

# End to End Entity Resolution

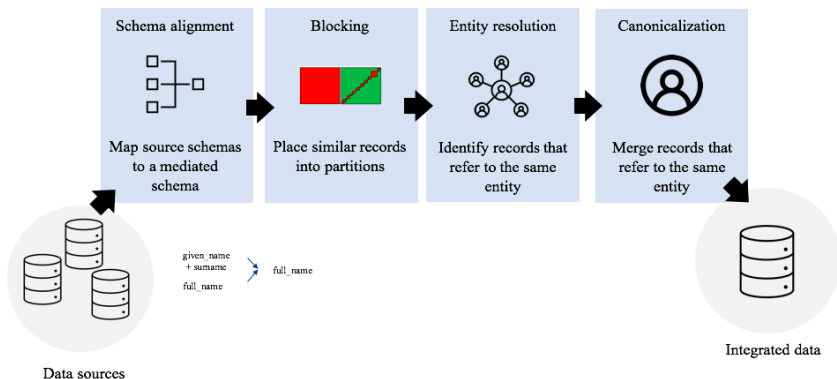
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Duke University and U.S. Census Bureau

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# Data Cleaning Pipeline



# Existing ER methods

- ① deterministic linking
- ② probabilistic linking (Fellegi Sunter, random forests, deep learning)
- ③ Bayesian Fellegi Sunter

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## Drawbacks:

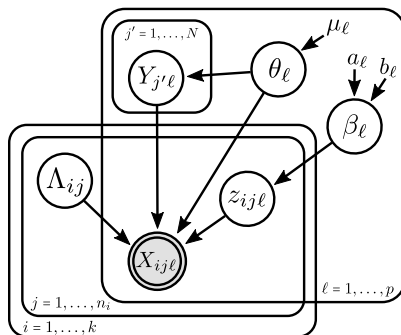
- subjectivity in setting the decision threshold
- lack of uncertainty quantification
- require training data

[Fellegi and Sunter (1969), Ventura et al. (2014), Christen (2012), Dong and Shrivastava (2015), Belin and Rubin (1995), Gutman et al. (2013), McVeigh et al. (2020), Sadinle (2014), Sadinle (2017), Sadinle (2018)].

# Graphical Entity Resolution

# Graphical Bayesian ER

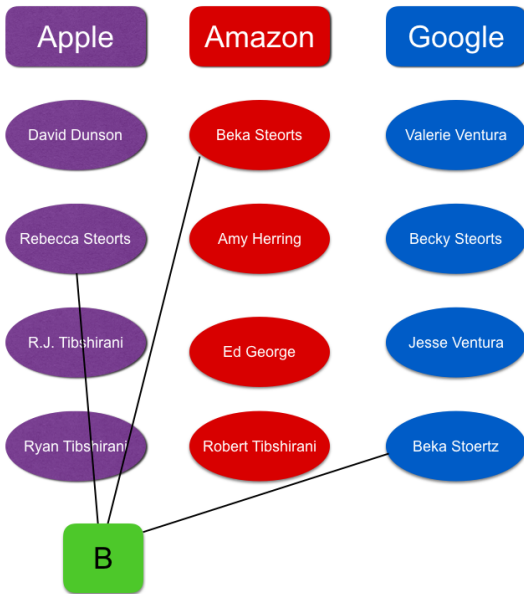
Builds off Copas and Hilton (2001), Tancredi and Liseo (2011).



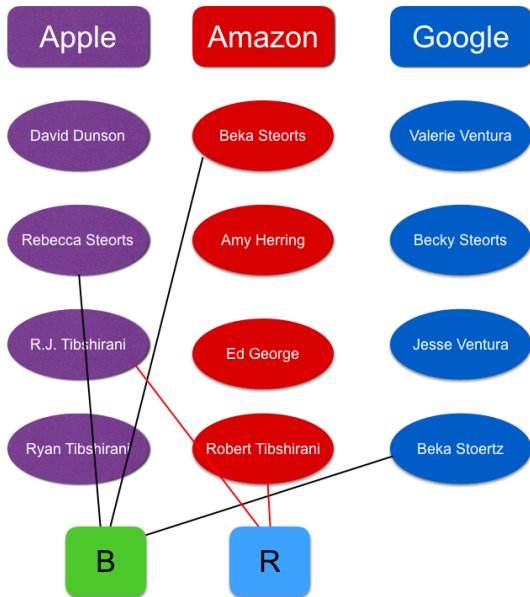
[Steorts+ 2014 AISTATS, Steorts+ 2016 JASA, Steorts 2015 BA]

# Why Graphical Bayesian ER

- 1 Handles any number of databases simultaneously
- 2 Handles both categorical and textual data
- 3 Handles missing data
- 4 Uncertainty quantification is natural
- 5 Transitive closures are nearly free
- 6 Has sound theoretical properties
- 7 Can scale to databases that contain millions of records
- 8 Generalizes to a wide variety of applications
- 9 Has equivalent or better performance than alternatives
- 10 All software is open source and freely available to non-profits







# Our Goal

To scale Bayesian ER methods to millions of records without sacrificing accuracy and provide uncertainty of the ER task

We propose a scalable joint (Bayesian) model for blocking and performing entity resolution, where the error from this joint task is measured exactly.

# Problem setup

Key assumptions:

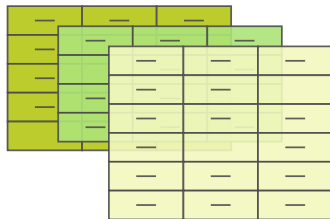
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- duplicates within and across tables
- attributes are aligned
- attributes are discrete
- some missing values
- no ground truth (unsupervised)



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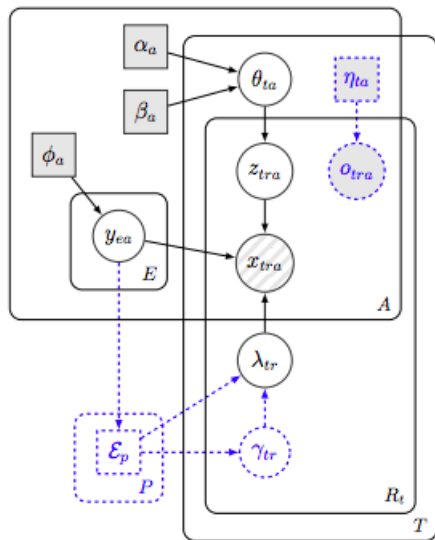
Output: approximate posterior distribution over the linkage structure

# Our contribution

- 1 We propose a joint Bayesian model for blocking (latent entities) and entity resolution.
- 2 We propose blocks (auxiliary partitions) that induce conditional independencies between the latent entities. This enables distributed inference at the partition-level.
- 3 The blocking function (responsible for partitioning the entities) groups similar entities together while achieving well-balanced partitions.
- 4 Application of partially-collapsed Gibbs sampling in the context of distributed computing.
- 5 Improving computational efficiency:
  - a) Sub-quadratic algorithm for updating links based on indexing.
  - b) Truncation of the attribute similarities.
  - c) Perturbation sampling algorithm for updating the entity attributes, which relies on the Vose-Alias method.

[Marchant, Kaplan, Rubinstein, Elazar, Steorts (2021)]

# dblink



# Distributed Markov chain Monte Carlo

Since the posterior for the linkage structure  $p(\Lambda|X)$  is not tractable, we resort to **approximate inference**.



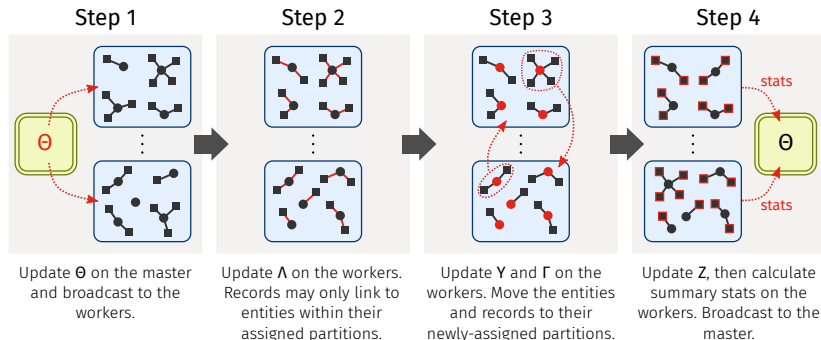
# Distributed Markov chain Monte Carlo

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We propose an MCMC algorithm based on the **partially-collapsed Gibbs** framework (van Dyk and Park, 2008):

- regular Gibbs updates for the distortion probabilities  $\theta_{ta}$ , distortion indicators  $z_{tra}$  and links  $\lambda_{tr}$
- “marginalization” and “trimming” are applied to jointly update the entity attributes  $y_{ea}$  and the partition assignments for the linked records
- order of the updates is important (to preserve the stationary distribution)

# Distributed Markov chain Monte Carlo



# Tricks for speeding up inference

Two main bottlenecks:

- ① linkage structure update  $\mathcal{O}(\# \text{ records} \times \# \text{ entities})$
- ② entity attribute update  $\mathcal{O}(\# \text{ entities} \times \text{domain size})$

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Solutions:

- ① Indexing: Maintain indices from “entity attributes  $\rightarrow$  entities” and “entities  $\rightarrow$  linked records.” This allows us to prune candidate links for a record
- ② Thresholding similarity scores
- ③ Express the distribution for the entity attribute update as a two-component perturbation mixture model

# Experiments

- ABSEmployee. A synthetic data set used internally for linkage experiments by the ABS.
- NCVR. Two snapshots from the North Carolina Voter Registration database taken two months apart.
- NLTCs. A subset of the National Long-Term Care Survey comprising the 1982, 1989 and 1994 waves.
- SHIW0810. A subset from the Bank of Italy's Survey on Household Income and Wealth comprising the 2008 and 2010 waves.
- RLdata10000. A synthetic data set provided with the RecordLinkage R package.

# Experiments

- Implemented dblink and baselines in Apache Spark
- Ran experiments on a local server and Amazon EMR
- (Mostly) used a sample size of  $10^3$  after burnin (of  $10^3$  iterations) and thinning (keeping every 10th iteration)
- 3 real and 2 synthetic data sets

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Data set	# records	# tables	# entities	# attributes	
				categorical	string
★ ABSEmployee	600,000	3	400,000	4	0
NCVR	448,134	2	296,433	3	3
NLTCS	57,077	3	34,945	6	0
SHIW0810	39,743	2	28,584	8	0
★ RLdata10000	10,000	1	9,000	2	3

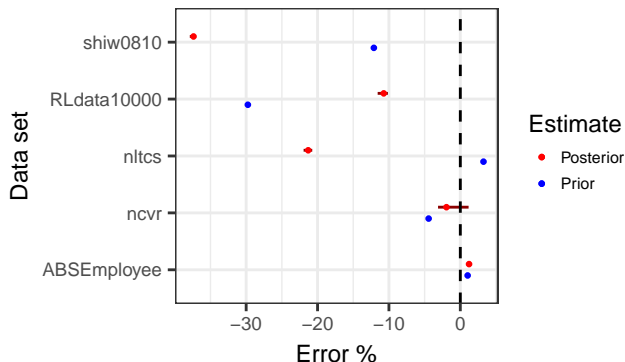
**Table 1:** Assessment of the pairwise linkage performance for dblink and FS method as our baseline. We note that FS is supervised and does not propagate the entity resolution error exactly compared to dblink.

Data set	Method	Pairwise measure		
		Precision	Recall	F1-score
ABSEmployee	dblink	<b>0.9943</b>	<b>0.8867</b>	<b>0.9374</b>
	Fellegi-Sunter (100)	0.9964	0.9510	0.9736
	Fellegi-Sunter (10)	0.4321	0.6034	0.9736
NCVR	dblink	<b>0.9179</b>	<b>0.9654</b>	<b>0.9411</b>
	Fellegi-Sunter (100)	0.8989	0.9974	0.9456
	Fellegi-Sunter (10)	0.8989	0.9974	0.9456
NLTC	dblink	<b>0.8363</b>	<b>0.9102</b>	<b>0.8717</b>
	Fellegi-Sunter (100)	0.7969	0.9959	0.8853
	Fellegi-Sunter (10)	0.1902	0.9999	0.3196

[Marchant+ (2021) JCGS]



# Posterior Bias Plot

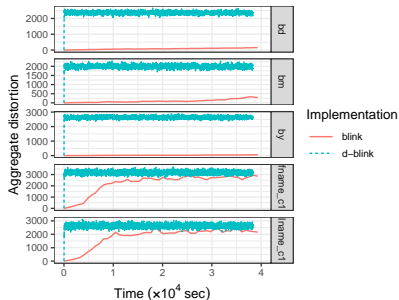
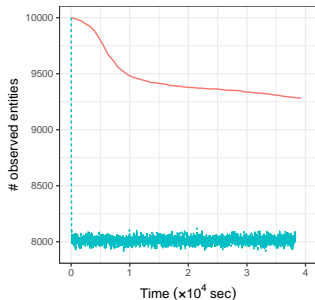


**Figure 1:** Error in the posterior and prior estimates for the number of observed entities for d-blink. The results show that the posterior estimate is very sharp and typically underestimates the true number, which is consistent with Steorts, Hall, Fienberg (2016).

[Marchant+ (2021) JCGS]

# Convergence of d-blink versus blink

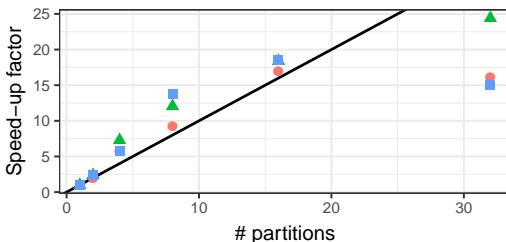
We examined the rate of convergence of d-blink versus blink on RLdata10000 without partitioning.



d-blink converges rapidly, however blink fails to reach the equilibrium distribution within 11 hours.

# Does partitioning result in efficiency gains?

- Measure efficiency using **ESS rate**—the effective sample size generated per unit time
- **Speed-up factor** is the ESS rate relative to a baseline without partitioning
- Observe a near-linear speed-up for the NLTCs data set (tapering off beyond  $\sim 20$  partitions)



Summary stat.

- # observed entities
- attribute distortion
- cluster size distribution

# Case Study Applied to the 2010 Decennial Census

**Table 2:** Results for ER of 2010 Census and Numident data in Wyoming. Pairwise evaluation measures are computed using ground truth identifiers available for a subset of the records, where the unadjusted count was reported to be 563,626.

Pairwise measures			Posterior population size	
Precision	Recall	F1-score	Mean	Std. error
0.97	0.84	0.90	616,000	5,000

[Marchant+ (2021) JCGS]

Thank you!  
Questions?

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Webpage: [resteorts.github.io](https://resteorts.github.io)

Binette and Steorts Review Article  
Entity Resolution Software  
Entity Resolution Tutorial