Efficient and Scalable Bayesian Bipartite Matching through Fast Beta Linkage (fabl) Google Version

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Table of Contents

- 1 Introduction to Record Linkage
- 2 Fast Beta Linkage
- 3 Simulation Studies
- 4 Conclusion
- 5 Possible Relevance to Google

What is Record Linkage?

- Record linkage is the task of identifying duplicate records over noisy datasets.
- Easy with unique identifiers, difficult when faced with errors
- **Bipartite matching** is the specific goal of matching one record in one dataset to most one match in another dataset

Record Linkage in Practice

Duke TODAY



MAKING SENSE OF SYRIA'S MURKY DEATH TOLL



DNC Announces New National Record Linkage System

APRIL 24, 2020



Algorithm developed by DNC expert in the field of record linkage will increase organizing efficiency by 9 percent and provide campaigns with more comprehensive view of the overall electorate

Linkage for Downstream Analysis

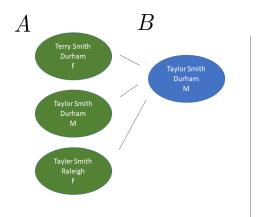
Response Variable	Personal Identification Information		

Personal Identification Information		Covariates		

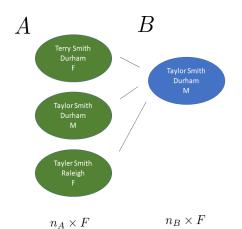
Linkage for Downstream Analysis

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		•		

Linkage through Comparison Vectors

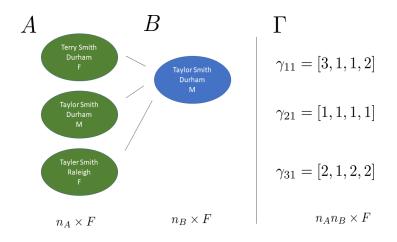


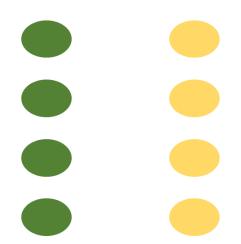
Linkage through Comparison Vectors



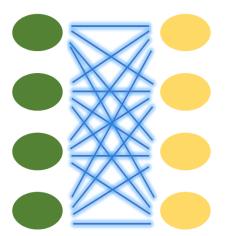
- n_A, n_B records in A, B
- ullet F=4 features for comparison
 - First name
 - Last name
 - City
 - Gender
- $L = \{3, 3, 2, 2\}$ levels of comparison

Linkage through Comparison Vectors

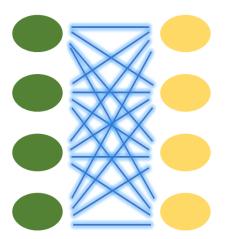




 $n_A n_B$ independent decisions

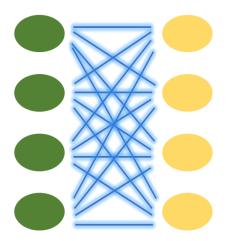


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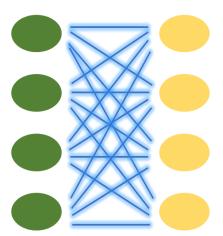
scalable to large
datasets (fastlink,
Enamorado et al
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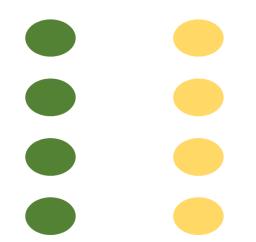


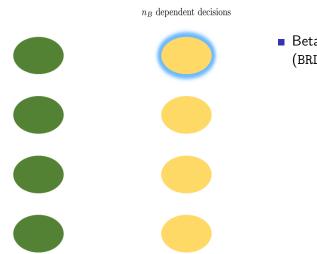
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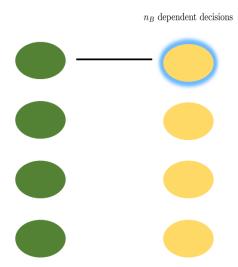
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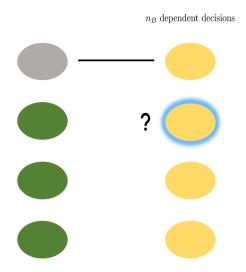


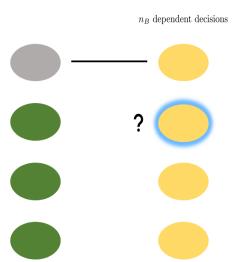
- scalable to large datasets (fastlink, Enamorado et al 2019)
- not bipartite, requires post-processing
- overmatches, leading to inaccurate parameter estimation



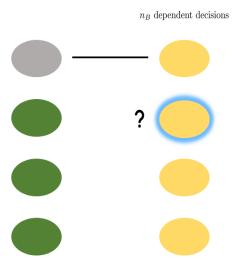




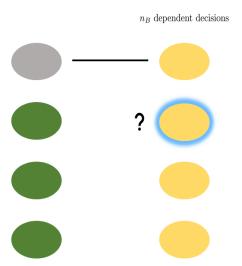




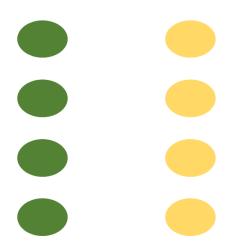
- Beta Record Linkage (BRL)
- strictly enforces one-to-one matching, no post-processing

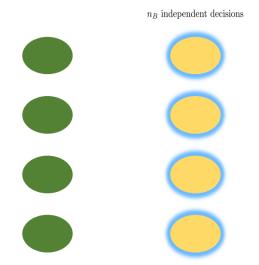


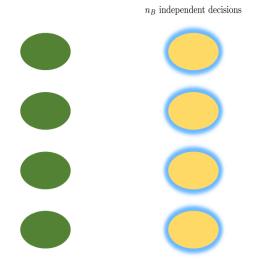
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- strictly enforces one-to-one matching, no post-processing
- high accuracy for linkage and other parameters



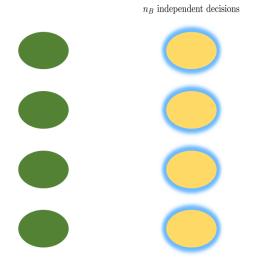
- Beta Record Linkage (BRL)
- strictly enforces one-to-one matching, no post-processing
- high accuracy for linkage and other parameters
- inherently serial, not scalable to large linkage tasks





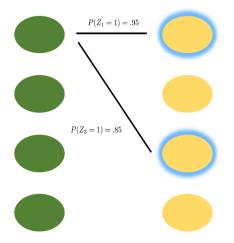


relaxation proposed by Heck Wortman (2019)



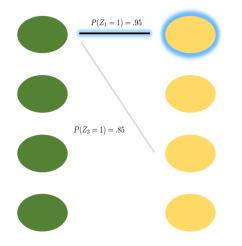
- relaxation proposed by Heck Wortman (2019)
- minimal loss of accuracy, large computational gains





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- allows for "one to many" matchings





- relaxation proposed by Heck Wortman (2019)
- minimal loss of accuracy, large computational gains
- allows for "one to many" matchings
- simple
 postprocessing to
 obtain bipartite
 matching

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Fast Beta Linkage (fabl)

$$\begin{split} P(\Gamma|\mathbf{Z},\mathbf{m},\mathbf{u}) &= \prod_{j=1}^{n_B} \prod_{i=1}^{n_A} \left[\prod_{f=1}^F \prod_{l=1}^{L_f} m_{fl}^{I(Z_j=i)} u_{fl}^{I(Z_j\neq i)} \right]^{I(\gamma_{ij}^f=l)} \\ \mathbf{m_f} &\sim \mathsf{Dirichlet}(\alpha_{f1},\ldots,\alpha_{fL_f}) \\ \mathbf{u_f} &\sim \mathsf{Dirichlet}(\beta_{f1},\ldots,\beta_{fL_f}) \\ Z_j|\pi \begin{cases} \frac{\pi}{n_A} & z_j \leq n_A; \\ 1-\pi & z_j = n_A+1 \end{cases} \\ &\pi \sim \mathsf{Beta}(\alpha_\pi,\beta_\pi) \end{split}$$

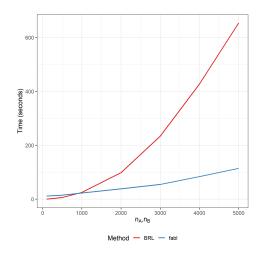
Note: the first three lines are common to many record linkage models, and bear similarities to a larger family of *latent class models*. The last two lines are the newly developed prior distribution for the set of matches.

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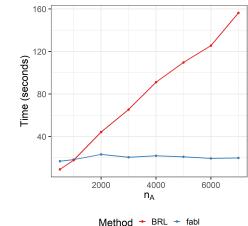
Speed Simulation 1

- F = 5 comparison fields
- L = {2, 2, 2, 2, 2}, all binary comparisons
- 32 possible patterns
- Increase both n_A and n_B



Speed Simulation 2

- F = 5 comparison fields
- $L = \{2, 2, 2, 2, 2\},\$ all binary comparisons
- 32 possible patterns
- Fix $n_B = 500$, increase n_A



Accuracy Simulation

- Sadinle (2017) used 900 simulated linkage tasks to show accuracy of BRL
- Find matches across two datasets, each with 500 records and 4 fields in common.
- One, two or three errors across matching records
- 10% matching, 50% matching, or 90% matching
- Calculate recall, precision, and F-measure

Accuracy Simulation

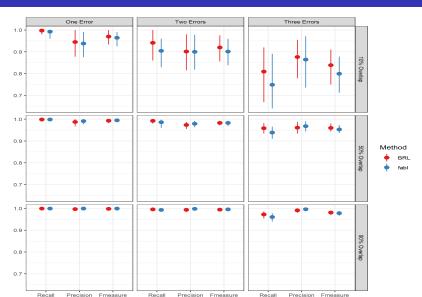


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Benefits of fabl

- Faster computation for larger linkage tasks
- Accurate estimation of linkage structure Z, and additional parameters m and u
- Bayesian model with natural uncertainty quantification

- Can you do record linkage with arbitrary amounts of duplicated files?
- Isn't $n_A \times n_B$ record pairs computationally infeasible?

Can you account situations when the reliability of information differs throughout the data?

Can you do record linkage on the records themselves, rather than transforming to comparison vectors?

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 - Yes! See Aleshin-Guendel and Sadinle (2021)
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 - Yes! See d-blink package from Marchant et al (2021)

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Latent Class Analysis

The record linkage model presented is a special case of a "latent class model". In my work, we attempt to classify record pairs into two distinct classes: matching, and non-matching pairs.

One can imagine however, that we can look at articles instead of records, look at blocks of text instead of record pairs, and look at attributes of those blocks instead of comparison vectors. This may provide a strategy for **entirely unsupervised** byline detection.

Additionally, if model parameters are accurate, we can train the model on a small set of articles, and then apply those parameters out onto a larger set of articles, for nearly instantaneous latent class analysis.