Algorithms For Finding The Bad Guys

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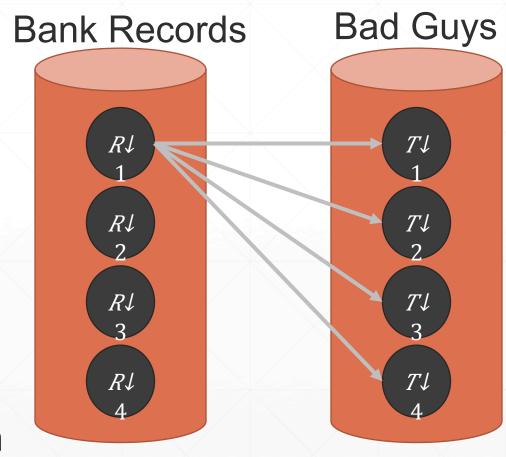
Entity Resolution in Theory

 $P(R \downarrow n \ reprents \ the \ same \ entity \ as \ T \downarrow m)$

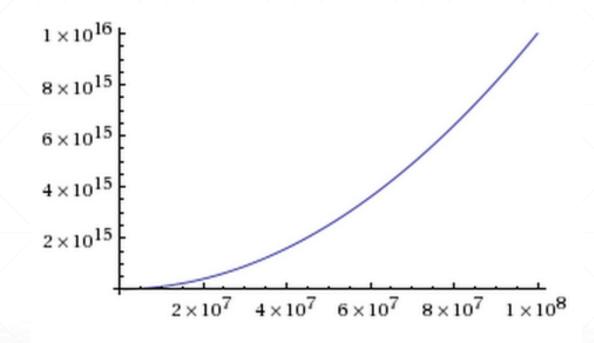
Example Variations:

- Aggregating Products
- Finding Medical Records
- Resolving Paper Authors
- Census
- Finding Bad Guys
- Database Deduping

Different tradeoffs per domain



Too Many Comparisons!



- 100 Million x 100 Million = 10 quadrillion pairs
- 86,400,000 milliseconds per day
- One pair per ms: ~116,000,000 days to compute (~317K years)

How do we beat N*M? Blocking Algorithms.

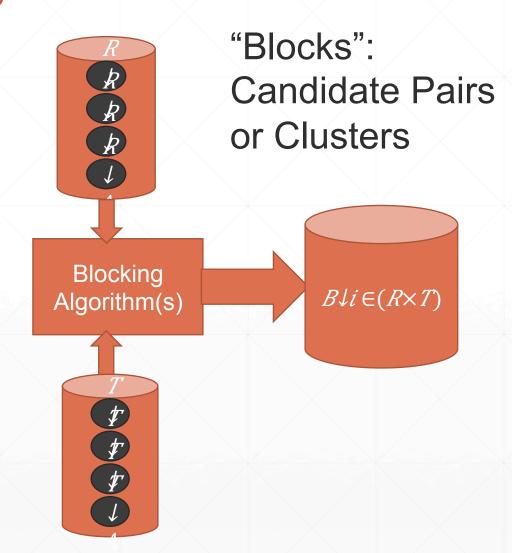
Input:

- Source Records R
- Target Records T

Output:

- Blocks of Similar Records

 $B \downarrow i \in (R \times T)$



Simplest: Key-based Blocking

RecID	GivenName	Surname	Postcode	Suburb
r1	peter	christen	2010	north sydney
r2	paul	smith	2600	canberra
r3	pedro	kristen	2000	sydeny
r4	pablo	smyth	2700	canberra sth

- Nothing's easier than a table lookup!
- Many ways to key, choosing is hard
- Small errors can cause misses
- What about missing data?

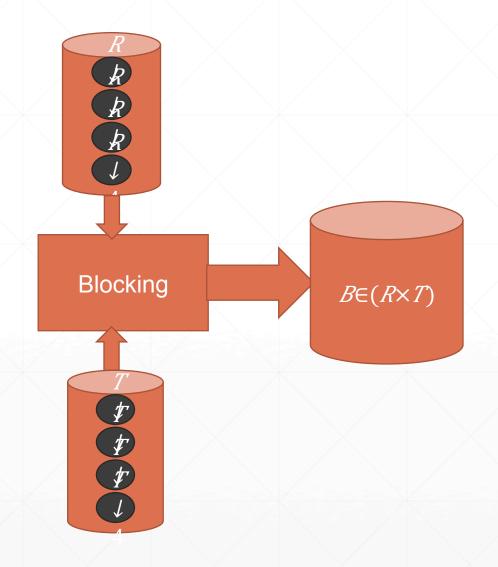
RecID	PC+Sndx(GiN) Fi	2D(PC)+DMe(SurN)	La2D(PC)+Sndx(SubN)
r1	2010-p360	20-krst	10-n632
r2	2600-p400	26-sm0	00-c516
r3	2000-p360	20-krst	00-s530
r4	2700-p140	27-sm0	00-c516

Table: Peter Christen - Data Matching 2012

Many ways to Block

- Sorted Neighborhood
- Suffix Arrays/Trees
- Various kinds of Q-gram Indices
- Metric Space Embedding
- Semantic Hashing
- Cluster-based approaches

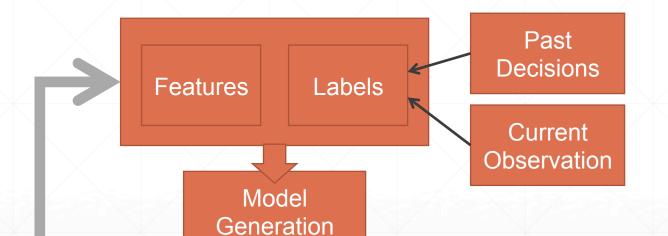
Best to use a mix.



The Basics of Pairwise Scoring

Model

Evaluation



NAME	LARRY O' BRIAN	
STATE	CANADA	
CITY	Montreal	
STATE	Quebec	
ADDRESS	121 Buffalo Drive	
ZIP	H3G 1Z2	
DOB	10/24/80	

- Features on the Similarity of Fields
- Labels on Pairs are True/False
- Standard Machine Learning Techniques Apply

Simplest: Empirical Summed Similarity

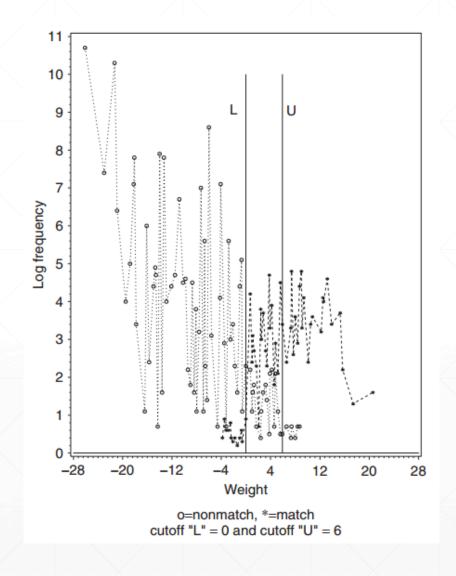
- F: feature functions (0 .. m) : (a,b) -> [0, 1]
- W: feature weights (0 .. m) : {0+}
- $SimSum(a,b) = \sum_{i=0}^{n} f \downarrow_i w \downarrow_i$

Thresholds such that:

Match: SimSum(a,b) >= Upper

Review: Lower <= SimSum(a,b) <= Upper

Discard: SimSum(a,b) <= Lower



The Pairwise Entity Resolution Process

Blocking

- Two Datasets (Customer Data and Sanctions)
- Pairs of Somehow Similar Records

Scoring

- Pairs of Records
- Probability of Representing Same Entity

Review

- Records, Probability, Similarity Features
- True/False Labels (Mostly by Hand)

JOHN DOE MAYORS.GOV Money Laundering RICHARD RO NEWS.COM Risk SENATE.GOV TOM SMITH DICK SMITH Same Person Probability

Another Dimension to aid review: Risk vs Probability

Useful in many domains:

- How Likely To Launder Money?
- How much money do I lose
 if I get the product wrong?
- Risk of Incorrect Medical Diagnosis

Simplest Ranking? You Can "Learn to Rank" with Regression.

- The features are the difference in would-be regression features
- The value to predict is the difference in label rank

Select 2 labeled samples randomly => (x1,y1) (x2,y2)

$$x = x1 - x2$$
$$y = y1 - y2$$

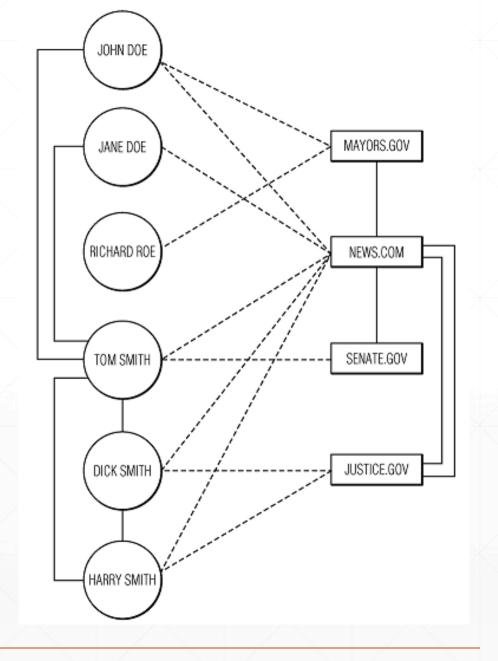
	Sa		mple 1		Sample 2	F	Result	
1	Names?			1		1		0
A	Addresses?			1		0		1
]	DOB?			0		1		-1
3	Same Persor	1?		0	3 X	0		0

Page Rank: The Easy Parts

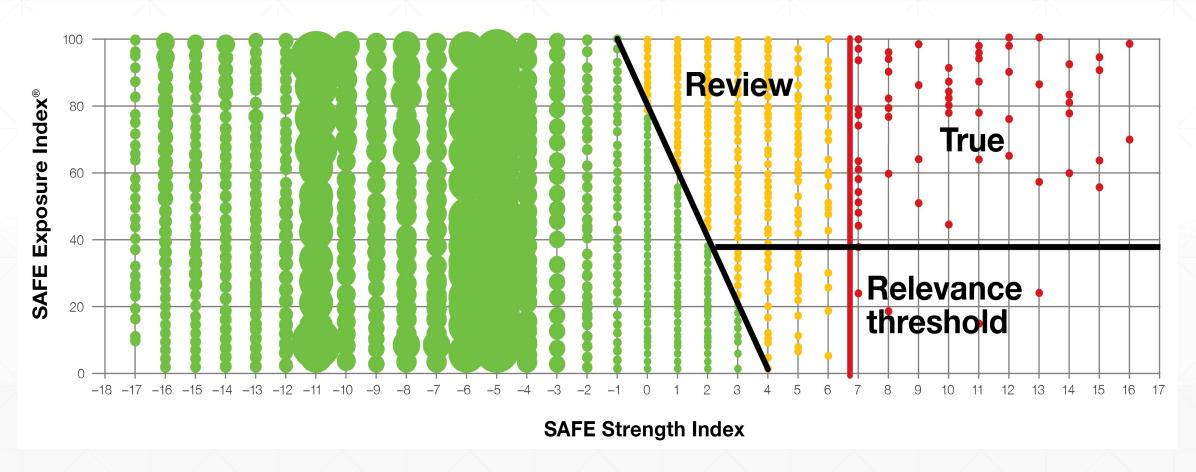
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\mathbf{R} = \begin{bmatrix} (1-d)/N \\ (1-d)/N \\ \vdots \\ (1-d)/N \end{bmatrix} + d \begin{bmatrix} \ell(p_1, p_1) & \ell(p_1, p_2) & \cdots & \ell(p_1, p_N) \\ \ell(p_2, p_1) & \ddots & & \vdots \\ \vdots & & \ell(p_i, p_j) & \\ \ell(p_N, p_1) & \cdots & \ell(p_N, p_N) \end{bmatrix} \mathbf{R}
```

Page Rank: The Hard Parts

- Domains, Websites, Pages in Context
- Determining Initial Risk for Sources
- 27 Pages of Data Transformation Code
- Fluctuation with no changes
- Prediction and Explainability



Combining Ranking and Probability: Big Picture



Thank You! Questions?



You can read more on my blog at: http://richardminerich.com

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Email me with questions:

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Check out the NYC F# User Group:

http://www.meetup.com/nyc-fsharp