frac{m}{|s_2|} + \frac{m-t}{m}\right) & \text{otherwise} \end{cases}$$

Where:

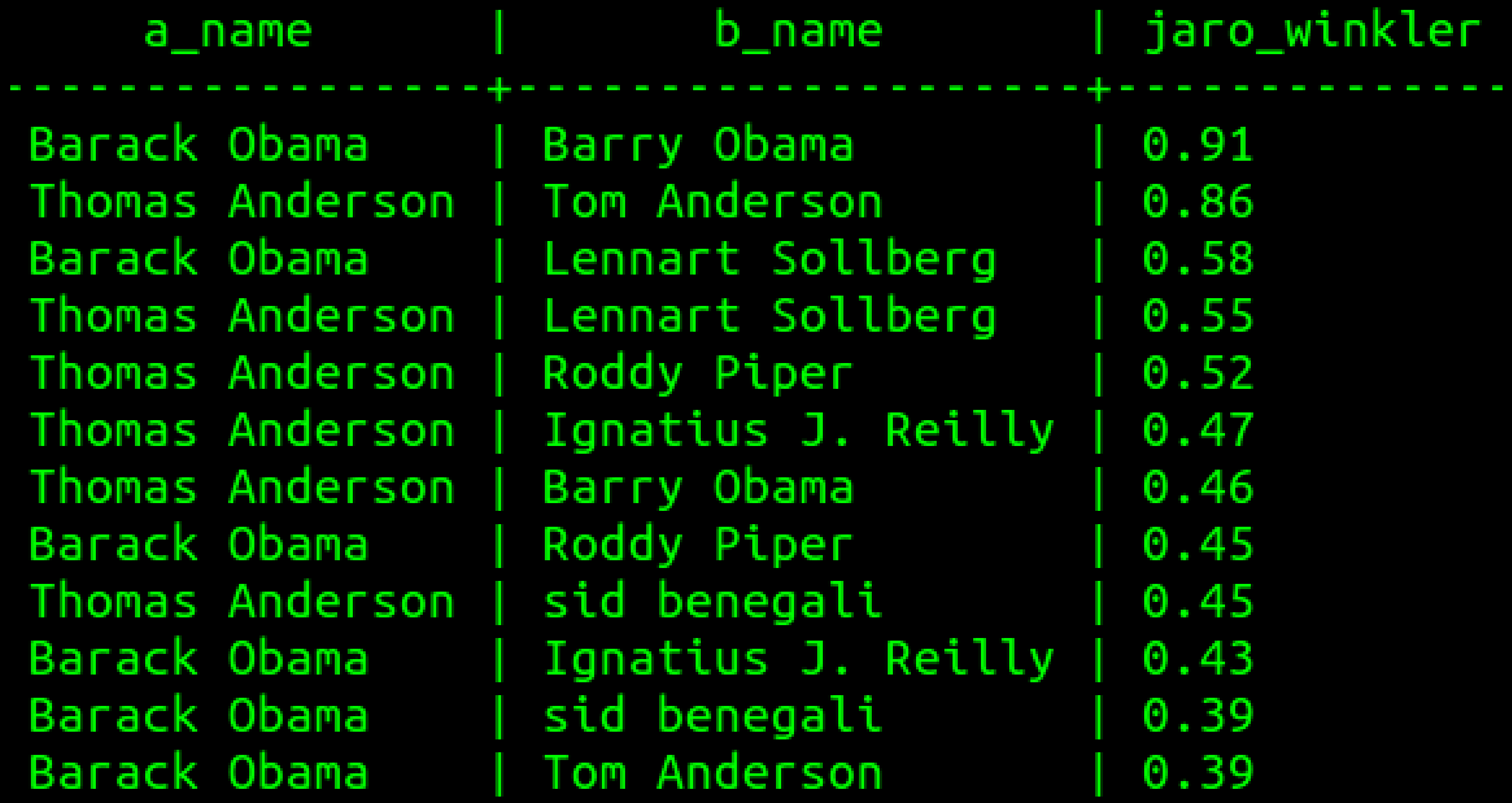
- m is the number of *matching characters*
- t is half the number of *transpositions*



	D	I	X	O	N
D	1	0	0	0	0
I	0	1	0	0	0
C	0	0	0	0	0
K	0	0	0	0	0
S	0	0	0	0	0
O	0	0	0	1	0
N	0	0	0	0	1
X	0	0	0	0	0

https://en.wikipedia.org/wiki/Jaro–Winkler_distance

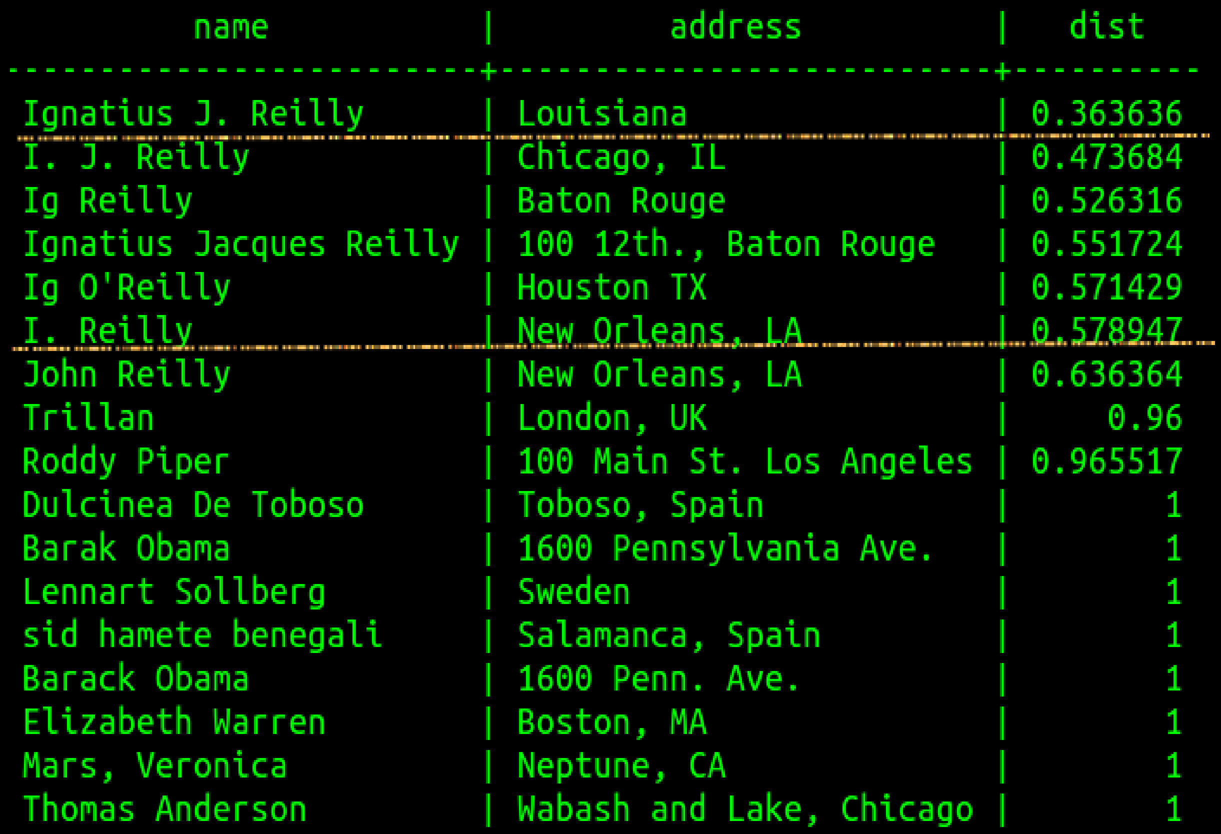
Jaro-Winkler Example



```
      a_name     |        b_name        | jaro_winkler
-----------------+----------------------+--------------
 Barack Obama    | Barry Obama          | 0.91
 Thomas Anderson | Tom Anderson         | 0.86
 Barack Obama    | Lennart Sollberg     | 0.58
 Thomas Anderson | Lennart Sollberg     | 0.55
 Thomas Anderson | Roddy Piper          | 0.52
 Thomas Anderson | Ignatius J. Reilly   | 0.47
 Thomas Anderson | Barry Obama          | 0.46
 Barack Obama    | Roddy Piper          | 0.45
 Thomas Anderson | sid benegali         | 0.45
 Barack Obama    | Ignatius J. Reilly   | 0.43
 Barack Obama    | sid benegali         | 0.39
 Barack Obama    | Tom Anderson         | 0.39
```

pg_trgm Example

- What is the optimal threshold?
- Only leverages information present in text field



```
          name           |         address          |   dist
-------------------------+--------------------------+----------
 Ignatius J. Reilly      | Louisiana                | 0.363636
 I. J. Reilly            | Chicago, IL              | 0.473684
 Ig Reilly               | Baton Rouge              | 0.526316
 Ignatius Jacques Reilly | 100 12th., Baton Rouge   | 0.551724
 Ig O'Reilly             | Houston TX               | 0.571429
 I. Reilly               | New Orleans, LA          | 0.578947
 John Reilly             | New Orleans, LA          | 0.636364
 Trillan                 | London, UK               |     0.96
 Roddy Piper             | 100 Main St. Los Angeles | 0.965517
 Dulcinea De Toboso      | Toboso, Spain            |        1
 Barak Obama             | 1600 Pennsylvania Ave.   |        1
 Lennart Sollberg        | Sweden                   |        1
 sid hamete benegali     | Salamanca, Spain         |        1
 Barack Obama            | 1600 Penn. Ave.          |        1
 Elizabeth Warren        | Boston, MA               |        1
 Mars, Veronica          | Neptune, CA              |        1
 Thomas Anderson         | Wabash and Lake, Chicago |        1
```

Black box Logistic Regression

$$P(truepair) = f(a, b)$$

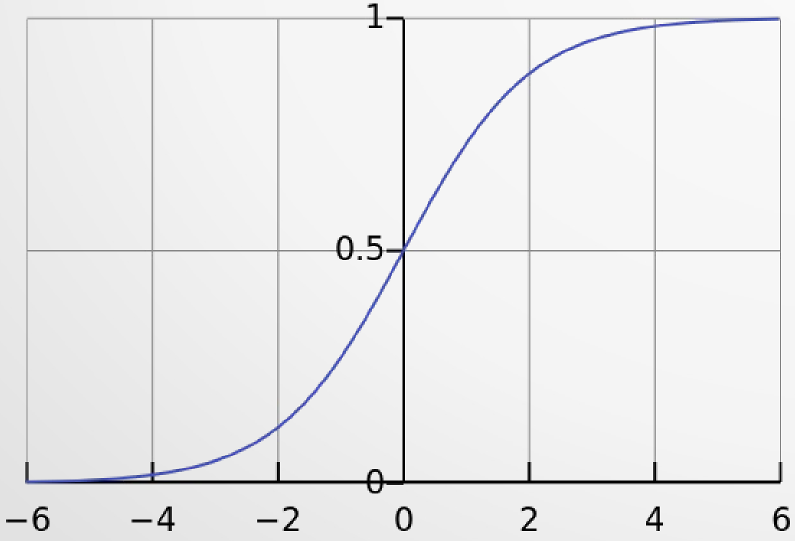
$$P(truepair) = f(x_1, x_2, x_3 \ldots x_n)$$

x_1 = Jaro-Winkler distance of name
x_2 = geospatial distance of addresses
x_3 = Share middle initial

Logistic Regression

$$g(t) = \frac{1}{1 + e^{-t}}$$

$$t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$



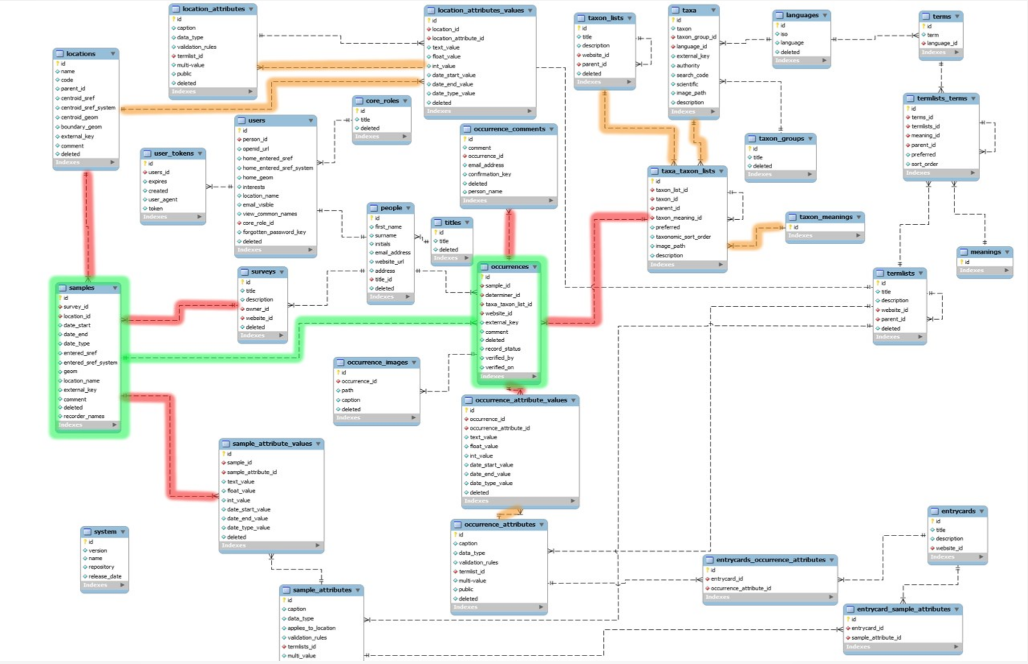
- Binary Classification
- t is a linear function of independent variables
- Returns a probability (number between 0 and 1)
- Widely Implemented
  - Available inside Postgresql through the Madlib extension.
  - http://madlib.net/

Feature Selection

- Choose a number of independent variables (for pairs)
  - x_1, x_2, ...
- Some useful string comparison features

Jaro-Winkler Distance	0-1
Levenshtein Distance	Z
length(Longest Common Substring)	Z
Shared Middle Initial	0/1
Shared n-gram features (Suffix/Prefix)	R
Word Shape	0/1
Binned length delta	Z

Pair Features From Relations



Same Company or Organization	1/0
Date of Activity	Z
Average Topic Distance	R
Geospatial Distance	Whatever ST_Distance returns
Same Phone Number	1/0

Installing Madlib

- pgxnclient install madlib
- Source:
  - https://github.com/madlib/madlib
  - Configure; make
  - madpack -p postgres -c user@0.0.0.0/db install

MADlib®: Big Data Machine Learning in SQL for Data Scientists

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Supports Postgres, Pivotal Greenplum Database™, and Pivotal HAWQ®

Powerful analytics for Big Data

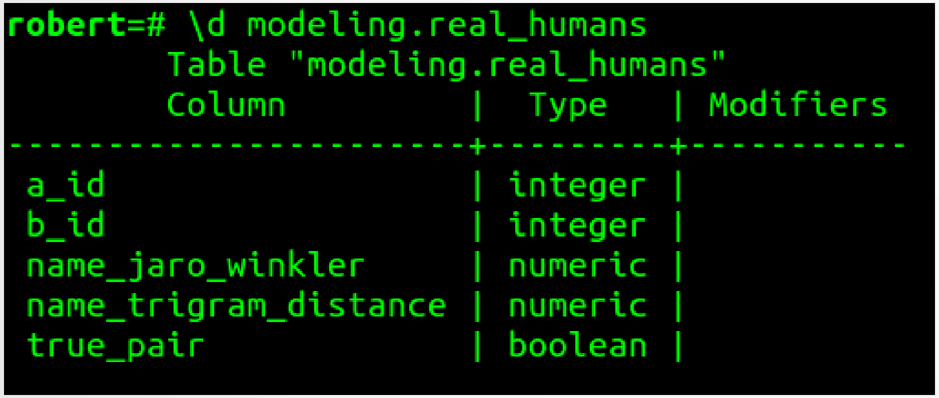
Read More ›

Madlib Modules

- Regression Models
  - Linear
  - logistic
- Tree Models
- Conditional Random Field
- ARIMA
- Latent Dirichlet Allocation
- K-means clustering

- Descriptive Statistics
- Inference
- SVM
- Cardinality Estimators
- Utility Functions
  - Linear algebra operations for arrays as vectors

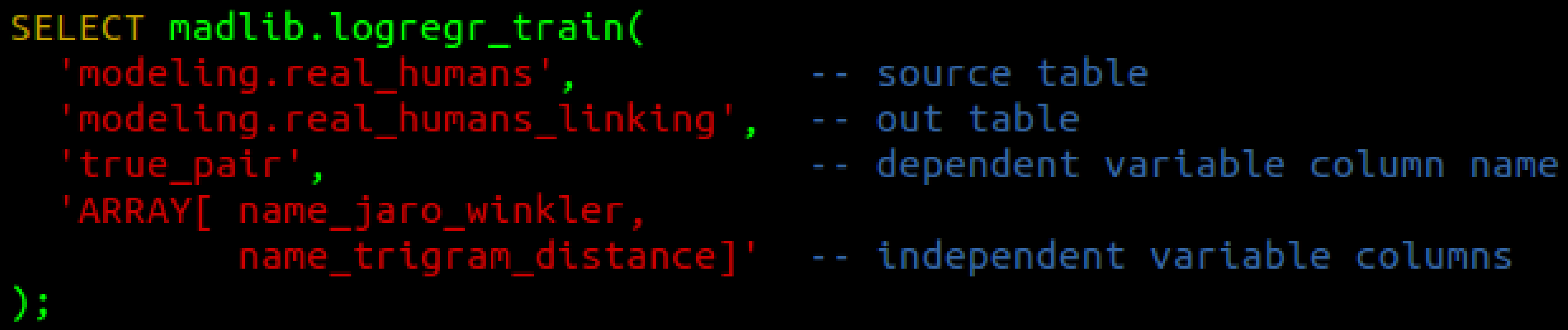
Create Training and Test Sets



```
robert=# \d modeling.real_humans
        Table "modeling.real_humans"
        Column         |  Type   | Modifiers
-----------------------+---------+-----------
 a_id                  | integer |
 b_id                  | integer |
 name_jaro_winkler     | numeric |
 name_trigram_distance | numeric |
 true_pair             | boolean |
```

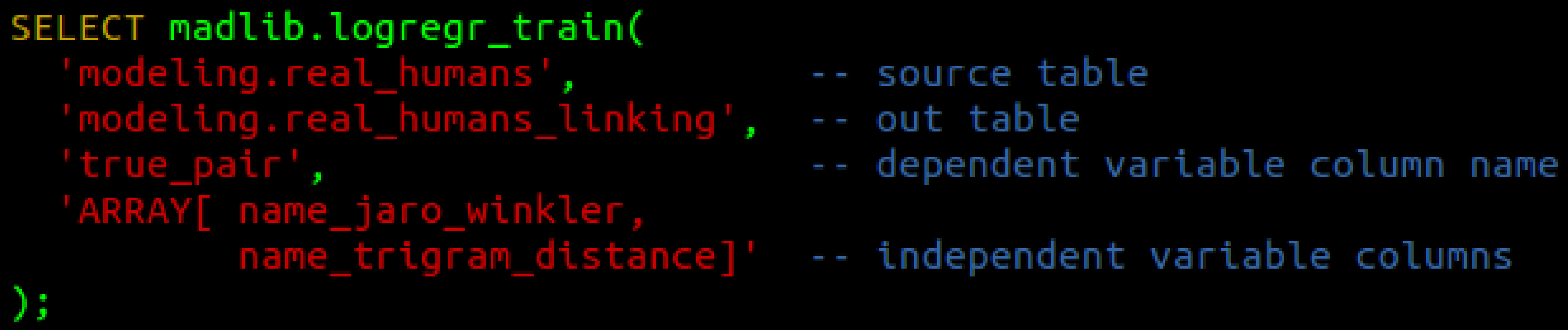
- Create a utility to manually add records
- If available, may be possible to match pairs based on a foreign key.
  - E.g. 20% of company_a and company_b records have an IRS TID you can link on, but still have representative typo and alternative spelling examples.

How To Train Your Model



```
SELECT madlib.logregr_train(
  'modeling.real_humans',             -- source table
  'modeling.real_humans_linking',     -- out table
  'true_pair',                        -- dependent variable column name
  'ARRAY[ name_jaro_winkler,
          name_trigram_distance]'     -- independent variable columns
);
```

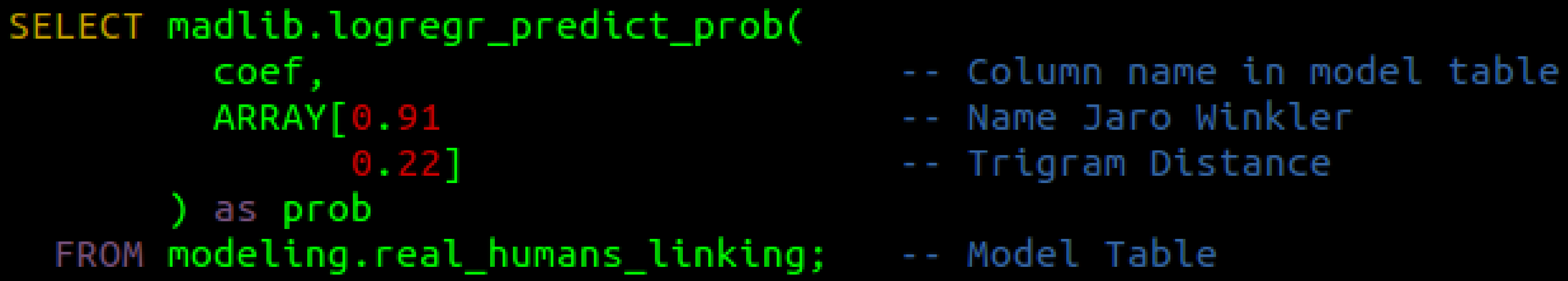
How To Train Your Model



```
SELECT madlib.logregr_train(
  'modeling.real_humans',            -- source table
  'modeling.real_humans_linking',    -- out table
  'true_pair',                       -- dependent variable column name
  'ARRAY[ name_jaro_winkler,
          name_trigram_distance]'    -- independent variable columns
);
```

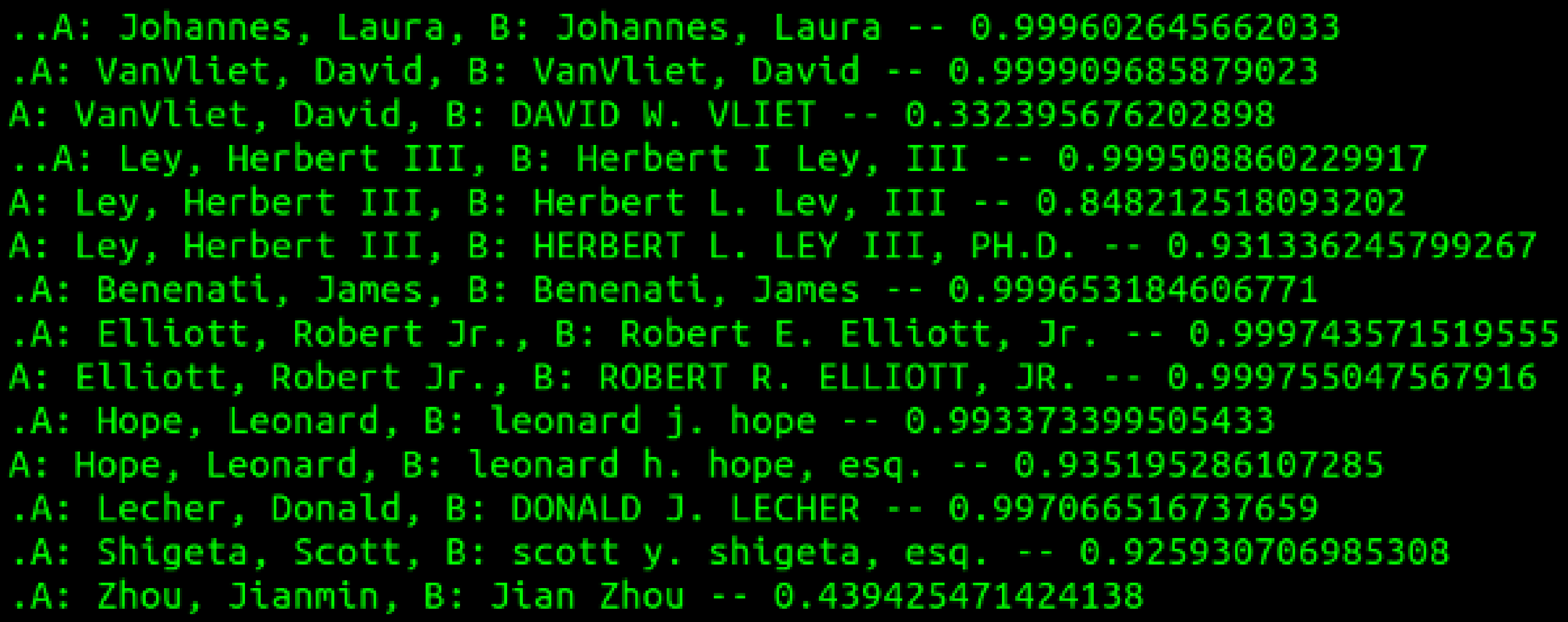
$$t = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

Making Predictions



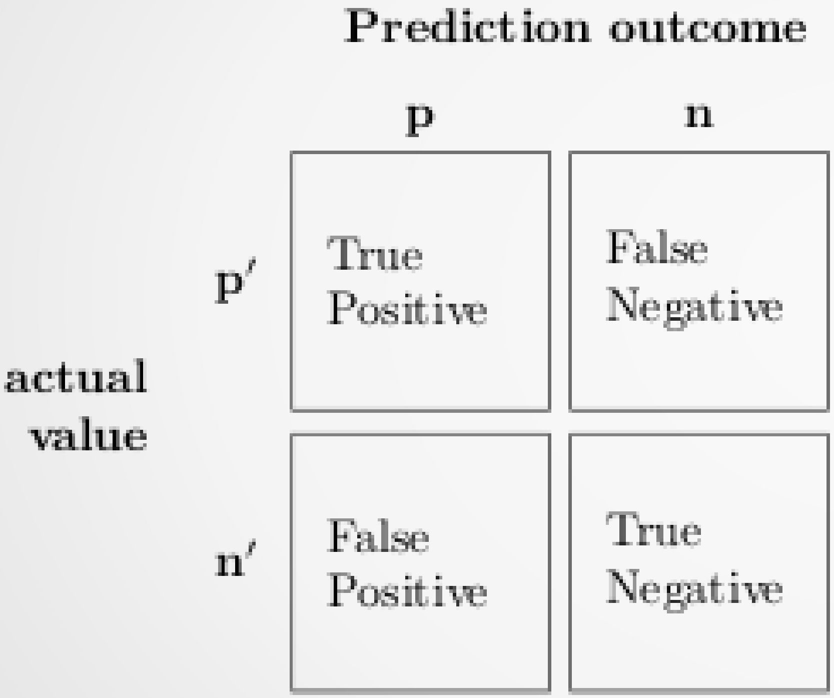
```
SELECT madlib.logregr_predict_prob(
         coef,                         -- Column name in model table
         ARRAY[0.91                    -- Name Jaro Winkler
               0.22]                   -- Trigram Distance
       ) as prob
  FROM modeling.real_humans_linking;   -- Model Table
```

Prediction Examples



```
..A: Johannes, Laura, B: Johannes, Laura -- 0.999602645662033
.A: VanVliet, David, B: VanVliet, David -- 0.999909685879023
A: VanVliet, David, B: DAVID W. VLIET -- 0.332395676202898
..A: Ley, Herbert III, B: Herbert I Ley, III -- 0.999508860229917
A: Ley, Herbert III, B: Herbert L. Lev, III -- 0.848212518093202
A: Ley, Herbert III, B: HERBERT L. LEY III, PH.D. -- 0.931336245799267
.A: Benenati, James, B: Benenati, James -- 0.999653184606771
.A: Elliott, Robert Jr., B: Robert E. Elliott, Jr. -- 0.999743571519555
A: Elliott, Robert Jr., B: ROBERT R. ELLIOTT, JR. -- 0.999755047567916
.A: Hope, Leonard, B: leonard j. hope -- 0.993373399505433
A: Hope, Leonard, B: leonard h. hope, esq. -- 0.935195286107285
.A: Lecher, Donald, B: DONALD J. LECHER -- 0.997066516737659
.A: Shigeta, Scott, B: scott y. shigeta, esq. -- 0.925930706985308
.A: Zhou, Jianmin, B: Jian Zhou -- 0.439425471424138
```

Evaluating the Model



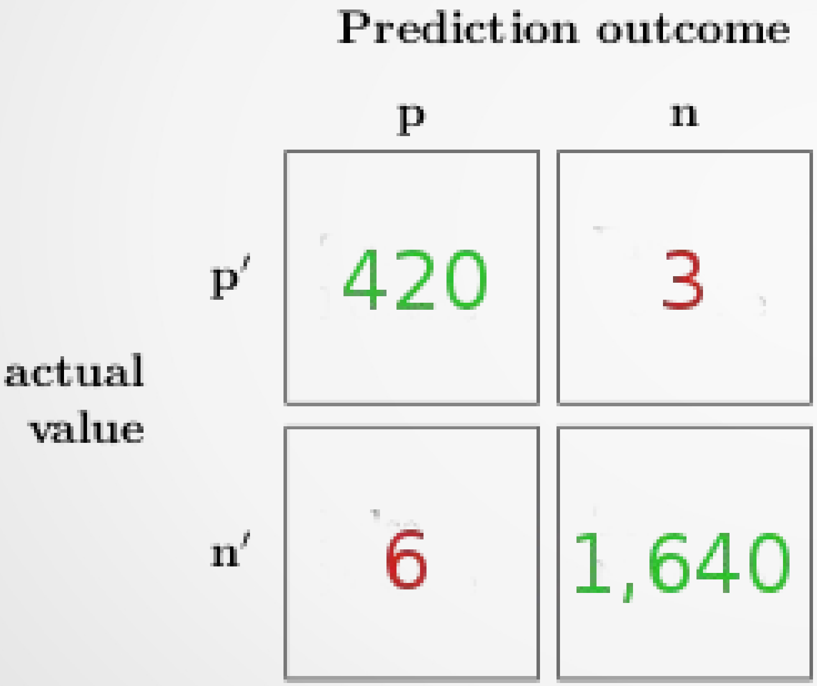
		Prediction outcome	
		p	n
actual value	p'	True Positive	False Negative
	n'	False Positive	True Negative

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Results for “banks” with name and address



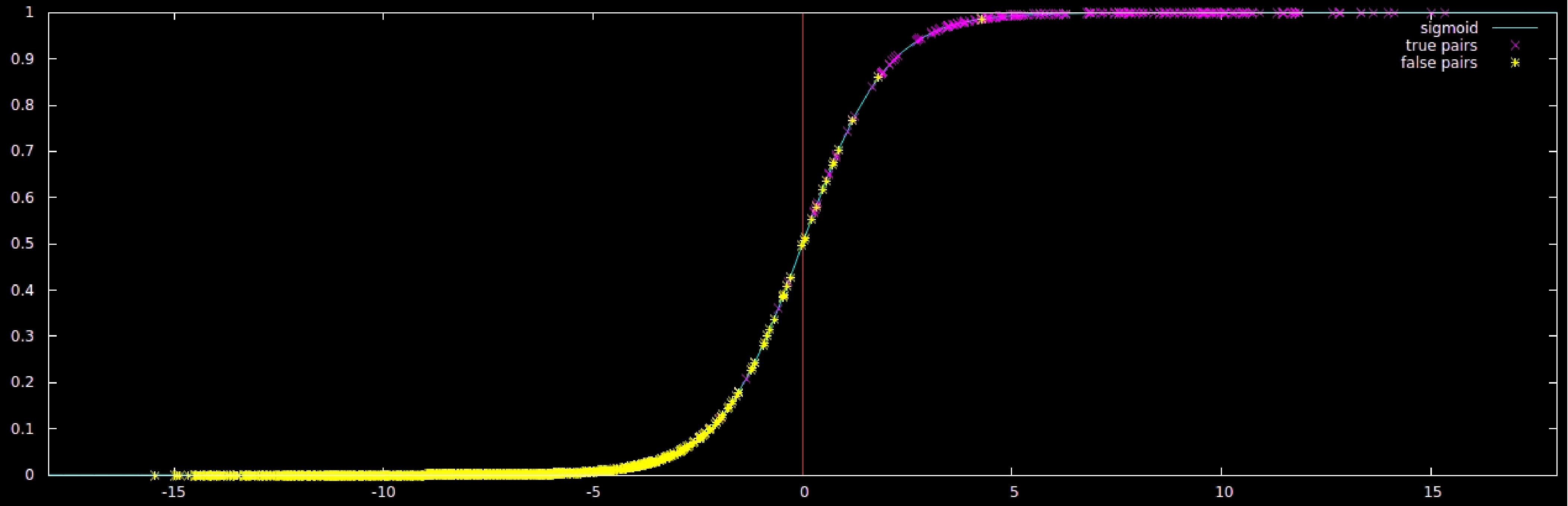
		Prediction outcome	
		p	n
actual value	p'	420	3
	n'	6	1,640

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}=0.995$$

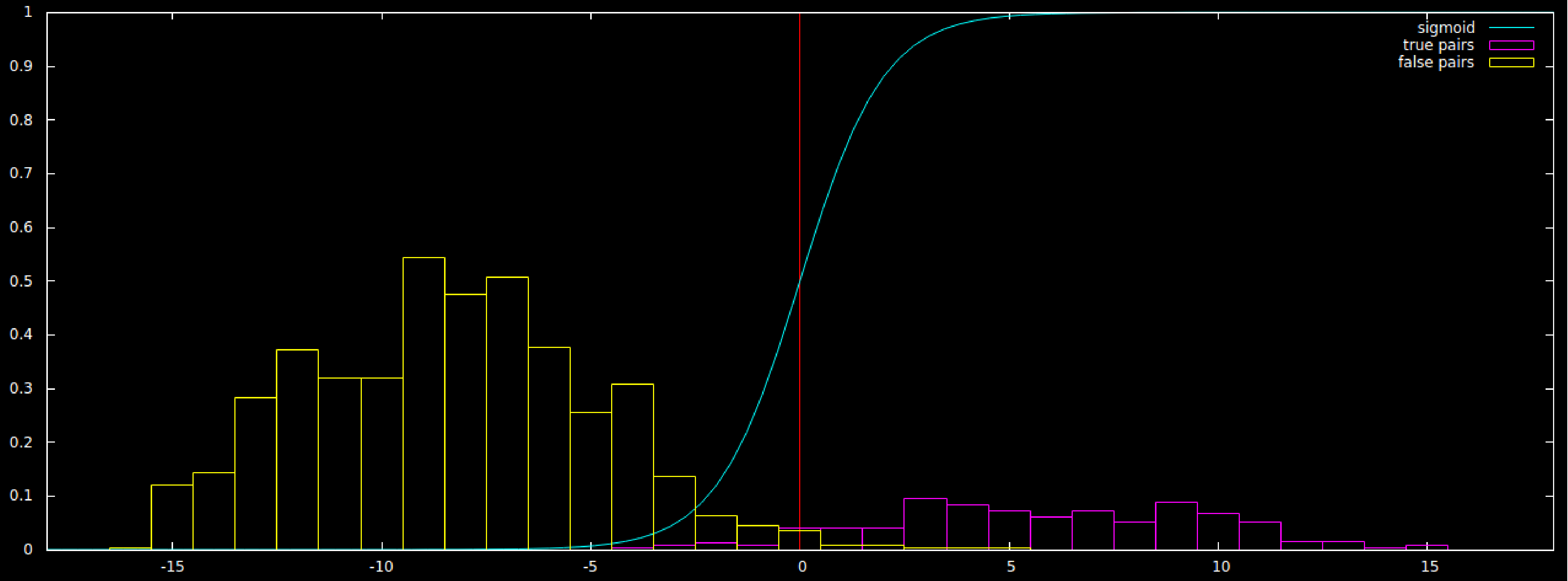
$$Precision=\frac{TP}{TP+FP}=0.985$$

$$Recall=\frac{TP}{TP+FN}=0.992$$

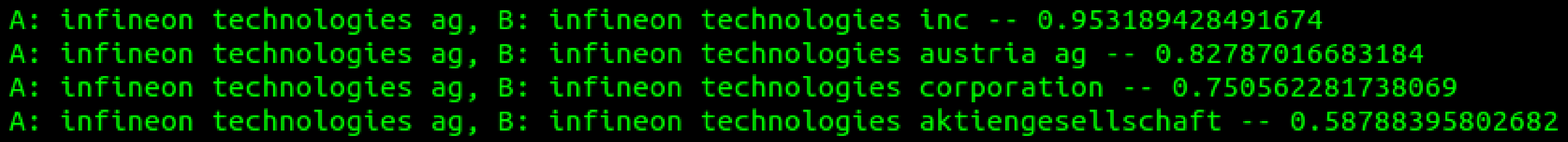
Results Points



Results Distribution

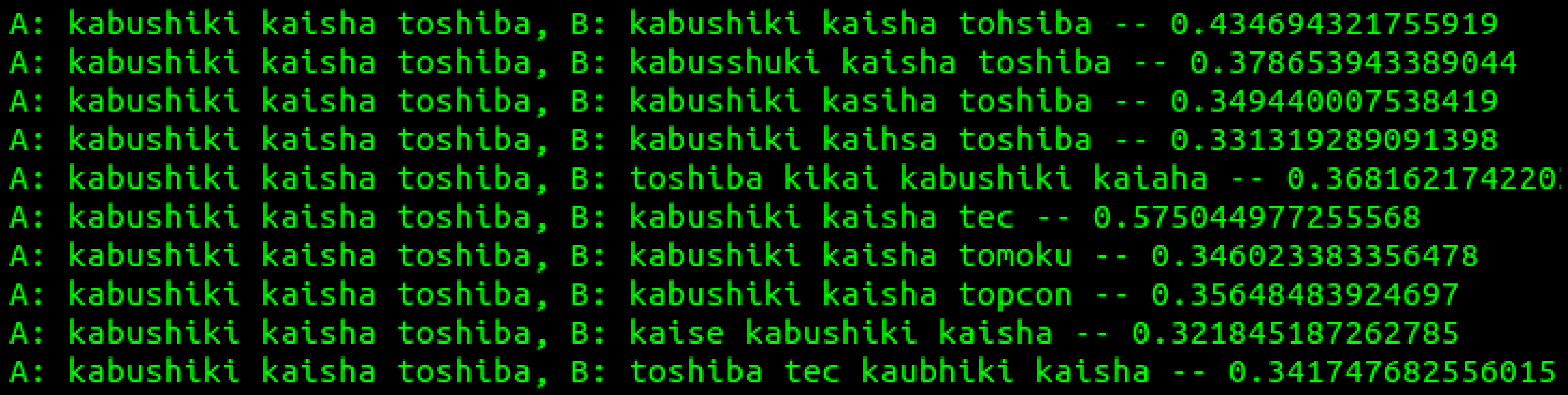


Generic Company Predictions



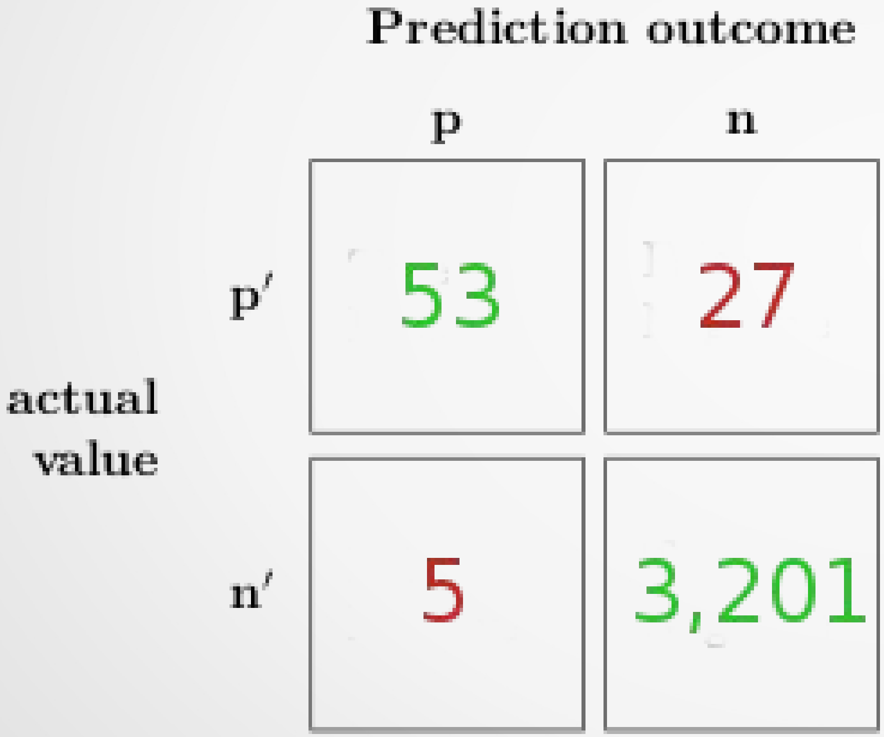
```
A: infineon technologies ag, B: infineon technologies inc -- 0.953189428491674
A: infineon technologies ag, B: infineon technologies austria ag -- 0.82787016683184
A: infineon technologies ag, B: infineon technologies corporation -- 0.750562281738069
A: infineon technologies ag, B: infineon technologies aktiengesellschaft -- 0.58788395802682
```

Less Good Generic Company Predictions



```
A: kabushiki kaisha toshiba, B: kabushiki kaisha tohsiba -- 0.434694321755919
A: kabushiki kaisha toshiba, B: kabusshuki kaisha toshiba -- 0.378653943389044
A: kabushiki kaisha toshiba, B: kabushiki kasiha toshiba -- 0.349440007538419
A: kabushiki kaisha toshiba, B: kabushiki kaihsa toshiba -- 0.331319289091398
A: kabushiki kaisha toshiba, B: toshiba kikai kabushiki kaiaha -- 0.368162174220
A: kabushiki kaisha toshiba, B: kabushiki kaisha tec -- 0.575044977255568
A: kabushiki kaisha toshiba, B: kabushiki kaisha tomoku -- 0.346023383356478
A: kabushiki kaisha toshiba, B: kabushiki kaisha topcon -- 0.35648483924697
A: kabushiki kaisha toshiba, B: kaise kabushiki kaisha -- 0.321845187262785
A: kabushiki kaisha toshiba, B: toshiba tec kaubhiki kaisha -- 0.341747682556015
```

Results for Generic Company Model with Names Only



		Prediction outcome	
		p	n
actual value	p′	53	27
	n′	5	3,201

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}=0.99$$

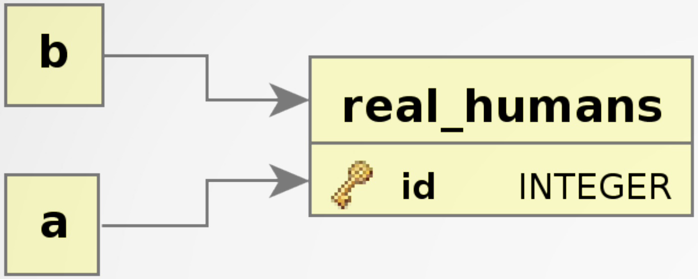
$$Precision=\frac{TP}{TP+FP}=0.914$$

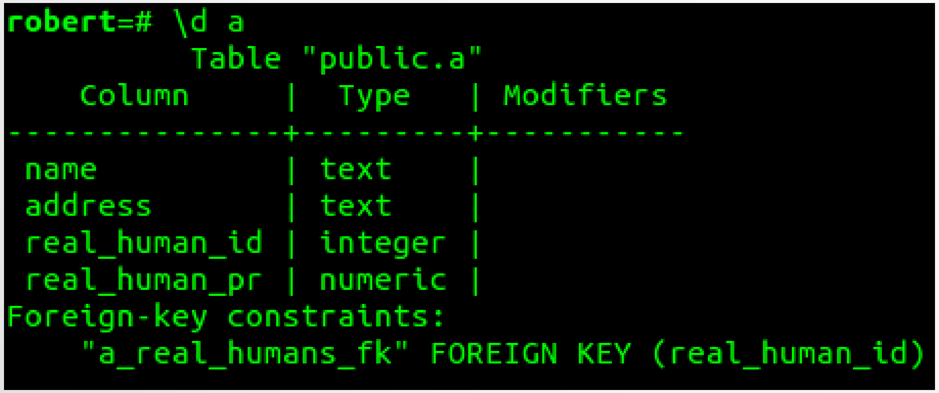
$$Recall=\frac{TP}{TP+FN}=0.662$$

Reviewing Model

```
coef                      | {1.38137269782965,-13.6632183471641,-1.76848128264876,0.64766158726839,0.0573998865389614,-0.0312569439210871}
log_likelihood            | -249.350905991252
std_err                   | {0.138741016539159,1.18221393113242,0.150065718029083,0.0648178241900955,0.0100528699209984,0.010743497686263}
z_stats                   | {9.95648390279572,-11.5573146173944,-11.7847120973094,9.99202912718808,5.70980098121681,-2.90938247802235}
p_values                  | {2.36271390487209e-23,6.77958569393987e-31,4.68016635121174e-32,1.65165583078925e-23,1.13108361062052e-08,0.003621435
12756168}
odds_ratios               | {3.98036171299827,1.16450046633336e-06,0.170591873027232,1.91106673712689,1.05907923725918,0.969226504220616}
condition_no              | 497.892659837498
num_rows_processed        | 9857
num_missing_rows_skipped | 0
num_iterations            | 11
variance_covariance       | {{0.0192490696703191,-0.152411777926995,-0.0107748318067199,-0.000407861281545256,-0.00037803844307969,-6.80469381585
367e-05},{-0.152411777926995,1.39762977896357,0.0555474037277723,0.000307181489771537,0.000515819222603641,0.00226006285334824},{-0.010774831806
7199,0.0555474037277723,0.0225197197275844,-0.0016087075510683,0.000516958963848291,-0.00100206819655989},{-0.000407861281545256,0.0003071814897
71537,-0.0016087075510683,0.00420135033273813,-6.85031548612453e-05,-2.24346225837082e-05},{-0.000378038443079689,0.000515819222603646,0.0005169
58963848291,-6.85031548612453e-05,0.000101060193648514,-5.4170776767714e-05},{-6.8046938158537e-05,0.00226006285334824,-0.00100206819655989,-2.2
4346225837082e-05,-5.4170776767714e-05,0.000115422742534738}}
```

Storing Link Information





```
robert=# \d a
          Table "public.a"
    Column     |  Type   | Modifiers
---------------+---------+-----------
 name          | text    |
 address       | text    |
 real_human_id | integer |
 real_human_pr | numeric |
Foreign-key constraints:
    "a_real_humans_fk" FOREIGN KEY (real_human_id)
```

- Does not require application changes
- Preserves Original Information
- Separates Speculation From Source Data
  - Easy to update
- “Probabilistic Foreign Key” Sounds Cool
- Reasonably Painless Access Pattern
- Duplication and Linking Case
- Pluggable Solutions
- Manual Review

What about that cross product?

- M*N ~ (N^2) pair comparisons to find best match
- Compare only against best candidates
  - Indexable value that can exclude candidates
    - trigram distance
    - Geographic restriction
    - Kmeans cluster id
    - LSH bucket
- Probably OK to have fairly loose comparison set
  - With 100,000,000 records, comparing 100,000,000 * **100** is quite a bit faster than 100,000,000 * 100,000,000.

Practical Tip: like-like comparisons

- Consider linking company pairs.
- Better results if comparing specific subset of companies with targeted features.
  - Banks
  - Blood Banks
- May be worthwhile to first classify records because feasible to easily distinguish between classes.

Practical Tip: Features > 1

- Odds ratios can be difficult to reason about when features are 0 to 1.
- Multiplying by 10 seems to work

Practical Tip: Organizing

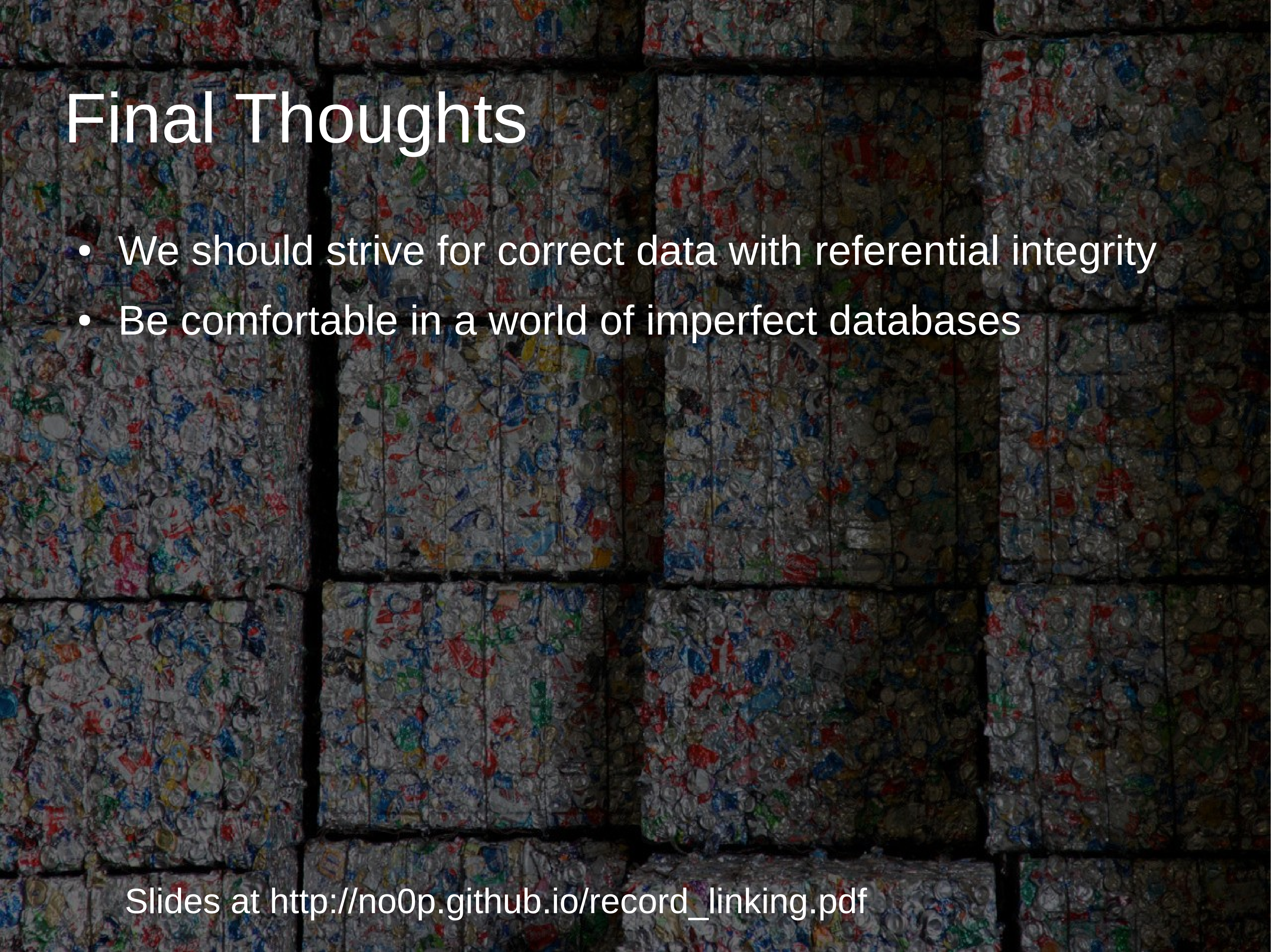
- Leverage Postgresql's data organizing features to organize your training and test data
- Schemas for isolating model tables and training tables
- Materialized views for partitioning examples into training and test sets
  - Tablesample
- Pair surrogate keys allows for generating new features from data relatively painlessly.

Practical Tip: Probabilistic Foreign Key

- Manual review of close calls to minimize human effort
- order by real_humans_pr where real_humans_pr < 0.55

Summary

- Identify Problem as multiple records for same entity without a key
- Set of true pairs in A X B
  - Binary Classification of pairs
- Solve binary classification in Postgresql with Madlib logistic regression module
  - String metric features & features from relations
- Create probabilistic foreign keys
  - Manual review to taste



Final Thoughts

- We should strive for correct data with referential integrity
- Be comfortable in a world of imperfect databases

Slides at http://no0p.github.io/record_linking.pdf